Communicative Competence:

Computational Simulation Approach to Public Emergency Management

by

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ABSTRACT

Public risk communication (i.e. public emergency warning) is an integral component of public emergency management. Its effectiveness is largely based on the extent to which it elicits appropriate public response to minimize losses from an emergency. While extensive studies have been conducted to investigate individual responsive process to emergency risk information, the literature in emergency management has been largely silent on whether and how emergency impacts can be mitigated through the effective use of information transmission channels for public risk communication.

This dissertation attempts to answer this question, in a specific research context of 2009 H1N1 influenza outbreak in Arizona. Methodologically, a prototype agent-based model is developed to examine the research question. Along with the specific disease spread dynamics, the model incorporates individual decision-making and response to emergency risk information. This simulation framework synthesizes knowledge from complexity theory, public emergency management, epidemiology, social network and social influence theory, and both quantitative and qualitative data found in previous studies. It allows testing how emergency risk information needs to be issued to the public to bring desirable social outcomes such as mitigated pandemic impacts.

Simulation results generate several insightful propositions. First, in the research context, emergency managers can reduce the pandemic impacts by increasing the percent of state population who use national TV to receive pandemic information to 50%. Further increasing this percent after it reaches 50%

brings only marginal effect in impact mitigation. Second, particular attention is needed when emergency managers attempt to increase the percent of state population who believe the importance of information from local TV or national TV, and the frequency in which national TV is used to send pandemic information. Those measures may reduce the pandemic impact in one dimension, while increase the impact in another. Third, no changes need to be made on the percent of state population who use local TV or radio to receive pandemic information, and the frequency in which either channel is used for public risk communication.

This dissertation sheds light on the understanding of underlying dynamics of human decision-making during an emergency. It also contributes to the discussion of developing a better understanding of information exchange and communication dynamics during a public emergency and of improving the effectiveness of public emergency management practices in a dynamic environment.

To my parents,

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for their love and support

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Introduction

Public emergency management or emergency management (EM) is “the discipline and profession of applying science, technology, planning and management to deal with extreme events that can injure or kill large numbers of people, do extensive damage to property, and disrupt community life” (Hoetmer, 1991, p. xvii).[1] Despite there are many ways to describe the importance of EM, it hardly seems necessary today to explain the value of a discipline and profession whose purpose is protecting lives and property in public emergencies. The increasing number and variety of public emergencies that are plaguing the world today promote the visibility and significance of EM.

In the United States, EM has been conceptualized as an essential role of government (Giuffrida, 1985; Wilson & Oyola-Yemaiel, 2001). As a discipline and profession, it emerges in the 1950s (Drabek & McEntire, 2003; Dynes & Drabek, 1992). A command and control approach since then has been adopted as the mainstream approach in public administration (PA) field to address EM issues. According to this approach, the goal of EM is to regain control over the social chaos created by an emergency and to reestablish social order (Dynes, 1983, 1989). Public EM system should be developed as a highly bureaucratic system, which is characterized by clearly defined objectives, a formal structure, a division of labor, and a set of guiding policies (Schneider, 1992). Management strategies

[1] This dissertation focuses only on the research and practices of EM in the field of public administration. Studies and practices of EM in private sectors are not considered. Within this study, public emergency management can also be simply called emergency management.

within this system mainly include centralized decision-making and communication, and the strict implementation of pre-planned operating protocol and procedures (Britton, 1986, 1989, 1991).

Over time many EM researchers have realized the ineffectiveness of this approach to address EM issues, despite its consistent and wide application. The highly bureaucratic EM system developed under this approach is designed to operate under stable and routine conditions (Schneider, 1992). Such a system inevitably becomes mismatched and ineffective in the rapidly changing circumstances of a public emergency. The dynamic nature of the environment requires a different approach than the traditional framework. This dissertation attempts to address some of those limitations in current EM literature in PA filed, by focusing on public risk communication during public emergencies (i.e., public emergency warning).

Public Risk Communication as an Important EM Issue

The crucial role public risk communication plays in EM has long been recognized by both academics and practitioners (Garnett & Kouzmin, 2007; Leibinger, 1980; Williams, 1964). Historical evidence has showed a community with the help of effective public risk communication can greatly reduce the potential consequences of an emergency (Drabek & Stephenson, 1971; Mileti & Sorense, 1990; Perry & Lindell, 2003a). It is therefore not surprising that many studies in the earliest research in EM area focused on the effectiveness of public risk communication (Drabek, 1969; Quarantelli, 1954; Williams, 1957). Meanwhile, practicing emergency managers have also been sharply reminded the missteps in public risk communication by the well-documented failed attempts in the 2001 anthrax risk communication debacle (Koplan, 2003; Reynolds & Seeger, 2005), the 2003 and 2004 flu vaccine shortages (CDC, 2004; Gilk, 2007), and the 2005 resident evacuation prior to Hurricane Katrina and subsequent flooding (Brodie et al., 2006; Wang & Kapucu, 2007). To improve the effectiveness of current public risk communication practices motivates this dissertation to focus on this issue among all other important issues in public emergency management.

In the EM field, the term of public risk communication is rarely used. Most studies in this field use the term of public emergency warning or public warning to refer to the transmission of messages to individuals, groups, or populations which provide them with information about the existence of danger and what can be done to prevent, avoid, or minimize the danger (Williams, 1964; Lindell & Perry, 1992; Reynolds, 2005). This dissertation uses these three terms interchangeably. Furthermore, the term of risk when used in studies of public risk communication in EM can be defined as "a condition in which there is a possibility that persons or property could experience adverse consequences" (Lindell, Prater, & Perry, 2005, p.84).

Traditionally, public risk communication during public emergencies is addressed through a 'command and control' centralized effort. Both researchers and practitioners in this area considered public risk communication as a linear, top-down and expert-to-lay process (Gladwin et al., 2007; Gutteling, 2001). The main concern for them is the top-down influence on direct preparedness and response orders, as well as the capacity and application of different communication technologies involved. Emergency managers in practice are preoccupied by a technical focus, particularly the interoperability of mechanical devices, such as radio, cell phones, and satellite telephone networks. With the successive failure of the traditional model to communicate emergency risk to the public and to elicit their appropriate response, EM researchers are challenged to reconsider the process of public risk communication.

To meet such a challenge, an extensive number of studies in EM have been conducted to explore the process of public risk communication. Most of these studies believe the most important aspect of the process lies in its social and human component, particularly how the warning target population responds to risk information and how public risk communication can facilitate timely and proper response. On the one hand, empirical findings have been provided to evaluate the traditional model emergency managers subscribe to for public risk communication practices. On the other hand, substantial and systematic knowledge has been accumulated regarding how individuals perceive and respond to risk information in emergency situations. These studies also provide important insights on the design of emergency risk information to encourage desirable public response.

While such knowledge has significantly influenced previous public risk communication practices in EM, some limitations remain: 1) few insights have been provided on how emergency risk information should be sent to the public; 2) little is known about how individuals use information for decision-making during their response process to emergency risk information; 3) little attention has been paid to how public response pattern to emergency risk information at the system or community level emerges; and 4) few studies have considered risk communication during emergencies as a dynamic process, through which public sectors and the public interact with each other through information exchange.

These limitations, while not overlooked, are made persistent concerns in public risk communication in EM, due to the methodological flaws inherent in this stream of literature (Donner, 2006; Drabek, 1969; Gladwin et al., 2007). Previous EM studies on public risk communication have either adopted a traditional view and focused on its technical aspect, or engaged themselves into the investigation of individual behavior. Methodologically, current EM studies are preoccupied by qualitative description or post-emergency survey and simple statistical analysis. Such research methods are not well equipped to connecting individual and system level while at the same time tracking the decision-making process at the individual level and including a dynamic and process view.

This dissertation aims to address the first three limitations out of four as discussed above in the public risk communication literature in EM filed, by employing agent-based modeling to explore whether and how emergency impacts can be managed through the effective use of information transmission channel for public risk communication.

Chapter 2

Literature Review

During the past decades, EM scholarship has been in a cross-road (Britton, 1999). Such a status becomes more salient with the occurrence of 9/11 attack and Hurricane Katrina. More academic efforts since then are stimulated to explore and develop new and revolutionary approaches to address EM issues.

This chapter summarizes previous research in the field of public administration on how the approach to emergency management in general and to emergency public risk communication in particular evolves in the context of ever-changing practical and academic environment. In this chapter, what is a public emergency is first defined. The traditional approach to emergency management is then reviewed, including its histories, characteristics, strengths, and particularly its weaknesses and previous insights on how to address the weaknesses. This chapter also purports to develop an understanding of the current literature on a key aspect of emergency management: public risk communication. Specifically, it shall address what has been discussed with regard to public risk communication in emergency management literature, and what are the inherent limitations in this stream of literature that constrain its potential for further theoretical development and practical application.

Emergency Management Research and Practice

What is a public emergency. One of the major problems that confront EM researchers is the dissent regarding how to name and define the subject matter. Different terms have been used in EM literature to refer to the major object of studies, including emergency, incident, hazard, disaster, catastrophes and calamities. Some researchers attempt to distinguish these terms from each other. According to them, all terms refer to environmental events with negative consequences on society (Lindell & Perry, 2004). They all can be called emergencies, but come with different sizes and impacts and need different response units (Birkland, 2006; McEntire, 2004a).

Generally speaking, small-size emergencies are often called incidents, hazards or simply emergencies (Kapucu & van Wart, 2006). These events cause minor consequences for a community, and can be successfully handled with the resources of a single local governmental agency (Lindell & Perry, 2004). Moderate-size emergencies can cause considerable losses in a community and are given the name of disaster. Although they can be entirely managed at the local level, multiple agencies are usually required for a regional response; sometimes they even need assistance from the state. A catastrophe or calamity refers to a top-level emergency, whose occurrence is "notable, rare, unique, severed, and profound in terms of impact, effects, or outcomes" (Kapucu & van Wart, 2006, p.290). Responding to such an event often exceeds the capacity of local jurisdictions and needs cooperation national wide (Lindell & Perry, 2004). Another term frequently used in EM studies is crisis. This term is even more comprehensive than emergency when used as a general term (Shaluf, Ahmadun, & Said, 2003). It refers to a situation or a turning point where important decisions have to be made. It is different from any other term discussed before since both positive and negative outcomes can result from a crisis. Based on the differences, what interest researchers and practitioners in EM are disasters or catastrophes, not all types of emergencies. However, the term of emergency and disaster are often used interchangeably in EM studies (Adelman & Legg, 2009).

Even for studies using the same term for the major subject, no definitive conclusions have been achieved regarding how to define the term. For example, a disaster has been defined from various perspectives, for example, as a physical happening outside society (e.g., Fritz, 1961), as a social disruptive event (e.g., Kreps, 1995), or as a non-routine social occasion (e.g., Quarantelli, 1989).

In this dissertation, the definition of a public emergency adopts what Lindell and Perry (2004) defined a disaster from the EM perspective, namely, "a non-routine event in time and space, producing human, property, or environmental damage, whose remediation requires the use of resources from outside the directly affected community" (p.7-8).[2]

Command and control approach. In United States, emergency management as a research field emerged in the 1950s as a response to institutional demand (Dynes & Drabek, 1992). US governments at that time were primarily concerned with the threat of outside nuclear attacks (Wilson & Oyola-Yemaiel, 2001). Disasters, particularly natural disasters, were viewed as small-scale analogues to nuclear attack situations and natural laboratories for testing the possible effects of armed aggression. Funds were provided by civil defense departments for the study of disaster and emergency management, to explore

[2] Since this dissertation focuses only on research and practices of EM in public sectors, a public emergency within this study can also be simply called emergency. Furthermore, following Lindell and Perry's definition (2004), the term emergency and disaster can be used interchangeably throughout this dissertation.

civilian response to nuclear attacks, as well as how to maintain social order in war situations (Alexander, 2002; Kreps, 1995; Tierney, Lindell & Perry, 2001). Such civil defense supports pressed researchers to develop a theoretical perspective that was consistent with military pattern (Dynes, 1983; Gilbert, 1995).

Command and control emerged from this circumstance as the first model of emergency management. It strongly reflects the wartime and national security roots (Perry, 2006). In this model, disasters bear a great resemblance to harmful attacks. They are considered as events external to a focal society. Human communities are systems with essential functions. After a disaster hits the system, social functions are disrupted; communities should react organically against the aggression, to restore the system back to normal.

Individuals are assumed to be inept and passive because of the social chaos created by a disaster (Dynes, 1994; Schneider, 1992); they behave in an irrational and anti-social way (Dynes, 1994; Britton, 1989a; Mileti, 1989). Local emergency personnel are considered self-centered and irresponsible; they leave their posts in the disaster situation (Dynes, 1983). Outside authorities and resources therefore become necessary, given the reduced capacity of individuals and organizations in the local community to cope with disasters (Dynes & Drabek, 1992).

The goal of emergency management is to regain control over the social chaos and to reestablish social order (Dynes, 1983, 1989). With this goal, the model provides a highly bureaucratic emergency management system (Dynes, 1994; Kapucu & van Wart, 2006). Schneider (1992) characterizes this system with four basic features: clearly defined objectives, a formal structure, a division of labor, and a set of guiding policies. Management goals are achieved through the centralization of power and decision making (Britton, 1989a; Dynes, 1983), a hierarchical, top-down communication and information system (Britton, 1989a, 1991; Dynes, 1983), strong paramilitary leadership (Drabek & McEntire, 2003; Neal & Phillips, 1995), and pre-planned detailed operating protocol and procedures (Britton, 1986, 1991; Schneider, 1992).

Management efforts are viewed effective only if they are made by public sectors. For example, information outside of official sources is considered inaccurate (Britton, 1989a). Ad hoc or emergent behavior, such as voluntary rescuing behavior after a disaster, is considered counter-productive, and should be prevented (Mileti, 1989). In fact, advocates of this approach contend that any departure from bureaucratic guidelines would create problems (Neal & Phillips, 1995). When government fails in responding to a disaster, the management system is viewed not as bureaucratic as it should be. The system therefore needs to be advanced toward a stricter and more centralized direction. Measures that are usually advocated by researchers favoring this model include more detailed pre-event planning and organizational reconstruction of government emergency management sectors (Britton, 1989a).

Methodologically, studies within this stream of literature take an individualist or case study approach to a specific type of disaster event (e.g., earthquake, hurricane, or flood) (Shaluf, Ahmadun, & Said, 2003). Researchers believe that different types of disaster are different qualitatively from each other, and each of them requires unique model of understanding and management (Lindell & Perry, 1992). As a result of this disaster-specific approach, various lines of research were developed for each type of disaster. This research strategy actually echoes the civil defense related funding priorities (Tierney et al., 2001). Studies are descriptive in nature, and they often focus on the fact of a specific disaster, particularly the characteristics of the disaster (e.g., magnitude and duration) (McEntire & Marshall, 2003; Porfiriev, 1995; Quarantelli, 1981) and social-systemic antecedents and consequences (e.g., numerical estimates of negative disaster results) (Tierney et al., 2001; Quarantelli, 2001).

In practices, the command and control approach was subscribed by most emergency managers (Britton, 1989b; Dynes, 1989; Siegel, 1985). The popularity even continues till today (Neal & Phillips, 1995; Drabek & McEntire, 2003). Some researchers attribute its wide practical application to the approach's simplicity and clarity, particularly to emergency managers (e.g., Dombrowsky, 1995). The founding fathers of EM filed were actually civil defense directors, who used to serve in armed forces (Drabek & McEntire, 2003; Haddow, Bullock, & Coppola, 2008). It is therefore logical to initiate the professional with a paramilitary approach. Many emergency managers also began their career in military, and the command and control approach makes particular sense to them (Dynes, 1983). Besides, the model is compatible with the classical management theory that has been commonly employed in public sectors (Britton, 1989a).

Command and control, as the first model to emergency management, influenced most of the work followed in EM field. Several models are proposed in later studies as variants of this model, for example, the rational model (Siegel, 1985), bureaucratic norm model (Schneider, 1992), and the better known model of Comprehensive Emergency Management (Sylves, 1994; Waugh, 1994). However, all these models maintain the same basic tenets, addressing issues of emergency management through a command and control approach. Neal and Phillips (1995) summarized three underlying points of such an approach. “They urge the strict use of bureaucratic structure and rules, argue that ad hoc efforts lead to failed emergency response, and suggest that effective emergency response occurs only through normal, rational, written bureaucratic procedures” (Neal & Phillips, 1995, p.328). As for emergency managers, they continue their concentration and application of classical management theory (Britton, 1999). EM training is attuned to skill-based emergency response activities (Britton, 1999). The public is considered as part of the external environment of EM, whose behavior should be controlled (McEntire, 2004a).

Critiques. Critiques on the command and control model have been emerging since the late 1960s. By that time, many EM researchers started to realize it was not effective to manage natural and technological disasters through a paramilitary system (Alexander, 2002; Britton, 1986, 1991; Quarantelli, 1986). The approach makes inaccurate assumptions on individual behavior in emergency situations. Individuals do not behave irrationally or anti-socially; nor would they become helpless and dependent (Dynes, 1989). The proposed emergency management system as an administrative hierarchy is designed to operate under stable and predictable conditions (Drabek, 1985; Perrow, 1979; Rosenthal & Kouzmin, 1997). Given the rapidly changing and unpredictable nature of disaster created environments, such a system inevitably becomes mismatched with the environment and ineffective.

Considering the inherent limitations of the traditional approach, some EM researchers attempted to explore alternative approaches of EM, for example, the emergent human resource model (Brouillette & Quarantelli, 1971; Drabek, 1985; Dynes, 1983), the comprehensive vulnerability management model (McEntire, 2001, 2002, 2004b), and the inter-governmental crisis management model (Comfort, 1985, 1988, 1999). Today, the research and practice of EM is still evolving. On the one hand, the rapid and extensive reorganization of EM system after the trauma of the 9/11 attack de-emphasizes all hazards other than terrorism (Birkland, 2006). Traditional model of command and control is reinforced (Comfort, 2006; Haddow et al., 2008; Kreps, 1990). On the other hand, the response failure to Hurricane Katrina relentlessly revealed the flaws and weaknesses in current EM system (Col, 2007; Jurklewicz, 2007; Kiefer & Montjoy, 2006; Menzel, 2006). More initiatives since then have been stimulated to search and develop an alternative approach for EM (e.g., Garnett & Kouzmin, 2007; Lester & Krejci, 2007; Morris, Morris, & Jones, 2007; Wise, 2006). Four common features identified by these efforts that should characterize the new approach can be summarized as below:

First, the EM system should be framed as a loosely-coupled inter-organizational system, with a flexible and networked structure (Comfort, 2005; Neal & Phillips, 1995). Components of the system include both organizations—public, private, and non-profit—and individuals (Kuban, 1996; McEntire, 2002).

These components are interdependent; they interact with each other and with the environment, through a continuous process of information exchange and behavior adjustment. Although public sectors bear the primary EM responsibility in this system (Comfort, 2006, 2007; Rosenthal & Kouzmin, 1997), the dynamics of the emergency-created environment require decentralized decision making, and local adaptation (Kapucu & van Wart, 2006). Furthermore, the effectiveness of EM practices depends upon the interaction among system participants, and communication is the key to integrate the system and coordinate the actions of multiple actors (Pijnenburg & van Duin, 1991).

Second, management strategies should be developed based upon systematic information about how people behave in a disaster, instead of trying to control their behavior (Dynes & Drabek, 1992; Quarantelli, 2005). When facing emergencies, people do not become passive and do what the authority tells them to do. They take actions based on their own decisions made in a bounded rational way (Quarantelli, 1982, 1984). Management practices therefore can no longer be understood as exerting control over individual behavior, but as designing and continuously adjusting strategies based on human behavior in disasters. Besides, the public should be viewed as resource and part of EM system, rather than what should be prevented from management practices (Drabek & McEntire, 2003).

Third, EM is essentially a dynamic process, particularly given the rapidly changing environment created by a disaster. Rosenthal and Kouzmin (1997) once argued that, a more comprehensive analysis of EM called for a more focused understanding of the process and of the challenges the process posed for public management. The new approach needs to take a dynamic and process view, which allows actors to trace the development of an emergency situation, rapidly identify and correct errors and adapt their performances.

Fourth, instead of focusing on technological knowledge and its application, EM research and practice should be based upon efforts from multiple disciplines (Petak, 1985; Wamsley & Schroeder, 1996). EM research and practice, by its very nature, is multidisciplinary (Dynes & Drabek, 1992). No one discipline can help see the big picture of disaster and emergency management; nor does any single perspective provide a comprehensive understanding and explanation. Efforts therefore should be made to develop an inter-disciplinary approach, in which "disciplinary differences will all be melded into one overall perspective" (Quarantelli, 1989, p.244).

The above four features have been repeatedly discussed by proponents of an alternative approach to EM, and they believe that such an approach characterized by these features could provide important insights on effective EM (Comfort & Kupucu, 2006; McEntire et al., 2002; Rosenthal, 't Hart, & Charles, 1989). Meanwhile, none of the existing EM approaches can simultaneously fulfill these four requirements. Efforts are still needed to develop another new approach.

Public Risk Communication Research and Practice in EM

What is public risk communication in EM. In emergency management, public risk communication or public warning has been defined as the transmission of messages to individuals, groups, or populations which provide them with information about the existence of danger and what can be done to prevent, avoid, or minimize the danger (Williams, 1964; Worth & McLuckie, 1977). It is conceived as a general social system consisting of three basic elements or activities: assessment, dissemination, and response (McLuckie, 1970; Quarantelli, 1983; Tierney, 1993). EM researchers usually consider the aspect of response as the most important aspect of the total communication system, since the ultimate goal of public risk communication is to initiate and motivate appropriate protective response by those to whom the information is directed (Lindell et al., 2005; Perry & Lindell, 1986; Tayag et al., 1997). Correspondingly, the effectiveness of public risk communication is evaluated based on the degree to which desirable public response is elicited to minimize losses from a disaster (Worth & McLuckie, 1977). In practice, emergency risk communication systems are complex communication systems (Sorensen, 2000). They link a variety of specialties and organizations and the public (Mileti, 1995; Mileti & Peek, 2000). They are also more than a technological system, and far extended beyond the official communication systems (Sorensen & Sorensen, 2007).

Public risk communication in EM under command and control. EM researchers have consistently demonstrated the difficulties for emergency warning to elicit desired public response (Donner, Rodriguez, & Diaz, 2007; Quarantelli, 1984, 1990). As a result, there is often inadequate protection provided for communities. While many efforts to mitigate the problem have been devoted to developing and using new technologies, such a solution is considered insufficient (Gladwin et al., 2007). It is argued that, the principle problem of public warning response lies at the oversimplified conception of warning process held by emergency managers (Balluz et al., 2000; Donner et al., 2007). Such a conception is developed under the roof of a command and control approach to EM, and usually called the "conventional wisdom" on public risk communication (Parker & Handmer, 1998). It includes the assumptions and model many researchers and practitioners use in public risk communication study and practice.

Common myth on public risk **communication.** Over the past seven decades, researchers have identified a set of common, but mistaken, beliefs among EM scholars and practitioners about emergency risk communication and public response (Drabek, 1986; Mileti & Peek, 2000; Wenger & James, 1994). Often referred in literature as "myth", these interrelated assumptions are considered as the central constraining factor in improving the effectiveness of public risk communication (Dynes & Quarantelli, 1973; Sorensen, 1993).

All individuals directly receive official warning. Information notification is the starting point in seeking to explain how people respond to public warnings (Parker, Priest, & Tapsell, 2009). Since people can only respond after they receive the warning, it plays an important role in most emergencies (Sorensen, 1993). In EM practices, it is generally assumed that, after disseminated, each warning message will directly reach all individuals (Mileti, 1995). Public officials also believe that it is better to have a single spokesperson to distribute emergency information (Tierney, 1993). Therefore, the authority becomes the single and only source from which all people can directly get risk information (Sorensen, 2000).

Individuals have limited capacity to process information in emergencies. Officials are usually concerned about overwhelming the public with too much information (Sorensen, 2000). They believe that people's ability to process information is reduced by emergency situations, and therefore they will be confused by long and detailed warning messages (Mileti, 1995). Emergency managers usually adhere to such principles as "keep the information simple and stupid", in order to hold people's attention and make the information more understandable (Mileti, 1999; Sorensen & Sorensen, 2006).

Previous studies also find that many researchers and emergency managers are worried about the so-called "cry-wolf" syndrome, which refers to the phenomenon that repetitive false alarms may decrease the effectiveness of people's response to a warning (Sorensen, 1992; Sorensen & Mileti, 1988). It is believed that repeated activation of the false alarm can lead the public to take unnecessary protective actions and therefore cause needless time and financial cost. More important, it will reduce the credibility of a subsequent and maybe true warning. In practice, emergency managers are sometimes too concerned about the syndrome to inform the public timely (Lindell & Perry, 1992).

Individuals become panic and irrational. Individuals, as emergency managers believe, respond to warning messages in a very disorganized or dysfunctional way (Perry, 1981; Perry & Lindell, 2003a). One assumed pattern of individual warning response is panic, which is one of the most common myths with regard to warnings of impending threats (Dynes & Quarantelli, 1973; Mileti, 1999; Perry & Lindell, 2003b). Quarantelli (1954) defined panic as "an acute fear reaction marked by a loss of self-control which is followed by non-social and non-rational flight" (p.272). In other words, after receiving warning messages, individuals are no longer able to make rational decisions and enter into an irrational panic status.

The assumption of individual panic status has two important implications for the practice of emergency management. Public flight has been considered a major problem (Perry & Lindell, 2003b). This concern prevents public officials from providing the public with complete risk information, in order not to cause a public panic (Mileti, 1999). The assumption also justifies the outside control from public officials over individual behavior (Dynes & Quarantelli, 1973). Since individuals become irrational and cannot decide for themselves what their best interest is, they need public officials to become the Big Brother and tell them what to do (Trainor & McNeil, 2008).

Individuals become passive and follow suggestions immediately. Another myth as stubborn as the panic assumption is that, warning messages are received by passive and isolated individuals, who cannot take care of themselves (Helsoot & Ruitenbery, 2004; Parker & Handmer, 1998). As a result, they wait around for the help from public officials (Dynes & Quarantelli, 1973). After receiving warning messages, each person responds directly and individually to the content of the warning and follows recommendations made in the message (McLuckie, 1970; Sorensen, 2000).

The presence of passivity may be caused by “disaster syndrome”, which is characterized by Perry and Lindell (2003a) as “a state of shock associated with docility, disoriented thinking and sometimes a general insensitivity to cues in the immediate environment” (p.223). Put it in a simple way, potential disaster victims upon receiving a warning are so stunned or shocked that they cannot adaptively respond. Nor do they have action initiatives. They wait childlike for the authority to tell them what to do (Dynes & Quarantelli, 1973). The presence of such passivity and docility further consolidates the authority of public emergency managers as commanders who give orders for the public to carry out. Moreover, emergency mangers consider an individual's responsive decision or action as a personal matter, which is made or taken independently (Sorensen, 1991, 1992).

These four interrelated disaster myths compose the main assumption many EM researchers and practitioners hold for public warning response (Dynes, 1994). They actually reflect the inaccurate assumptions the command and control approach made on individual behavior in emergency situations. On the other hand, they have been empirically demonstrated not just erroneous, but restrain the effectiveness of emergency warning (Perry, Lindell, & Greene, 1981; Perry & Lindell, 2003b; Tierney et al., 2001). For example, Perry and Lindell (2003a) argued that the myth of panic often justified emergency managers' behavior of withholding information from the public, which "is particularly troubling because it has been shown repeatedly that people are more reluctant to comply with suggested emergency measures when they are provided with vague and incomplete information" (p.50). Similar situation can also be triggered by public managers' concern with people's incapability for information processing. Moreover, since they believe the authority is the only warning source, emergency managers may ignore the risk information from other sources. Such risk information may be inconsistent with or contrary to the official risk information, and the public may use minor points of inconsistency to resist suggested protective actions (Drabek, 1999; Reynolds, 2005). What makes the influence of such common myths more complex and worse on EM practices is that, they laid the foundations for and qualify the traditional model used to frame the public risk communication process and design communication strategies.

Traditional model of public risk communication. Traditionally, public risk communication during emergencies is considered as a linear, top-down and expert-to-lay process (Gladwin et al., 2007; Gutteling, 2001). Public sectors identify the presence and make predictions of an extreme event and inform public emergency officials; public emergency officials then make decisions and disseminate risk messages to the public (Sorensen & Sorensen, 2006).

The process of public risk communication, when viewed from this traditional approach, is nothing more than a linear transmission of risk messages from public officials to the public (Quarantelli, 1990). The risk information flows out from its exclusive official source down to the public, which is visualized as an aggregate of individuals (Tierney, 1993). Upon the receipt of the information, these individuals become passive and docile, and incapable of processing information and making decisions. They respond directly to the risk information as suggested by public officials in it. In essence, the risk information acts as a stimulus which impinges directly on all individuals, and then evokes a response as the reaction to it (Quarantelli, 1983).

Such message transmission model to understand public risk communication and human response is primarily based on the classic theory of persuasive communication (Lindell & Perry, 2006; Sorensen & Sorensen, 2007). According to this theory, all communication messages go uni-directionally from generating sources, to transmission channel, and finally to targeted receivers. The purpose of communication is to elicit some kind of changes from the audience group (Lindell et al., 2005). Sorensen and Sorensen (2006) described this one-way communication process as an engineering theory of communications that most closely resembles the defunct hypodermic effect in mass communication.

For public risk communication during emergencies, the source, medium, audience and effect can be clearly defined. The source is an authority, the message includes information about a hazard and protective actions, and the public are expected to receive the message and take actions described in the message. As shown in Figure 1, the public risk communication process is actually framed as a simple linear and strictly unidirectional model of "warning dissemination, public receipt, and warning response" (O'Brien, 2003).

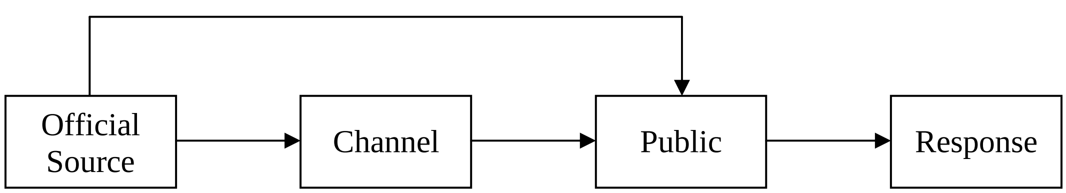

Figure 1. Traditional model of public risk communication in EM

Based on the model, emergency managers in practice direct their attention towards improving the trustworthiness and expertise of official sources on the one hand, and developing rational communication strategies on the other (Gutteling, 2001; Lindell & Perry, 1992; Lindell et al., 2005). Meteorological efforts, especially advancing scientific knowledge and modernizing communication equipments, are emphasized, in order to improve the accuracy of hazard forecast (Gladwin et al., 2007; Sorensen, 1993, 2000). Warning messages are formulated from a technical view, typically containing quantitative information and communicated to the public in an analytical and logical style (Gutteling, 2001). Emergency managers believe people after receiving warnings will replace their irrational and subjective judgment with the rational and objective opinion in the message, and take actions as suggested right away.

These two efforts are actually interrelated with each other. They both illustrate the essence of the traditional model: we experts know and tell you people what is important and you do whatever is told (Sorensen & Sorensen, 2006). When people fail to follow recommendations on protective actions, public managers ascribe the ineffectiveness to the warning message; the message is considered not scientific and objective enough to correct people's misperception and motivate them to adopt recommendations (Lindell et al., 2005; Tierney et al., 2001). Such reasoning inevitably leads to further efforts on technical progress and developing more rationalistic warning strategies and messages.

The message transmission model of public warning has dominated the practice of public risk communication in EM for more than 50 years (Sorensen & Sorensen, 2006, 2007). It is developed and widely used under the background of a command and control approach to EM. EM scholars and practitioners are also tempted to use this model because of its clarity and simplicity for both explanation and management practices. However, they are at the same time deluded by its oversimplification of the complex reality (Qurantelli, 1984). The realization that the model is a deficient representation of reality motives researchers to complement and extend the understanding of public warning process, particularly the ways in which individuals respond to warning messages (Lindell & Perry, 1987, 2004; Lindell et al., 2005). By now, it has formulated one of the most important research traditions in disaster and emergency management research (Trainor & McNeil, 2008).

Findings from EM studies on public risk communication. EM researchers have explored the process of public risk communication in emergency context for more than six decades (Trainor & McNeil, 2008). They believe the most important aspect of the process lies in its social or human component, particularly, how the warning target population responds to risk information. On the one hand, empirical studies are conducted to find evidence to evaluate those underlying common myths held by emergency managers (Dynes, 1994; McLuckie, 1974; Sorensen, 1991). On the other hand, a significant level of knowledge has been developed about how individuals respond to emergency risk information in the presence of impending threats (Aguirre, 2003; Gray, 1981).

Empirical finding of individual response to public risk information.

Official warning cannot reach everyone. Previous research has consistently revealed that, not everyone in the public can receive risk information when it is disseminated (Donner, 2007; Schware, 1982; Sorensen & Sorensen, 2007). Various factors, both physical and social, may prevent individuals from hearing a warning (Parker & Neal, 1990; Parker et al., 2009; Perry, 1985). Furthermore, the authority is not the only source from which people can get warned (Mileti et al., 2004; Perry & Greene, 1983; Perry & Hirose, 1991). Individuals usually find out the possibility of impending hazard in a variety of ways (Parker et al., 2009; Sorensen, 1992). For Lindell et al (2005), public warning "should be represented by a network in which multiple sources are linked to intermediate sources who receive information and relay it to the ultimate receivers" (p.88). As shown in Figure 2, recited from Lindell et al. (2008, p.89), ultimate receivers can receive information directly from the original source, or indirectly from many intermediates which are linked to the original source. They can also get messages from each other.

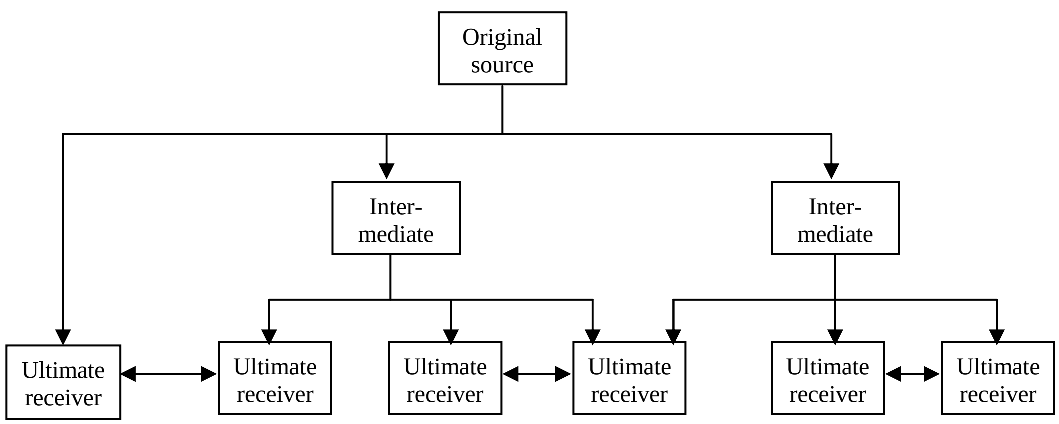

Figure 2. Communication network model
(Recited from Lindell et al., 2008, p.89)

The public is "information-hungry" rather than overloaded. After receiving warning messages, the public is rarely overloaded by too much information; neither is their capacity to process information deteriorated by risk messages (Sorensen, 1993, 2000). Instead, the warning information creates an information void, which makes the public information "hungry" or "starving" (Mileti, 1995, 1999; Mileti & Frizpatrick, 1992). People in this case usually need more and detailed information, and want to receive it frequently. Furthermore, people at risk need information from multiple sources, rather than one single source or spokesman (Mileti & Peek, 2000; Sorensen, 2000). If the official source cannot meet their information demand, people will turn to other sources from which in most cases they will get inaccurate or inconsistent messages (Mileti, 1999).

For the cry-wolf syndrome, EM researchers found that repetitive false risk information did not always have a negative effect on people's response (Mileti & Sorensen, 1990; Sorensen, 2000; Sorensen & Sorensen, 2006). People usually prefer to risk hearing false messages rather than not being informed after emergencies occur (Parker & Neal, 1990). Furthermore, the syndrome mostly occurs when emergency managers make no attempt to explain why false information is sent (Sorensen, 2000). If the reasons are told to and understood by the public, the integrity of subsequent risk messages and the effectiveness of public response could not be influenced (Sorensen & Sorensen, 2006, 2007).

Individuals are bounded rational. The record of panic as a reaction to public emergency warning could be dated back to the early 1950s (Perry & Lindell, 2003a). However, disaster research indicates the phenomenon can be evoked only when certain circumstances, probably simultaneously, occur (Sorensen, 2000; Sorensen & Sorensen, 2006). These circumstances include 1) there is an immediate and severe danger, as a clear source of death, 2) there are inadequate exit routes that are accessible to everyone before the danger occurs, and 3) there is insufficient communication about the situation (Quarantelli, 1983, 1984; Sorensen, 1993). An example of panic situation among a large group of people occurs in the 1972 Sao Paulo high-rise fire in Brazil, since these people believed it impossible for them to get rescued (Beitel & Iwankiw, 2002). Perry and Lindell (2003a) also argue that whether these conditions are met is based on the perception or belief of people who are at risk, instead of what emergency managers know at the time.

Empirically, individual or collective disorganization after receiving warning information is rarely observed in the context of any type of disaster (Blanchard-Boehm, 1998; Donner et al., 2007; Drabek, 1985). Potential disaster victims do not simply break into behaviors characterized by irrational decisions, such as panic flight, or illogical actions (Dynes & Quarantelli, 1973). Research into different aspects of public warning response illustrates that most potential disaster victims behave in a bounded rational way (Helsloot & Ruitenbery, 2004; Quarantelli, 1983). They typically “rise to the occasion” (Trainor & McNeil, 2008). Based on their limited understanding and available resources, they act in the way which they believe is best for themselves and their significant others (Perry & Lindell, 2003a). EM researchers therefore argue that emergency managers in practice should consider the issue of individual or collective panic as an insignificant practical problem, given its rare occurrence in any emergency warning context (Dynes, 1994; Quarantelli & Dynes, 1972, 1977).

People respond to risk information proactively and collectively. Contrary to what emergency managers believe, emergency risk information is not passively received and followed by people’s direct, immediate and individual response (Ikeda, 1982; Perry, 1979a, 1979b). After receiving the message, people tend to interpret and evaluate it in the social context at that time (Lindell & Perry, 1983; Nigg, 1987; Perry, Lindell, & Greene, 1980). They develop their own understanding of the message they received (McLuckie, 1970, 1973). The same information may be perceived and interpreted by different people in different ways. As a result, there is no such thing as a risk message for all people. For emergency management, as Quarantelli (1983) argued, “it is necessary to lay aside the idea that any message is in itself a warning message” (p.178). What is crucial is the meaning people attach to the message, which may or may not correspond to what emergency managers intend at the first place (Mileti, 1995; Quarantelli, 1983). It is therefore important to achieve a shared meaning of the warning message between the public and emergency managers (Pfister, 2002).

The finding of personal understanding or perception of warning messages also questions the rationality and validity of current public risk communication efforts. According to Gutteling (2001), the application of a rationalistic communication strategy may actually increase the public disbelief of risk messages. Peters, Covello, and McCallum (1997) also argue that the top-down communication may decrease public trust in risk communication sources, such as government agencies. Since emergency managers will attempt to develop more rationalist and scientific messages when people disbelieve and do not follow their recommendations, a vicious circle can actually be formulated. In this circle, the public keeps questioning the risk information because its style and content, which makes emergency managers keep changing the communication style and content to what is more difficult for the public to believe and follow.

Furthermore, most people upon receiving warning attempt to verify what they heard, as well as what they understand, through the so-called “confirmation process” (Donner, 2006; Drabek & Stephenson, 1971; Sorensen, 1993). During this process, people employ their personal networks to search for additional information and discuss the warning with known others (Parker & Handmer, 1998; Perry & Lindell, 2003b). The reason why people engage in such confirmative behaviors is to see how others are interpreting and reacting to the warning (Dynes & Quarantelli, 1973; Mileti, 1995; Perry & Greene, 1982). Additional information collected from the process is then used to assess the validity of their initial understanding and perception. The next outcome following the confirmation process is people’s definition of their current situation, specifying whether they believe they are personally endangered (McLuckie, 1970; Quarantelli, 1990).

Given research findings discussed above, EM researchers argue that, people do not directly respond to risk information as soon as they receive it (Mileti & Sorensen, 1990; Sorensen & Mileti, 1992; Sorensen & Sorensen, 2006). Time is needed for people to understand and verify it, especially when they are facing unfamiliar hazards (Worth & McLuckie, 1977). Neither will they respond as individual persons. People normally respond in a social context. They interact with each other during the confirmation process, which produces a situational definition based upon which individuals will respond (Quarantelli, 1983). Put it another way, the social interaction during confirmation mediates how people interpret the warning, define their situation and respond. Therefore, both warning interpretation and response are no longer individual matters (Donner 2007;

Trainor & McNeil, 2008). “It is a complex and, if time and a group of people are involved, usually a highly social process” (Wlliams, 1964, p.96).

Furthermore, even if people share the meaning of warnings with emergency managers and have obtained the confirmation of danger, they will not blindly follow the suggestions emergency managers propose in the warning (Pfister, 2002; Sorensen, 1993, 2000). People at risk normally react in a proactive, rather than passive way (Dynes & Quarantelli, 1973). They do not just wait and do what the authority asks them to do; they make decisions and undertake their own protective actions they perceive appropriate. Besides officially advised response, a variety of alternative responsive behavior is possible. Also, the way in which individuals respond is affected by numerous factors, and official warning message is just one element among these influential factors (McLuckie, 1970; Quarantelli, 1983).

Another important finding from previous studies is that, disaster syndrome occurs infrequently in emergency situations (Dynes, 1994; Dynes & Quarantelli, 1973; Quarantelli & Dynes, 1977). Even when it occurs, it only lasts for a maximum of a few hours and hardly influences individuals’ capacity for decision making and active response (Perry & Lindell, 2003a, 2003b). This finding further disproves the assumption that the public is passive and docile in emergency warning situations. EM researchers actually argue the disaster syndrome is “of negligible significance for emergency operations” (Perry & Lindell, 2003a, p.51).

Summary. Recognizing the above empirical findings is crucial for public risk communication. The process, according to previous research findings, is no longer what emergency managers and policy makers normally believe and practice; it is a much more complex course than getting the scientific information out and people will do what they are told. Emergency warning must be based on accurate knowledge of likely human warning response (Perry & Nigg, 1985). Emergency managers, instead of forcing people to change their behavior, should adjust their strategies according to the probable behavior of people. Besides discovering how people respond to warning messages empirically, EM researchers also argue that, better understanding of human warning response also depends on better understanding of how and why individuals come to respond in their way (Donner, 2006; Quarantelli & Dynes, 1972; Trainor & McNeil, 2008). Emphasis is therefore placed on the development of models of individual response to emergency risk information that can be applied to a variety of emergency situations (Donner, 2007; Lindell & Perry, 1992; Mileti & Sorensen, 1988). Among these models there is a high degree of agreement: 1) individuals respond to emergency warning through a social process, 2) such a process consists of a sequence of stages, and 3) a wide range of factors could influence individual behavior at each stage. Such agreement provides a general picture of individual emergency warning response, and will be discussed in detail as below.

Individual warning response as a complex social process. When researchers first began to study individual response to emergency risk information, they quickly found they were exploring a highly complex process (e.g., Drabek & Boggs, 1968; Quarantelli, 1954; Williams, 1957). Quarantelli is one of the earliest researchers studying the human aspect of disasters. In his 1983 article, “people’s reactions to emergency warnings”, he summarized previous research findings on individual reactions to information about possible emergency. According to him, there is a difference between individual reaction and response to emergency risk information. Reaction, as he defined, “is the broader set of activities involved in exposure to and use of disseminated warning messages, as well as other observations regarding a dangerous situation” (Quarantelli, 1983, p.177). Response is “the adjustive behavioral outcome of the reaction pattern” (Quarantelli, 1983, p.177). Individuals after receiving risk messages would first go through a reaction process, and responsive behavior is the result of this process.

The reaction process involves sequential cognitive and behavior stages. Five constituent stages have been identified, accepted and utilized by most EM studies. They are information receipt, understanding, believing or initial perception, social confirmation, and risk personalization or situational definition.

Information receipt. Individual response process to emergency warning is initiated by receiving or hearing risk information. People can receive it from different types of channels, among which the most common is mass media (Donner, 2006). The failure to be notified generally prevents people from or at least postpones their responses (Donner, 2006; Mileti & Sorensen, 1990). In public warning literature, fewer studies have focused on the hearing phase, compared with other stages. Researchers are usually interested in when individuals can hear the warning after it is disseminated (Drabek, 1999; Sorensen, 1991). Relatively scant empirical findings exist to document why some individuals receive the message while others do not, and how the coverage of warning can be maximized (Donner, 2007; Mileti & Sorensen, 1990).

Understanding. Upon receiving the warning, individuals develop their own interpretation of the message. Personal understanding varies among the public and may not conform to what emergency managers originally intend to convey. Therefore, there is no message that is inherently a warning message for all people. Donner et al (2007) argue that there are two categories of individual warning misunderstanding; people may misunderstand the level of risk or the geography of the risk area. EM researchers also found that the social context in which one receives the warning plays an important role for people to grasp the meaning of the message (Mileti & Sorensen, 1990). During the stage, if people understand the warning and interpret it as implying the existence of some risk, they will engage in the next stage; otherwise, they will ignore the message and go back to their previous activities before hearing it.

Belief. The stage following understanding is belief, during which individuals develop their initial perception regarding whether the risk communicated is real. In previous studies, it has been long recorded that the understanding of risk existence triggers immediately skepticism or disbelief for most people (Drabek, 1999; Drabek & Boggs, 1968; Worth & McLuckie, 1977). Instant belief may occur, but only among a few individuals "who are psychologically set to believe the worst in any situation or those who have recently experienced a 'near miss' disaster" (McLuckie, 1970, p.31). EM researchers name this phenomenon "normal bias", and consider it a common reaction to risk information (Okabe & Makami, 1981; Parker et al., 2009; Rogers, 1998). The occurrence of this phenomenon is explained in the way that there is an "everydayness" for each individual (Lefervbe, 1987). Since it is defined by individual routine activities, the disruption of such "everydayness" signals that something goes wrong (Goffman, 1956). However, on the part of individuals, they tend to assimilate all these signals to normal, and deny there may be something wrong. In the context of emergency warning, most people prefer to believe they are not endangered. Unless further proven otherwise, conditions are evaluated as normal, even if they receive and understand what the information is trying to convey (McLuckie, 1973, 1974). The burden of proof lies within risk communication efforts (Tierney, 1993). Through risk communication emergency managers need to help the public overcome normal bias and correct their tendency to act in normal.

Three types of actions can be elicited at this stage as the result of the degree of belief, or skepticism, of the warning (Drabek, 1969, 1986; Worth & Mcluckie, 1977). At one extreme individuals completely deny the existence of potential danger. The warning message is therefore ignored and people continue with their routine activities. At the other extreme individuals completely believe the warning, and take protection actions immediately. Most people develop skeptical attitude as between these two extremes and react investigatively. They attempt to seek more information to verify their own perception. For emergency management, both taking protective action and seeking confirmation among the public manifest the warning has some effect on individual behavior. But whether the effect is desired by emergency managers, or whether such attempts can actually decrease or eliminate personal risk, is another matter (McLuckie, 1970).

Social confirmation. It is typically referred to as the social confirmation stage that people seek additional information to verify their prior understanding and perception on risk messages. Three categories of sources for confirmative information have been found by previous studies: authority, personal contacts and environment (Donner et al., 2007; Parker et al., 2009;). The personal contact includes friends, neighbors and relatives, and it is constantly considered as the most important confirmation mechanism (Drabek & Stephenson, 1971; Mileti, 1995; Parker et al., 2009). People tend to use personal networks to get known others' response to risk information (Parker & Handmer, 1998). The communication could be face-to-face, or usually via telephone (Drabek & Stephenson, 1971). People can also substantiate the warning by making observations on their surrounding environment. They can monitor how the physical environment changes, such as changes in the river level before a flood (McLuckie, 1970). Government agencies or even quasi-official organizations are seldom contacted by individuals, unless other sources are exhausted (Perry & Lindell, 2003b). On the other hand, people give greater credence to the information they get from personal sources and known others than impersonal mechanism and strangers. Therefore, the responsive action of significant others are crucial for social confirmation.

The confirmation process actually manifests the nature of individual warning response as a complex social process. Individuals during this stage interact with each other through information exchange. The warning message is not simply handled by single individual person; it is processed by a group of others, whom the individual turn to for confirmation. Because of the interactive process, people become interdependent on each other in terms of how to respond to risk information. The social confirmation stage characterizes the process of individual warning response as a matter of collective behavior.

Risk personalization. Individuals who have confirmed the presence of some risk do not necessarily believe they are personally endangered (Donner et al., 2007). In fact, EM researchers found a persistent and all-too-common phenomenon among the population at risk. Like the occurrence of normal bias, people tend to depersonalize the risk. In other words, even if individuals can hear a warning, understanding it and develop a high level of initial risk perception, they still hardly believe they will be personally affected (Drabek & Boggs, 1968; Tinerney, 1993). Such an "it cannot happen to me" syndrome usually makes people respond too late, or ignore the warning and not respond at all (Donner, 2006; Mileti & Sorensen, 1990).

The stage of risk personalization is also named situational definition by Quarantelli (1983, 1990) and other disaster researchers (e.g., McLuckie, 1970; Parker & Handmer, 1998). According to Quarantelli (1983), individuals' situational definition, namely whether they believe themselves the targets of some risk, is tightly connected with and influenced by previous two stages: belief or initial risk perception and social confirmation. During this stage, individuals relate their initial beliefs to the confirmative information they collected, to define their own situation. While later studies also identified other factors affecting individual risk personalization, answers to whether the threat exists and what others are doing are still considered as exerting the major influence (Donner, 2007).

Risk personalization or situational definition is also argued by EM researchers as the central component of individual warning response process (Quarantelli, 1983, 1990). It is actually the very fundamental assumption of almost all efforts toward emergency warning response that, “the actor acts toward his world on the basis of how he sees it and not on the basis of how that world appears to the outside observer” (Drabek & Boggs, 1968, p.445). Therefore, in order to understand individual behavior in the context of emergency warning, it would be essential to understand how they define their own situation based on the information received and collected from previous stages (Drabek & Boggs, 1968).

Response. After the reactive process, individuals enter the response stage, during which they take protective action that they consider most appropriate to reduce or eliminate their personal risk. Researchers found individuals typically attempt to maintain their routine ways of behaving (Quarantelli, 1983, 1990). Therefore, even if a warning is believed, socially confirmed and personalized, they are still reluctant to take actions. Furthermore, just as there are differentiated interpretations and levels of risk perception, people respond in a variety of ways. Generally they prefer to consider and take actions that are least disruptive in the situation (Qurantelli, 1983, 1990). The effectiveness of emergency warning is ultimately measured by whether individuals adopt protective actions as officially suggested (Worth & McLuckie, 1977). In practice there often is a difference between whether people respond and how they respond. Certain protective actions other than official advices are especially more likely under some circumstance. That people take these actions does not necessarily provide enough protection and indicate the success of public emergency warning.

Influential factors on individual behavior during response process. Individual behavior during the process of warning response is not free (Drabek, 1999). Although they make their own decisions and autonomously take actions, the range of their choices is constrained. Previous studies of public risk communication in EM have identified a wide variety of factors that can influence individual behavior at each stage of their response process (McLuckie, 1973; Mileti & Sorensen, 1990; Trainor & McNeil, 2008). These factors can be generally grouped into five categories, which are sender, receiver, contextual, event, and social-culture factors.

Receiver factors. Receiver factors are those influential factors as related to the characteristics of people who receive risk information. They can be further divided into five groups: demographics, physical attributes, psychological attributes, social attributes and resources (Mileti & O'Brien, 1992; Perry, 1987; Turner et al., 1979). Table 1 summarizes the literature of public risk communication in EM on what receiver factors are included in each group, and how each of them influences individuals' behavior during each stage of their response process to emergency risk communication.

Table 1. *Influence of Receiver Factors on Individual Response Process to Emergency Risk Information*

	Receive	Understand	Believe	Confirm	Personalize	Respond
Demographics						
Age	D	+	D	D	D	D
Gender	+	D	D	D	+	+
Race	D	D	D	D	D	
Ethnicity	D	D	D	D		D
Language		D	D		D	D
Religion		D		D		
Education		+				D
Socioeconomic status	D	+	D	D	D	D
Presence of dependents	+		+			D
Family size						-
House ownership						-
Price of home						-
Length of residence		+				
Physical attributes						
Impairments	-					-
Psychological attributes						
Cognition						
Locus of control	+		+		+	D
Stress						D
Fatalism	-					D
Self-confidence						D
Normalcy			-			-
Selective perception	D					
Risk awareness	D		D		D	D
Knowledge						
Hazard	+			-		+
Protective action	+			-		+
Emergency plan	+			-		+
Experience						
Type	+	D	D	D	D	D
Recency	+	D	D	D	D	D
Habituation	D					
Common-sense belief	D			D		D
Social attributes						
Association membership	D	D				D
Social network	D	D	D	D	D	D
Resources						
Physical	+	+	D		D	D

Social	+	+	D	D	D
Economic	+	+	D	D	D

Note. In this table, "+" represents a positive association between a specific factor and individuals' tendency to take corresponding action at a given stage. "-" represents a negative association. "D" indicates an inconclusive finding with regard to how the factor influences individual behavior within a stage. For example, while females are more likely to receive, personalize and respond to risk information, no consistent conclusion has been achieved when it comes to such gender difference in risk information understanding, belief and confirmation.

First, individual demographics include age, gender, race, ethnicity, language, religion, education, socioeconomic status, presence of dependent, family size, house ownership, price of home and length of residence. For most of these factors, inconclusive, or even contradicting, findings exist in terms of their influence on how individuals behave during certain process stage. For example, some researchers argue people occupying marginal social position, such as the elderly, members of lower socioeconomic classes and minority ethnic groups, are less likely to take preparative or protective actions (e.g., Drabek, 1969; Mileti & Darlington, 1997; Parker et al., 2009). Meanwhile, empirical evidence exists demonstrating such factors can either encourage or have no effect on individual responsive behavior (e.g., O'Brien, 2003; Perry & Lindell, 1991).

The discussion on the influence of physical attributes is scant, but more consistent. Physical disabilities and impairment, such as being deaf or blind, can significantly constrain individuals' ability to hear and respond to a warning (Mileti & Sorensen, 1990, 1998).

The third group of receiver factors consists of individual psychological characteristics. It includes: 1) cognitions such as the locus of control (Sorense & Sorensen, 2006), psychological stress level (Mileti & Sorensen, 1990), fatalism (what will happen will happen regardless of what is done) (Sorensen, 1991), self-confidence (sense of personal efficiency) (Mileti & Sorensen, 1990), normalcy (Donner, 2006), selective perception (people accept only what they want to) (Mileti, 1999), and pre-event risk awareness (Donner, 2006; McLuckie, 1970), 2) knowledge about the potential threat (Sorensen, 1991), about protective actions (Mileti & Darlington, 1997), and about making emergency plans (Lindell & Perry, 2004), and 3) the type and recency of experience with the risk (Foster, 1980; Perry & Greene, 1983; Perry & Lindell, 1986) and pre-event habituation (Drabek, 1969) and common-sense belief (Gray, 1981; Quarantelli, 1990).

Among these psychological factors, EM researchers show more interests in pre-event risk awareness and emergency experience. Risk awareness measures "the degree to which a hazard resides in the conscious awareness of the public" (O'Brien, 2003, p.358). The salience of a risk before it occurs generally increases the probability for warning receipt (O'Brien, 2003). However, risk awareness does not necessarily lead individuals to believe and personalize the risk, and respond to risk information. A case in point is Hurricane Katrina. In the field work in Louisiana and Mississippi after the disaster, Donner (2006) found that there was strong risk awareness among interviewees before the hurricane struck the region, but few took protective actions until visible environmental cues arose.

Previous emergency experience can also help individuals hear a warning, especially when they are facing the same type of risk that occurred recently (Sorensen, 1991; Trainor & McNeil, 2008). On the other hand, whether and when experiencing a disaster does not shape people's reaction to future events in a predictable way (Sorensen & Sorensen, 2006). Inconsistent empirical evidence exists regarding the influence of disaster experience on individual understanding, belief, confirmation, personalization, and response to a warning (Donner et al., 2007; Farley et al., 1993; Perry & Greene, 1983). For example, both Parker et al (2009) and O'Brien (2003) found that people with prior disaster experience are more likely to respond to a warning; also, the more recent the experience, the more likely people will respond actively. Trainor and McNeil (2008), however, discovered the "survivor confidence" phenomenon; namely, individuals, who have lived through a disaster or received warnings which did not develop into a personally harmful situation, tend to react to the current situation in a less cautious way. Therefore, people without previous hazard experience were more likely to take protective actions and take them more quickly. For Lindell and Perry (2004), the influence of prior experience was even not found. They argue that the hazard experience has no affection on the warning interpretation, information seeking, decision-making or response (Lindell & Perry, 2004).

A range of social attributes can make a difference in the warning response process, such as association membership and the characteristics of social network. Depending on the type of association, individuals inside can be either encouraged to or prevented from hearing, understanding, and responding to warning (Donner, 2007; Perry et al., 1981; Sorensen, 1991). Characteristics of social network can include, for example, participation in certain type of social network (e.g., involvement in the community or kinship), and the strength of social ties (e.g., the degree of family cohesion, interaction frequency with friends). Social networks, particularly informal ones, serve as very important means of receiving and confirming a warning (Gray, 1981; Mileti, 1995). Generally, people who are part of and maintain close relationships within large and well-established social networks, both formally and informally, are more likely to receive and confirm a warning (Landry & Rogers, 1982; Mileti & Sorensen, 1990). As a result, they are more likely to personalize the risk and take protection actions. But the influence of social network varies by the type of the network, like the influence of association membership.

Finally, there are the influences of resources. Having more physical, social and economic resources can enhance the probability for individuals to receive and understand a warning, but has a complex influence on behaviors at other responsive stages (Waugh, 2009). For example, while these resources enable people to undertake protection action, such as, car and enough money for evacuation, they also create some concerns holding people back from taking any action (Balluz et al., 2000; Drabek & Boggs, 1968; Perry, 1979b). Fear of looting is one of such concerns consistently found by EM researchers which prevent individuals from taking necessary evacuative behavior (Donner, 2006).

Sender factors. The sender factors characterize how the risk information is designed and sent to its target population. Previous research on public risk communication in EM categorizes them into five groups: attributes of 1) the information source, 2) the transmission channel, 3) the communication frequency, 4) the message content and 5) the message style. Table 2 shows how factors in each category influence individual behavior at each responsive stage to emergency risk information.

Table 2. *Influence of Sender Factors on Individual Response Process to Emergency Risk Information*

	Receive	Understand	Believe	Confirm	Personalize	Respond
Information source						
Number		+	+			+
Credibility			+		+	+
Familiarity			+		+	+
Transmission channel						
Number	+	D	D			D
Type	D	D	D			D
Credibility	D	D	D			D
Communication frequency						
Number	+	D	D	D		D
Pattern	+					+
Message content						
Hazard		+				+
Location			+		+	
Guidance		+	+			+
Time						+
Source						+
Format		D	D			
Message style						
Consistency		+	+	D	+	+
Continuity			+			
Certainty			+			+
Urgency			+	D		
Sufficiency		+			+	
Specificity		+	+	D	+	+
Clarity		+	+	D		
Accuracy		+	+		+	+

Note. In this table, "+" represents a positive association between a specific factor and individuals' tendency to take corresponding action at a given stage. "-" represents a negative association. "D" indicates an inconclusive finding with regard to how the factor influences individual behavior within a stage.

An information source refers to the organization or person who disseminates risk messages. Public agencies, scientific community and individual experts can all become information resources. According to previous studies, emergency warnings are more likely to be understood, believed and responded to if they come from a mixed set of sources (Donner, 2007; Mileti, 1999). Regarding source credibility, people are more likely to believe, personalize and respond to a warning from the source they perceived more credible (Perry, 1987). Similar influences can also be elicited by a warning from the sources individuals are more familiar with (Mileti & Fitzpatrick, 1992).

A transmission channel is the medium through which a risk message is conveyed from its source to its target recipients. Previous studies usually grouped information channels into the authority, mass media and peer, and empirically compare which type of channel is more utilized and perceived more credible (e.g., Donner, 2006; Lindell & Perry, 1992). They find that mass media and peers are important information channels; they are more used than the authority. However, the authority is generally considered with higher expertise. These studies also find that influential channel-related characteristics on individual warning response include the number of different types of channel used to send risk information, the type of channel in use, and the credibility level of channel perceived by a recipient (Donner, 2007; Mileti, 1995). These factors can influence whether individuals hear and how they understand, believe and respond to risk information.

The third group of sender factor is communication frequency. Both the pattern and number of times risk information is disseminated can influence individual response process. For the former, it is defined as “the degree to which message repetitions occur in a predictable pattern” (Mileti & Sorensen, 1990, p.5-5). The more predictable the repetition pattern is, the more likely individuals are to hear and respond to risk messages. For the latter, it is an important influential factor of individual warning hearing, understanding, believing, confirming and responding (Trainor & McNeil, 2008). Inconsistent influences of this factor have been found by previous studies on these individual reactions. While some EM researchers argue for its encouraging or discouraging impact (Nigg, 1982; O'Brien, 2003), Tierney (1993) and Mileti (1995) found a curvilinear relationship; there is a point of diminishing returns after which repetition of the same message may be counterproductive. But the optimal number of repetitions is not known.

At last, message content and style are the characteristics of warning information itself. Previous EM studies found individual response process can be influenced by whether the information encompasses answers to the following questions: 1) what the risk and its characteristics are, 2) what geographical area or location is threatened, 3) what people can do to protect themselves, 4) when the risk occurs and how much time is left before the impact, 5) who the information is issued from, and 6) whether the information includes graphical information besides verbal messages. By answering the first five questions, a warning can increase the probability for individuals to understand, believe, personalize and respond to a warning (Mileti, 1995; Mileti & Darlington, 1997; Parker et al., 2009). For the last question, the inclusion of graphical information, such as picture, graphics and video, has mixed influence on warning understanding and belief (Donner, 2007; Quarantelli, 1990).

The same content in a message can be conveyed in different styles. The influence of risk information itself is therefore not only generated by what questions are answered in it; how these answers are expressed and conveyed to recipient also matters. Previous studies have identified eight components of the style of a risk message. They are consistency, continuity, certainty, urgency, sufficiency, specificity, clarity and accuracy. Generally, when the degree of each component is enhanced for the answer to each of the six question mentioned before, for example, the message becomes more specific about risk, location, time and guidance, people are more likely to understand, believe, personalize and respond to the warning (McLuckie, 1970; Perry et al., 1981; Reynolds, 2005). An exception is that inconsistent evidence is found regarding the influence of message style factors on individual confirmative behavior. For example, while Sorensen (1992) argues the probability of confirmation decreases with increased information specificity, Donner (2007) finds receivers are more likely to confirm the information when it is more specific.

Contextual factors. Contextual factors include the characteristics of the context in which individuals receive and react to emergency risk messages. These characteristics are further divided into four groups: 1) environmental attributes, which include environmental cues, geographical proximity to threat and lead-time to impact; 2) social settings, which include family union, social cues, social time, social role and social activity; 3) individual psychological attributes in the context, including emotional status, fear of looting and concern, and 4) decisions and actions at previous response stages. For the influence of each contextual factor on individual behavior at each response stage, see Table 3.

Table 3. *Influence of Contextual Factors on Individual Response Process to Emergency Risk Information*

	Receive	**Understand**	**Believe**	**Confirm**	**Personalize**	**Respond**
Environmental attributes						
Environmental cues	D	D	D	D	D	D
Proximity to threat	+		+	+	+	+
Lead-time to impact	+		-	+		-
Social settings						
Family union			+	+		+
Social cues			D	D		D
Social time	D			D		
Social role	D	D		D		D
Social activity	D		D	D	D	D
Psychological attributes						
Emotional status			D			
Fear of looting						-
Concern	+		+	D		D
Previous decisions & actions						
Receipt		+				
Understanding			+		+	+
Belief					+	+
Confirmation					+	+
Personalization						+

Note. In this table, "+" represents a positive association between a specific factor and individuals' tendency to take corresponding action at a given stage. "-" represents a negative association. "D" indicates an inconclusive finding with regard to how the factor influences individual behavior within a stage.

Environmental attributes refer to the physical characteristics of a warning setting (Mileti, 1995). In such a setting, physical cues can exist to support or contradict what people are being warned of. For example, how individuals react to a flood warning they receive in a heavy rainy day is quite different from how they react in a cloudless day. Supportive environmental cues therefore constitute an important type of factor that can elicit people to understand, believe, personalize, confirm and respond to an emergency warning (Donner, 2007; Perry & Greene, 1982; Worth & McLuckie, 1977). The geographical proximity to the site of emergency has similar influence as supportive environmental cues do. Individuals who are geographically closer to the potential danger are more likely to receive and react to risk information (Donner et al., 2007; Sorensen, 1991; Trainor & McNeil, 2008). The third factor in this group is the length of lead-time to impact. This factor is actually related to individuals' perception of the situation urgency, namely, how much time individuals believe available for them to respond before an emergency occurs. Generally, with the increase of the lead-time length, the sense of urgency decreases, which enhances the probability for people to confirm a warning on the one hand, but makes them less likely to believe and respond on the other (Mileti & Sorensen, 1990; Perry et al., 1981; Quarantelli, 1983).

Besides physical attributes, the context of public risk communication also possesses social features. The first social feature that has been persistently reported by previous studies is family union, that is, whether individuals are united with their family when risk information is received. Family union can encourage individuals to believe, confirm and respond to a warning (Drabek, 1969; Drabek & Boggs, 1968). The second social feature concerns how others, particularly familiar others, are seen as reacting to the warning, which is also called the social cues. Social cues can be consistent or inconsistent with the warning message, and their influence on response process varies depending upon their supportiveness on the potential threat (Donner, 2006; Donner, 2007; McLuckie, 1970). Social time, social role and activities are three closely-related factors. For social time, it refers to a community's patterned time for certain activities (Gray, 1981). It is different from chronological time, and varies among communities and over time. Previous EM studies found social time had important influence on warning reception, confirmation and response (Donner, 2007; McLuckies, 1970). The other two factors can affect what role people is playing in the warning context, for example, whether there is care-giving responsibility, and what people are doing, such as sleeping, working or engaging in recreation (Gray, 1981). These two factors can further exert complex influence on almost the whole individual response process (McLuckie, 1970; Quarantelli, 1990; Trainor & McNeil, 2008).

The psychological attributes here are different from those psychological attributes in the receiver factor. The former formulate when or after an individual receives a warning, while the latter are pre-warning characteristics. In the emergency context, individual emotional status can influence whether and to what extent the risk information will be believed (Parker et al., 2009). Increased degree of concern with safety can increase the probability for people to hear, believe, confirm and respond to risk information (McLuckie, 1970; Quarantelli, 1983).

Lastly, decisions and actions at current reactive stage are at least partially influenced by those at previous stages. Specifically, people can only understand a warning after it is received, and a clear understanding enhances the chance to believe the message (Mileti & Sorensen, 1990). Warning messages are more likely to be accurately personalized by people who have formed correct understanding, developed high level of belief and possessed confirmative information about the risk (Nigg, 1982, 1987; Perry & Greene, 1982). Also, people are more likely to take responsive actions if risk information is understood, believed, confirmed, and personalized (Mileti & Darlington, 1997; Perry & Mushkatel, 1986; Quarantelli, 1983). The only exception regarding the influence of these contextual factors occurs at the confirmation stage. Previous research findings, to my knowledge, have not documented whether individual confirmative behavior is influenced by previous warning understanding or belief.

Event factors. Factors of this category refer to the characteristics of an emergency. Specific attributes associated with an emergency and their implications for management have been the major concern of geography and other natural scientific fields (Tierney, 1993). For public risk information in EM, researchers argue that, the knowledge of individual emergency warning responsive transcends emergency type (Lindell et al., 2005; Mileti, et al., 2004). Individual warning response is more about the human nature, especially, how individuals respond to a stressful situation (Worth & McLuckie, 1977). Therefore, regardless of how they vary in characteristics, “the basic social psychological process that directs public response is similar across hazards” (Mileti, 1995, p.1).

On the other hand, EM researchers did find some event related factors which have a bearing on individual warning response. For example, the level of objective risk, which indicates based on scientific estimation the seriousness and destructive power of the potential danger, was weakly associated with the warning recipient, belief, confirmation, personalization, and response (Mileti & Darlington, 1997). There are also other factors which can influence whether and how individuals will respond, such as the controllability of an emergency, the length of forewarning (rapid- or slow-onset emergencies), and the accessibility of escape routes in the emergency (Tierney, 1993). Table 4 summarizes the influence of each event factor on individuals' behavior during their responsive process to emergency risk information.

Table 4. *Influence of Event Factors on Individual Response Process to Emergency Risk Information*

	Receive	Understand	Believe	Confirm	Personalize	Respond
Objective risk	+		+	D	D	+
Controllability						-
Length of forewarning						D
Accessibility of escape routes						D

Note. In this table, "+" represents a positive association between a specific factor and individuals' tendency to take corresponding action at a given stage. "-" represents a negative association. "D" indicates an inconclusive finding with regard to how the factor influences individual behavior within a stage.

Social-cultural factors. The last general category of influential factors concerns with the social and cultural characteristics of the local area potentially impacted. Specifically, these include the culture developed in the area, spirit of the times, features of the local public risk communication system, and local preparedness efforts. Table 5 summarizes how these social-cultural factors influence individual behavior at each responsive stage.

Local culture, particularly the disaster culture developed in the area, plays an important role in the whole public responsive process. It is most formulated within a community that often experiences the same or similar risks (Mileti & Darlington, 1997). Because of such relatively high occurrence, cultural defenses are formulated to prepare and respond to the recurrent danger. Moore refers to such standard coping tradition within a community for a specific hazard as "disaster culture", which includes "those adjustments, actual and potential, social psychological, and physical, which are used by residents of such areas to cope with disasters which have struck or which tradition indicates may strike in the future" (Moore, 1964, p.195). For public risk communication, disaster culture shapes the way in which each individual reacts to the risk information, from the very beginning of hearing to the final response (Donner et al., 2007; Perry & Hirose, 1991; Perry et al., 1981). Both encouraging and depressive influence can be generated by a disaster culture, depending on whether the standard reaction implied by it is adequate or not for a particular risk.

Table 5. *Influence of Social-cultural Factors on Individual Response Process to Emergency Risk Information*

	Receive	**Understand**	**Believe**	**Confirm**	**Personalize**	**Respond**
Culture	D	D	D	D	D	D
Spirit of the times			D			
Local warning system			D	D		D
Local preparedness effort						D

Note. In this table, "+" represents a positive association between a specific factor and individuals' tendency to take corresponding action at a given stage. "-" represents a negative association. "D" indicates an inconclusive finding with regard to how the factor influences individual behavior within a stage.

The spirit of the times is another aspect of the social setting. It consists of those anticipations and expectations that are widespread within an area at certain time (McLuckie, 1970). People inside such time-space boundary are more likely to accept any cue that is supportive of the spirit. What is relevant to emergency risk communication is the belief by individuals. The public is more likely to believe messages that are warning an anticipated or expected risk, while ignore the information against such anticipations and expectations.

For local public risk communication system, researchers argue for its influence, but arrive at inconclusive findings. One feature of the local system that has been widely studied is its efficiency, particularly the false alarm rate. Although previous studies found that the false alarm rate can influence whether individuals believe, confirm and respond to a warning (Donner et al., 2007; Trainor & McNeil, 2008), whether or not the influence is encouraging for individual responsive behavior varies among different contexts. In most cases, the response process could be exempted from the influence of false warnings as long as efforts are made to explain why they are disseminated.

The last set of influential factors is about local or community preparedness efforts, for example, public education and information programs. Previous research has examined the effectiveness of pre-emergency education programs, and reported inconsistent evidence in terms of whether such efforts can enhance individual response to emergency risk information. While some studies found a positive influence, others found the influence to be negative or make no difference (Sorensen & Mileti, 1988). At present, EM researchers are more likely to agree with each other that, although the effectiveness of a good pre-emergency education or information program is in question, a poor program will not likely have a positive influence (Sorensen, 2000; Sorensen & Sorensen, 2006). In addition, consensus has been reached with regard to what topics should be covered by these programs (Sorensen, 1993; Sorensen & Mileti, 1992).

Summary. For each influential factor, it affects individual response process to emergency risk information in a complex way. The influence is both nonlinear and contextual. On the one hand, the same factor can have distinct affections on individual behavior at different stages and make its influence on the final response sophisticated. On the other hand, whether one factor has an influence on behavior at a specific stage and what the influence is depend on the emergency context and study settings (Turner, 1981; Turner, et al., 1979). What adds a further layer of complexity is the inter-connection and interaction among these factors. In most cases the influence of a specific factor may be reduced, enlarged, or complicated by other factors, whose affections may be changed by this factor at the same time. For instance, low economic status or poverty can make it more difficult for individuals to understand a warning; but these difficulties can be overcome if individuals have a large-size social network (Donner, 2006). Similarly, the gender difference in taking protective action may fade away as females' education level and work experience get closer to that of males (Drabek, 1999). Furthermore, both factors can simultaneously complicate the influence of other factors, such as social time (Donner, 2007). It is self-evident that what white middle-class are doing when receiving emergency warnings is quite different from that of a lower-class African-American female, or a upper-class Asian college student. Considering such complexity, researchers argue that how specific individuals may react in an emergency warning context is influenced by very intricate combinations of factors (McLuckie, 1970). An invisible web of constraints actually exists that patterns individual warning response (Drabek, 1999).

Previous studies also argue for two more interesting findings. First, individual behavior at all stages of the warning response process, except message receipt, is influenced by almost identical sender and receiver factors (e.g., Mileti & Sorensen, 1990). This may be caused by the interaction among these factors. The second finding concerns which category of factors is more influential, and some EM studies find the context in which warning is received is more influential in affecting individual responses (e.g., Dynes & Quarantelli, 1973).

Critiques. Over a period of several decades now, EM researchers have been attempting to describe a more accurate picture of how individuals perceive and respond to risk information in emergency situations. Substantial and systematic knowledge has been accumulated. Individual response process is social and complex, consisting of sequential stages. Individual behavior at each stage is patterned by a series of inter-connected factors. Furthermore, these stages and factors are interlinked, which together produce individual responsive behavior to emergency risk information.

Such knowledge needs to be understood and considered by emergency managers when they plan for and respond to future emergencies. They need to correct their unrealistic assumptions on individual response to emergency risk information. Also, instead of making people what they are not and blaming them for not changing themselves for the response plan, emergency managers should understand how individuals are likely to behave and adaptively adjust their plan in accordance with these behaviors. Previous studies also provide useful guidance for emergency managers to design emergency communication strategies. For example, a certain degree of consensus has been achieved regarding what makes for effective risk messages. These factors, among the wide range of factors identified influential on individual reaction, can be utilized by emergency managers to enhance the probability of sound public response.

While previous studies on emergency risk communication can greatly assist emergency managers, further investigation is still needed. In current literature at least four major limitations remain: 1) few insights have been provided on how emergency risk information should be sent to the public; 2) little is known about how individuals use information for decision-making during their response process to emergency risk information; 3) little attention has been paid to how public response pattern to emergency risk information at the system or community level emerges; and 4) few studies have considered risk communication during emergencies as a dynamic process, through which public sectors and the public interact with each other through information exchange.

First, very limited insights have been provided on the effective way to issue risk information. Sender factors are crucial for emergency risk communication research and practice. That is because emergency managers can relatively easily manipulate these factors to influence individual response to risk information. All the other four types of factors cannot simply be accessed and changed (e.g., such demographics as gender and age). Among sender factors, systematic knowledge has been developed on how to design risk information, for example, what its content should be and how its style needs to be framed. There is little information in term of how certain risk information should be disseminated, for example, which type of channel should be used and what the dissemination frequency should be. Particularly, previous studies simply narrow all types of mass media into one general channel type. During an emergency, most individuals receive risk messages through a variety of mass media, such as television, newspapers, or social media. Emergency managers can also easily change their communication strategies through changing the types of mass media used for sending information. More systematic knowledge on the interaction of different types of communication channels—particularly different types of mass media— and individual warning response is needed to help public managers develop effective risk communication strategies.

Second, the individual reactive process after warning receipt is clear in EM literature, in terms of what stages individuals go through and how their behavior at each stage may be influenced by various factors. However, ambiguousness arises when it comes to how individuals behave at the social confirmation and situational definition stage. According to previous studies, warning confirmation almost always occurs after individuals receive an emergency warning and formulate their initial risk perception. Individuals within the two stages attempt to obtain additional information mainly from personal contacts, namely friends, family and neighbors, in order to verify their initial perception. Based on additional information collected and their initial perception, individuals then define their own situation in terms of whether they are personally endangered.

Important information that has been missing is how individuals evaluate collected information from diverse informal sources and assess their personal risk based on the information. In other words, disaster researchers find what occurs at the beginning and end of the two stages, but do not know the social process between. Specifically, questions remain with regard to 1) what criteria individuals use to select personal contacts for additional information, for example, is it based on geographical proximity or relationship familiarity; 2) how individuals evaluate information from different contacts; and 3) how they use information received and collected to formulate their situational definition, especially when information obtained is inconsistency, or even contradicting.

Third, how emergency managers plan for and respond to an emergency need to be based upon system-level data, rather than individual information. For example, essential resource estimation before an emergency is community- or group- based; seldom is it based upon an individual's needs. For public risk communication, practices should start with what we know of how groups are likely to react, rather than with what individual response might be (Quarantelli, 1983). However, few studies have explored the response pattern at the system level. Almost all studies consider it the most common and effective way for improving warning effectives to find out empirical evidence about individual warning response and developing individual response model. While such knowledge can help emergency managers identify and incorporate incentives to enhance individual warning compliance, it provides little information regarding the system pattern of public warning response. Given the highly interactive and collective nature of individual response, such public pattern, although closely related to how each individual respond, cannot be easily inferred from it. What both researchers and practitioners need is the possible mechanism that links individual behavior and system-level dynamics. The latter therefore can easily be derived through the mechanism from previous knowledge. Also, since influential factors on public response pattern may be different from those on individual behavior, we need to investigate what these factors are and how they exert their impacts at the system level.

Fourth, in emergency situations, public managers need to continuously monitor the public's response. Feedback must be received to indicate whether the risk message is received and understood and how further warnings can be developed for behavior correction if people are not responding in the desirable way. Meanwhile, people may adjust their responses accordingly to the updating risk messages, and the consequences of their behavioral adjustment may lead to further modification of risk communication. Figure 3 shows such a dynamic and interactive process, which is highly effective for public self-protection but rarely practiced by emergency managers.

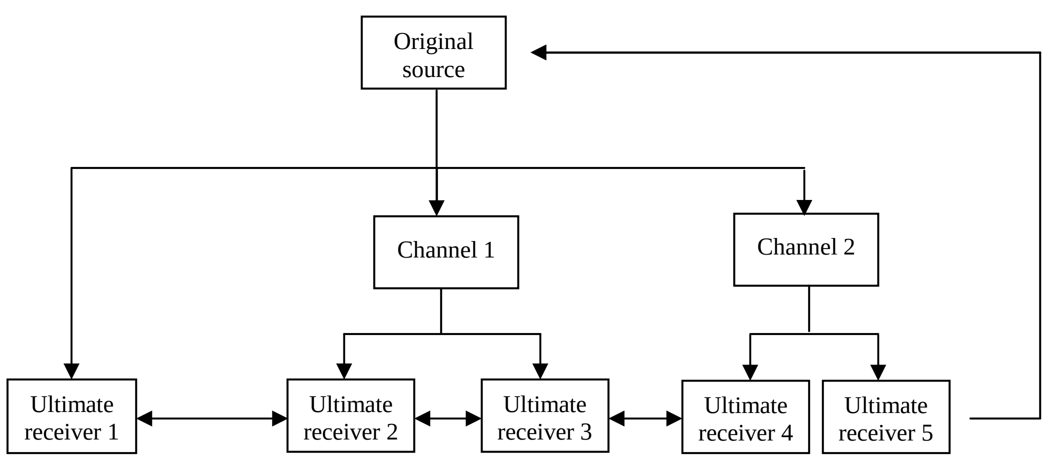

Figure 3. A dynamic model of emergency risk communication

In practice emergency managers are more tempted by the uni-directional communication model which obviously is more manageable and less time- and resource-consuming. With regard to previous studies, the importance of a dynamic and two-way risk communication process has been emphasized by several EM researchers (e.g., Chowdhury, 2005; Tierney, 1993; Williams, 1964; Worth & McLuckie, 1977). However, few of them have included the interactive process into their empirical studies or theoretical development. Knowledge therefore is absent in terms of how the public and emergency managers adjust to each other during the public risk communication process. To provide more insights for effective emergency warning, such a gap must be filled.

Although these limitations are not ignored by previous studies on public risk communication in EM, the methodological flaws inherent in this stream of literature make them persistent concerns (Donner, 2006; Drabek, 1969; Gladwin et al., 2007). For example, previous studies on public risk communication in EM have either adopted a traditional view and focused on its technical aspect, or engaged themselves into the investigation of individual behavior. Responsive pattern at the community level and the interaction between public sector and the public therefore can hardly become a research focus. Furthermore, current EM studies are preoccupied by qualitative description or post-emergency survey and simple statistical analysis. Such research methods are incapable of connecting individual behavior and system-level pattern while at the same time tracking individual decision-making process and including a dynamic and process view.

Chapter 3

Research Design

Research Question

This dissertation explores whether and how emergency impacts can be mitigated through the effective use of information transmission channel for public risk communication. To answer the research question requires addressing the following questions:

- How do individuals make decisions regarding their response to risk information in emergency situations?
- How do the characteristics of information transmission channel influence individual response to emergency risk information?
- How does public response pattern to emergency risk information emerge at the community level?
- How can information transmission channel be appropriately used by emergency managers to mitigate emergency impacts?

Research Scope

Public risk communication for a long time has been an important topic in a variety of research and applied areas, such as environmental risk communication (e.g., Fishoff, 1985; Fischhoff, Slovic, & Lichtenstein, 1979; Slovic, 1986), emergency management (e.g., Quarantelli, 1954; Williams, 1957), and health promotion and communication (e.g., Klaidman, 1985; Sharlin, 1987). This dissertation focuses only on the research and practices of public risk communication in the field of EM. Studies and practices of public risk communication in other fields are not covered.[3]

Among all problems related to public risk communication in EM, this dissertation focuses on how the response process to risk information at the individual level and emergency impacts at the community level are influenced by the characteristics of information transmission channel emergency managers use to send risk information. The key aspect of emergency public risk communication lies in the extent to which risk information can elicit appropriate public response to minimize losses from an emergency. Previous studies in public risk communication in EM have identified a wide range of factors that can influence individual response to risk information. Compared with others, emergency managers are more easily to utilize one specific type of factor, called sender factor, to influence individual response and further emergency impacts. Sender factors characterize how the risk information is designed and sent to its target population. Among these factors, the influence of information source and information content and style on individual response process has been conclusive. But inconsistent insights have been provided regarding the influence of the characteristics of information transmission channel, including the number and type of channel used to send risk information, and the perceived credibility and use frequency of each type of channel. This dissertation attempts to explore whether and how emergency impacts could be influenced by the characteristics of transmission channel used to send risk information. The strategy for public risk communication

[3] There is a very large literature on risk communication between experts and citizens that is not related to EM.

in this study is only indicated by those characteristics of information transmission channel. Other strategy indicators for public risk communication in EM would not be considered.

In this dissertation, the specific type of public emergency focused on is influenza pandemic.[4] The scale of analysis is a medium-size community.[5] The specific research context is the 2009 H1N1 influenza outbreak in Arizona.

Research Method

Methodologically different from conventional EM research on public risk communication, this dissertation employs the computational simulation approach of agent-based modeling (ABM) to address the research question. An agent-based model is a class of computational models, which attempts to explain and anticipate social phenomenon by simulating the interactions of interdependent agents (Srbljinovic & Skunca, 2003). It is also called multi-agent simulation or individual-based model. ABM as a simple concept emerged in the late 1940s. With the development of game theory, computer science and artificial intelligent, it became a research method in the 1990s. By now it has been extensively applied in various domains.

Contrasted with more traditional mathematical models, agent-based models are characterized by four distinguishing features. These comparative features make ABM particularly well suited, or even necessary, to better understand

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[4] Why influenza pandemic is selected as the focused type of emergency would be explained at the beginning of Chapter 3.

[5] Why a medium-size community is select as the scale of analysis would be explained in Chapter 4.

problems in emergency risk communication, including the research question of this study.

ABM simulates interactions between adaptive agents. Agent-based models consist of agents and action rules. Agents are the basic action unit; they may be persons, organizations, or countries. An agent in ABM is programmed to be autonomous and boundedly rational; it makes use of decision rules based on local information. Action rules specify how agents interact with each other. These interactions need not be physical; they can also occur through information exchange. Because of the interaction, agents become interdependent and adaptive to one another.

ABM is process-oriented. Agent-based models require a high degree of precision regarding the underlying processes (i.e., mechanisms) involved. Every aspect of how agents interact must be well specified. This requirement enables ABM a process-oriented approach, which can explicitly describe and track agents' interactions (Rakowski et al., 2010). Such feature further makes ABM inherently dynamic, and a natural way to explore the dynamic behavior of a system.

The above two features of agent-based modeling enable this approach framing public risk communication as a dynamic process. Individuals and public sector can be considered as adaptive agents. During the process, they interact with each other through information exchange, and mutually adjust their behaviors. The model can track each agent's action, as well as the whole interaction process. Insights therefore can be provided from a dynamic and process view.

ABM is also a bottom-to-up modeling approach. Many existing analytic tools follow top-down logic, and represent system relationships between aggregate variables in the system (An et al., 2005). For example, regression analysis usually attempts to do so by inductively fitting empirical data with regression models. Bottom-up approach analyzes system behavior in an opposite way. It starts with the understanding of the low-level processes, and generates aggregate system pattern by simulating the individual entities in the system. ABM therefore can bridge the gap between micro and macro level by generating large-scale macroscopic phenomena from micro-level agent interactions. For public risk communication, individual response process to risk information could be simulated in an agent-based model, and the response pattern at the system or community then can be automatically generated through the simulation over time.

ABM can serve as a knowledge integrating framework. ABM can be applied to integrate knowledge from different fields into a united framework (Gong & Xiao, 2007). It can also integrate qualitative and quantitative data (Polhill, Sutherland, & Gotts, 2010). Therefore, ABM can make assumptions based on both theories and empirical data from a variety of disciplines, and create artificial societies in which agents could be expressed more directly and detailedly. Considering this feature, ABM can learn from previous studies in other research fields than emergency management and public risk communication, to make reasonable assumptions on how characteristics of information transmission channel influence individual response to risk information, and how individuals collect confirmative information and make decisions during their response process. These assumptions then can be included and tested in the model.

Besides being a promising approach to answer the research question, ABM also possesses the four features previous studies have repeatedly proposed for a new approach to EM. All types of organizations and the public within EM system can be included in an agent-based model as agents. These agents interact with each other through communication and make their own decisions. The artificial EM system formulated in the model therefore becomes a network-structured inter-organization system, with decentralized decision making and open communication. Meanwhile, since agents are interdependent and adaptive to others' actions, public sector as one type of agent must base their actions—the management strategy—on the action of other types of agents, for example, the public. Furthermore, ABM's process-oriented feature and capacity of integrating knowledge make a dynamic and inter-disciplinary perspective to EM possible.

Another reason why ABM makes an appropriate approach to EM is that it provides unique opportunities for social experiments. Emergencies are those social phenomena as only occur rarely. Considering ethnical, resource and other factors, it is very difficult to conduct experiments in real social setting (Skvortsov et al., 2007). On the other hand, the artificial world in an agent-based model can be fully observed, recovered and repeated. It is a convenient and very cost effective tool to formalize, refine and conduct what-if simulation and analyses for EM issues. Researcher and public managers by using this modeling approach can easily and systematically analyze different policy options at their disposal.

No single approach or tool is suitable for all questions, and it is certainly unreasonable to claim ABM universal and almighty. However, the constellation of features offered by ABM does make it a very promising approach to gain new insights into EM in general and public risk communication in particular.

In the specific research context, agent-based simulation among other modeling approaches has the most potential to appropriately simulate the spread dynamics of a pandemic influenza. Previous literature identifies two key features that should be simultaneously included in a computational model for pandemic influenza simulation. First, the spread dynamics of pandemic influenza cannot be understood without some knowledge of social network, particularly knowledge on the underlying inter-personal contact network for virus transmission (Mollison, 1995). Researchers have realized that the way in which contact network was parameterized in previous models for pandemic influenza simulation is problematic (e.g., Edmunds et al., 2006). Meanwhile, empirical contact data is considered a more appropriate base to structure and parameterize the artificial contact network (Keeling & Eames, 2005).

Second, the knowledge of contact network must be combined with a modeling approach which is capable of simulating the bottom-up aggregation of micro-interaction to macro-pattern (Eames, 2007). The impact of an influenza pandemic at the community level emerges from the interactions between individuals and interactions between individuals and public sectors. Therefore, the simulation model should have the capacity of tracking the contacts of each individual with others in the relevant contact network, and how public interventions influence those contacts. Meanwhile, it should be bottom-up instead of top-down modeling, to simulate how thousands of micro-interactions in the population contribute the emergent patterns of infection, death, and survival at the aggregate level.

These two key features can be simultaneously included in agent-based simulations. Other modeling approaches previously used for pandemic influenza simulation may have addressed one of them, but rarely both at one time. An agent-based model consists of a population of heterogeneous and autonomous actors or agents, an environment, and a set of action rules. Modeling in epidemiology using this approach can track the contacts of each individual, and simulate the spread progress of a pandemic influenza through those contacts. Rules for agent contacts and infection transmissions are explicit. Agent-based modeling is also a bottom-up approach. The main difference between this approach and those traditional pandemic influenza simulation models based on differential equations lies in that the latter is used at the macro level while the former bridges the gap between micro and macro level by producing emergency global effects from local agents' interactions. Although data collected at the macro level are still important in agent-based simulations, they are mainly used to compare the results from different simulation scenarios or compare modeling results against empirical data (Gong & Xiao, 2007). Furthermore, the theory of social network can be easily integrated into agent-based models. The nodes in a social network can be considered as agents in an agent-based model, while connections between nodes as interactions between agents.

Organization of the Dissertation

This dissertation consists of six chapters. Chapter 1 briefly introduces the background and motivation of this dissertation. Chapter 2 reviews the traditional approach to EM in general and public risk communication during emergencies in particular, and critiques on these approaches. Chapter 3 proposes the research question, the research scope, and the research method to be employed to answer the research question. Chapter 4 first explains why an influenza pandemic is chosen as the focused public emergency. It then reviews previous computational models in literature for pandemic influenza simulation, and explains how the agent-based model created in this study can be distinguished from previous pandemic influenza simulation models, how the model is created, and why it is created in such a way. Chapter 5 uses a case to demonstrate how the methodological framework developed can be used to answer the research question in the influenza pandemic context, and utilized by emergency managers in practice to develop effective communication strategies. Chapter 6 summarizes the answer to the research question based on the simulation results from Chapter 5. Theoretical and practical contributions of this dissertation, as well as its limitations and further extensions, are also discussed in this chapter.

Chapter 4

Modeling an Emergency for Public Management

Influenza Pandemic as a Public Emergency

The specific emergency focused on in this dissertation is an influenza pandemic. An influenza pandemic is “a global outbreak of disease that occurs when a new influenza virus appears or emerges in the human population, causes serious illness, and then spreads easily from person to person worldwide” (CDC, 2012).[6] It is different from the seasonal epidemics of influenza, since the latter are caused by those influenza viruses that already exist among people (Nicholls, 2006). Such an emergency situation is selected based on two reasons. First, as a relatively new type of public emergency, past influenza pandemics have caused serious consequences on human societies, including high levels of illness, death, social disruption and economic loss (CDC, 2012). For example, the 1918 Spanish flu is estimated as being responsible for the deaths of 50 million to 100 million people worldwide (Barry, 2005). In the past century, there occurred three influenza pandemics—in 1918, 1957 and 1968 respectively, which were followed by the most recent 2009 H1N1 pandemic. Given the estimated high probability of another influenza pandemic, both CDC and HHS have made it a priority to understand its spread dynamics in communities and to develop effective spread-control strategies (Das, Savachkin, & Zhu, 2008; Ferguson et al., 2005).

The importance of effective public risk communication becomes more salient in the context of an influenza pandemic. Interventions for pandemic prevention

[6] Influenza pandemic is different from pandemic influenza. The latter refers to the influenza which causes a global outbreak of the disease.

and control are usually grouped into two categories: pharmaceutical measures (typically vaccination and antivirals) and physical or non-pharmaceutical measures (typically social distance measures). Researchers and practitioners commonly consider the former more effective than the latter (Longini et al., 2004). However, when novel pandemic strain of influenza occurs, time and production capacities are usually insufficient to develop, produce and distribute enough effective vaccine or antivirals to protect the general public (Mniszewski et al., 2008; Monto, 2006). Whether individuals take physical measures for self-protection in this case becomes an importance influence on the duration and severity of the outbreak.[7] Meanwhile, previous studies found that individuals are reluctant to take protective actions (Rodríguez et al., 2006; Rogers & Sorensen, 1989). Understanding individual response to emergency risk information and developing effective communication strategies to encourage the public to take protective measures therefore become one key intervention public managers can employ for pandemic control.

Traditional Approaches for Pandemic Influenza Simulation

Given the rare occurrence of an influenza pandemic, computational simulation has been an efficient approach to systematically understand its spread and control. Simulation models enable researchers to formalize, refine and conduct thought experiments. Conspicuous quantities of artificial data therefore can be generated, which are hardly available in the real world because of the

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[7] The term of pandemic when used alone in this dissertation refers to influenza pandemic. For example, a pandemic means an influenza pandemic, and pandemic impacts the impacts caused by an influenza pandemic.

elevated costs or the rarity of the phenomenon. Such data further allows researchers to do preliminary "what-if" analyses to examine systems' behavior when different control measures are adopted.

Compartment models in epidemiology. The foundations of modern epidemiology are based upon classic compartment models, which began with a series of studies conducted by Kermack and McKendrick (1927, 1932, 1933). In their research, the total population, depending on their status relative to an epidemic, is divided into three subdivisions or compartments: 1) Susceptible, the population who are healthy and can be infected by the epidemic, 2) Infected, the population who have been infected and are infectious to the susceptible, and 3) Removed, including people who either recovered from the epidemic (Recovered) or are killed by it (Died). Individuals can move from one compartment to the next, as shown in Figure 4. Transition rates of movement between two adjacent compartments are defined in the following set of ordinary differential equations.

$$\frac{dS}{dt} = -\alpha\beta S\frac{I}{N}$$

$$\frac{dI}{dt} = \alpha\beta S\frac{I}{N} - \gamma I$$

$$\frac{dRe}{dt} = \gamma I$$

$$\frac{dD}{dt} = \mu I$$

In these equations, S, I, Re, and D refer to the number of susceptible, infected, recovered and died individuals, respectively, in a population of size N. The other parameters are the infection rate, α, which represents the probability for a susceptible individual to get infected after a contact with an infectious individual, and the contact rate, β, representing the average number of people each individual contacts within a time step. μ is the mortality rate among infected individuals; it represents the probability for an infected individual to die at each time step. γ is the recovery rate, which refers to the probability for an infected individual to recover from the epidemic at each time step, if the individual has not died. Its reciprocal is the infected period, representing the period between the moment an individual becomes symptomatic and the moment the individual recovers from the disease. Using this set of equations, the spread of some epidemic in a population is treated as a non-stationary process. It is dynamically simulated through the fluctuations over time in the number of individuals in each compartment.

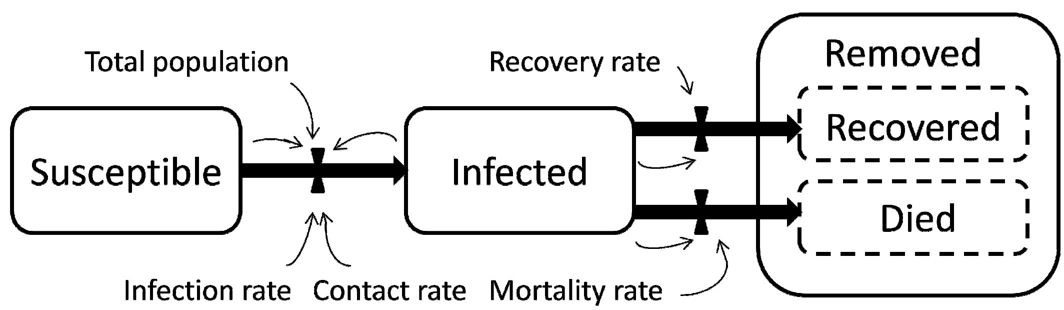

Figure 4. SIR model of an epidemic infection progress

Such a model is known as the SIR model. It is the point of reference for mathematical models used for simulating epidemic spread (Dangerfield, Ross, & Keeling, 2009). Over the years, the model has been extended to consider other compartments and flow patterns between them, for example, the SEIR, SEIRS, SEI, SEIS, SI and SIS model. All these models are called the deterministic compartment model. They simulate the spread process of an epidemic through a population-based approach. Conceptually, this approach is rooted in the general population model which divides a population into different segments (Perez & Dragicevic, 2009). A system of differential equations is then developed to model the population change in each segment.

Deterministic compartment models have been used for mathematically modeling the spread process of a pandemic influenza for over a century. They capture the nonlinear nature of the spread dynamics in a population. They also simplify the factors and variables that should be considered to understand the dynamics, and can be easily processed with a set of mathematical equations.

Despite the long and successful history, the compartment model is also criticized in that it is too simple to provide insightful information to understand and control a pandemic, particularly considering the complex nature of the issue (Gong & Xiao, 2007). Two limitations within the model constrain its utility. First, compartment models fail to consider social phenomena associated with individual interactions. Since the population is assumed homogeneously mixed and modeled as continuous entities in compartment models, the characteristic of inter-personal interactions are neglected (Mollision, 1995; Watts, 2004).[8] Second, compartment models fail to express the relationship between micro and macro levels (Gong & Xiao, 2007). The spread process of a pandemic influenza at the system level is produced by countless interactions between individuals, through which the influenza virus is transmitted. Pandemic control measures also aim to change individual behavior, but their effectiveness is measured at the system level

[8] By homogeneous mixing, an individual is assumed to meet or contact any other individual in the population with the same probability (Larson & Nigmatulina, 2009).

(Eames, 2007); for example whether and by how much the vaccination reduces the impacts of a pandemic influenza in a community. Hence, how individual behaviors marked by local parameters translate into global patterns indicated by global parameters is vital for understanding the spread dynamics and anticipating the impact of control measures. Since both input and output parameters in differential equations are at the macro level, compartment models fail to describe such a translation.

As Eidelson and Lustick (2004) once stated, traditional mathematical modeling tended to consider social issues as Newtonian physics problems. The world is fully predictable, and "comprised of traceable vectors and governed by known laws operating at the macro level" (Eidelson & Lustick, 2004). These top-down models are typically incapable of capturing the underlying dynamics in most social systems where a great number of autonomous and interdependent micro-actors interact with one another.

Social network models and massive agent-based models. Alternative simulation models to traditional compartment models for pandemic influenza simulation have been developed, with the main purpose of including the structure of interpersonal contacts in the simulation. Two types of models are common among previous studies: social network models and massive agent-based models.

Social network models have played an important role in shaping the understanding of pandemic influenza spread process over the past decades (Hu & Gong, 2009; Newman, 2002). In these models, individuals are considered as nodes in a network and the links between them their contacts. Each individual has a set of links or connections to others, who are usually selected through certain preference. The homogeneous population mixing assumption in traditional compartment models therefore is avoided since individuals can only contact those who are connected to them in the network. Infection is transmitted along links, and individuals can only transmit infection to or get infected by those people connected (Dangerfield et al., 2009). Current social networks models have been integrated with a variety of other techniques for epidemic simulation, including cellular automata (e.g., Leung et al., 2008; Pfeifer et al., 2008) and agent-based modeling (e.g., Epstein, 2009; Yang, Atkinson, & Ettema, 2011).

Compared with social network models, agent-based modeling for pandemic influenza simulation is more recent efforts. As described before, ABM could be integrated with social network to simulate influenza spread. It could also be used without the assistance of network (e.g., Rakowski et al., 2010; Stroud et al., 2007). In the latter situation, agent-based models are normally large scale, spatially explicit and parameterized to construct a synthetic population to match the actual population of the region studied. Such models are usually called massive agent-based models. Each individual in the model has a schedule of daily activities, and each activity has a specified start and stop time and a specified sub-location. Possible sub-locations include households, schools, workplaces, and so on. Infection occurs between individuals when they occupy the same sub-location at the same time. Contact network also exists in the model, but it is not set up at the very beginning of simulation and guides how individuals contact with each other during the simulation. The network in massive ABM emerges as the result of agents' interactions based on their action rules. That is why massive ABM is not considered as a social network model. That is also how a social network model integrated with ABM is different from a massive agent-based model.[9]

Critiques on the above two types of models for pandemic influenza simulation have been centered on how individuals contact with each other is simulated in the model (Edmunds et al., 2006; Wallinga, Teunis, & Kretzschmar, 2006). First, disagreements have been raised in terms of the stability of contacts, namely, whether the set of people each individual contacts is transient, stable or both. Edmunds et al (2006) categorized simulation models for pandemic influenza into two groups, according to their assumptions on contact stability: those using the mass action assumption in which contacts are independent and instantaneous, and those in which individuals have stable contact connections. For social network models, their initial usage for epidemic simulation is intended to capture the permanent nature of interpersonal interactions to substitute the random mixing assumed in compartment models (Edmunds et al., 2006). Many social network models therefore fall into the second category; the links in the network remain constant over time (Keeling & Eames, 2005). Each individual has a fixed set of contacts. The focus of simulation is on how the disease spread over the static network. For massive agent-based models, Edmunds, O'Callaghan, and Nokes (1997) argue that they typically employ the mass action assumption, essentially random contacts, although those random contacts are restricted to a sub-population decided by a sub-location. According to a few of more recent studies,

[9] Models integrating ABM and social network can also be considered as agent-based models. But they are different from massive agent-based models.

interpersonal interactions should have a hierarchical structure (Grabowskia & Kosinskia, 2005; Mikolajczyk & Kretzschmar, 2008; Read, Eames, & Edmunds, 2008). While some of individuals' daily contacts are stable, others are constantly changing. In fact, most daily encounters are random and non-repeated. Those encounters reflect the mobility of a community; they can occur during commuting or in public places. Stable and repeated contacts also exist, but with a smaller amount than the number of random encounters. For epidemic simulation, these studies argue that the transmission route for infection in the model should include a strong random component, as well as a stable element (Grabowskia & Kosinskia, 2005; Mikolajczyk & Kretzschmar, 2008; Read et al., 2008).

The second concern with individual contact pattern in the two types of models is that the epidemiologically relevant contact pattern in both cases are first assumed and then calibrated to epidemiological data (Edmunds et al., 2006; Mossong et al., 2008). These assumptions could be very simple, or very detailed. For example, massive agent-based models for pandemic influenza simulation usually demand a variety of individual behavioral assumptions, particularly those related to individual movement. Several issues make such a way to construct artificial contact pattern problematic. For example, there are often a larger number of parameters related to contact pattern that need estimation than that of epidemiological parameters which the model can be calibrated against (Edmunds et al., 2006). Meanwhile, Wallinga et al (2006) argued that, for specific infectious diseases, particularly for the transmission of airborne infections, models parameterized by empirical social contact data offer a better description of observed incidence than those that employ assumed and calibrated assumptions on contact pattern. Following that study, there are other studies using and demonstrating empirical data from survey can be utilized as a valid proxy for unobservable distributions of actual at-risk contacts for respiratory infections (Mikolajczyk et al., 2008; Mikolajczyk & Kretzschmar, 2008). Since the pattern of contact is crucial in determining the spread of an epidemic, a reconsideration of how it should be approximated in simulation models is needed.

A Network-based ABM for Pandemic Influenza Simulation

In this dissertation, a network-based ABM is created to simulate the spread dynamics of a pandemic influenza within a community. This model integrates both key elements identified by previous literature for pandemic influenza simulation. It is different from compartment models in that it employs heterogeneous mixing assumption on contact pattern instead of homogeneous mixing, and meanwhile leverages the power of "bottom-up" instead of "top-down" modeling. It is different from previous social network models, including those incorporating agent-based simulation technique, since the contact network included in the model for influenza transmission is based upon both social theory and earlier empirical findings. It is also different from massive agent-based models in how the contact pattern is assumed and structured. Table 6 shows the difference between the dissertation model and other modeling approaches used in previous studies for pandemic influenza simulation. A more comprehensive understanding of pandemic spread and control is expected via the usage of the new model.

Table 6. *Differences between Dissertation Model and Other Modeling Approach for Pandemic Influenza Simulation*

	Compartment Models	Social Network Models	Massive ABM	Dissertation Model
Assumption on contact pattern	Homogeneous Mixing	Heterogeneous Mixing	Homogeneous Mixing	Heterogeneous Mixing
Basis for assumption	/	/	/	Social theory Empirical data
Modeling logic	Top-down	Bottom-up	Bottom-up	Bottom-up

An agent-based model can be best described in order of its three components: environment, agents, and action rules (Perez & Dragicevic, 2009). The following parts outline the design and implementation of an agent-based simulation system. They first explain in detail for each component how it is designed based on previous literature. The whole system is then implemented in the Netlogo toolkit, a multi-agent programmable modeling environment (Wilensky, 1999).

Environment. In this model, the community is simulated as a friendship network, mainly based on two reasons. First, according to public warning literature, most people after receiving risk message tend to seek more information from known others, particularly friends, to make their responsive decision (Donner et al., 2007; Lardry & Rogers, 1982). Second, the contact between friends constitutes an important component of individuals' daily contacts for virus transmission in a pandemic (Mollison, 1995). Friendship network therefore provides the necessary basis to simulate individual communication and contact pattern in the research context.

The friendship network is set up based on the approach developed by Hamill and Gilbert (2008, 2009, 2010). The following part first reviews the key characteristics of a friendship network, and then explains why such an approach is selected and how the friendship network is built in the model.

Key characteristics of friendship networks. In a friendship network, nodes represent individuals, and edges represent the relationship of friend between two individuals (nodes). Each node has an egocentric friendship network, which represents the relationship between this node or individual and others. The friendship network, at the macro level, is the aggregation of all egocentric friendship networks and represents the whole set of relationships.

Key characteristics of a friendship network can be grouped into the characteristics of egocentric networks in a friendship network and those of the friendship network itself. For egocentric networks, they are of limited size. Since the maintenance of relationship needs time and effort, people can only have limited number of friends (Gilbert, 2006). Also, egocentric networks vary in size among individuals, with a few individuals having a very large number of friends and many much less so (Boissevain, 1974; Roberts et al., 2009). This characteristic often indicates a positive-skewed, even fat-tailed, distribution on the degrees of connectivity for the whole friendship network (Boase, 2008; Fischer, 1982; Wagner & Fell, 2001).[10]

The third characteristic of egocentric or personal friend networks is their dynamic feature. A dyadic friendship can decay over time (Burt, 2000). Boissevain once noted that, “a person’s network is a fluid, shifting concept”

[10] In a network, a node’s degree of connectivity is its number of connections to other nodes; the distribution of degrees of connectivity is the probability distribution of all nodes’ degrees of connectivity over the whole network (Knoke, 2008).

(Boissevain, 1974, p.48). As a result, the size, structure and membership of a personal network may change over time. Such changes can be caused by demographic reasons, such as fertility and mortality, or by geographical and social reasons, for example, people drift apart physically or change their social behavior (Hamill & Gilbert , 2008, 2010). At the macro level, the whole friendship network is dynamically evolving because of individual behavior at the micro level with regard to friendship relationships and changes in their personal networks (Zeggelink, 1995). The dynamic feature characterizes both individual personal networks and the whole friendship network.

Besides a right-skewed distribution on the degrees of connectivity and dynamic nature, a friendship network is also sparse and highly clustered (Watts, 1999). The network is sparse in the sense that only a few of the potential links in the network actually exist (Michell & Amos, 1997). The density of the whole network therefore is low. Meanwhile, most of the few connections each individual has are tied up in local interactions within "cliques" of individuals (Wagner & Fell, 2001). Since members of an individual's egocentric network tend to know each other, most personal networks are strongly overlapping. The presence of a high clustered friendship network is a result of homophily, which is defined as the principle that "a contact between similar people occurs at a higher rate than among dissimilar people" (McPherson, Smith-Lovin, & Cook, 2001, p.416). In other words, people are more likely to be friends with others who are similar in demographic and social characteristics, such as race, ethnicity, age, education and gender (McPherson, et al., 2001)

The principle of homophily also results in another key feature: positive assortativity by degree of connectivity (Bruggeman, 2008). According to Newman and his colleagues, positive assortativity is a key feature which distinguishes social networks from other types of network (Newman, 2003; Newman, Barabasi, & Watts, 2006; Newman & Parker, 2003). It refers to the phenomenon that well-connected nodes or individuals tend to be linked with other well-connected nodes and vice versa. Several studies have also found such a phenomenon in friendship networks (e.g., Bollen et al., 2011; Hallinan & Williams, 1989; Kandel, 1978). They explained its emergence as the outcome of homophily: sociable people like other sociable people (Bruggeman, 2008).

Another characteristic of friendship networks is their short path lengths (Wagner & Fell, 2001). The path length is the shortest routine between two nodes. It is measured by the minimum number of links from one node to the other. With short path lengths, individuals within the network can reach any other individual in a few steps, even if the two are perceived to be far away (Watts, 1999). Such a phenomenon is also called the small world effect (Milgram, 1967), or more popularly six degrees of separation (Guare, 1990).

Community, or the existence of “giant component”, is the last characteristic of friendship networks that have been widely discussed in previous literature. In a network, a giant component is a group of nodes that are highly connected to each other, directly or indirectly, but loosely connected to the nodes within other groups (Newman, 2001). It represents the connectedness of a network, which can be measured by “the extent to which adding ‘friends-of-friends’ would increase the size of agents' personal networks" (Hamill & Gilbert, 2010, p.85). The existence of giant components makes the friendship network highly inter-connected, while its absence makes the network composed of tiny groups which do not interact with each other (Hamill & Gilbert, 2010).

Given the key characteristics discussed above, the ideal model to set up a friendship network should simultaneously have dynamically changing personal networks with limited and varying size and a whole friendship network at the macro level showing high clustering, low density, positive assortativity, short path length and giant component.

A model for friendship network. In previous literature, four basic types of network model are commonly used to simulate a friendship network: regular lattice, random, scale free, and particularly small-world. While these standard models fit well with some networks, researchers found none of them can adequately reproduce the typical features of real friendship networks (Hassan, Salgado, & Pavon, 2008; Singer, Singer, & Herrmann, 2009). For example, personal networks within a random network normally are of the same size (Barabasi & Bonabeau, 2003). For small-world networks, while they are considered by some researchers as the best illustrated for friendship networks (e.g., Wagner & Fell, 2001), they does not display giant components or positive assortativity (Hamill & Gilbert, 2010). The scale-free network has also been criticized as a model for friendship network given its low clustering and zero assortative index (Hamill & Gilbert, 2008; Newman, 2002).

This dissertation adopts the approach developed by Hamill and Gilbert (2008, 2009, 2010) to set up a friendship network. The characteristics of the network generated by this approach correspond to the key features of a friendship network. Overall, it constrains and varies the size of personal networks, permits a right-skewed distribution of degree of connectivity, and allows network changes over time. The whole network has a low network density and displays high clustering. Positive assortativity by degree of connectivity, giant components and short path lengths can also be found in it. Hamill and Gilbert (2009) consider this model particularly suitable for simulations of artificial societies. Here it is used to simulate a community, which is conceptualized as a friendship network.

Basic concepts used to set up the network include social space, social circle and reciprocity (Hamill & Gilbert, 2008, 2009, 2010). A social space is similar as a geographic space, but shows the social distance among people. In the social space, two points (individuals) locate close to each other if they are close socially (Hamill & Gilbert, 2008). The closer they are, the stronger the relationship between them. Social circle here is used as a metaphor (Hamill & Gilbert, 2010). Each point (individual) within the space has a circle with itself being the center. Within the circle are all the individuals in the map whose distance from the center individual is less than the radius. Hamill and Gilbert (2010) called this radius social reach, and consider all the points within the social circle as potential friends of the center individual. Reciprocity is used to specify which potential friend within the social reach of an individual is actually a friend. According to this idea, two individuals are permitted to link only when they can reciprocate, namely, when they are within each other's social reach (Hamill & Gilbert, 2010). If A has a larger social reach than B, then B may be in A's social circle but not vice versa. In this case, A knows B while B does not know A. A relationship cannot be formulated between them.

Hamill and Gilbert (2008, 2009, 2010) implemented this network model as an agent-based model, with agents representing individuals or nodes. Certain number of agents is randomly distributed across an unbounded grid—which represents the social space—to achieve a population density of 1%. All agents are then split into two groups, with each group having a different social reach. For each agent, personal network is formulated through creating links to other agents who are reciprocal to each other. The whole friendship network is then formulated as all agents' personal networks are completed. The percent of agents within each group and the large and small social reach can be adjusted to change the mean and standard deviation of the distribution of the degree of connectivity. To accommodate the dynamic mechanism, some agents are randomly selected at each time step to move randomly in the social space.

Simulation setup. While the original model could produce a social network with typical characteristics of friendship networks, it does not calibrate parameters to adjust the mean, median and standard deviation of the distribution of degree of connectivity to reasonable values. According to Wang and Wellman (2010), the mean, median and standard deviation of the number of personal off-line friends in US in 2007 is 11.3, 5, and 15.23, respectively. An off-line friend here is defined as people whom individuals contacted face-to-face and by phone at least weekly (Wang & Wellman, 2010). Such positive-skew distribution, where the mean is substantially higher than the median, indicates the pattern found in other studies on personal network size: a minority of Americans has a much larger number of friends than the rest majority (Boase, 2008). Wang and Wellman (2010) also found that for individuals, friends whom they meet or speak with are substantial. Despite the extensive usage of internet, just about 15% of people have one or more friends who are online only (Wang & Wellman, 2010). Therefore, it is assumed in this dissertation that the distribution of degree of connectivity in friendship network follows a positive skew distribution with a mean of 11, a median of 5, and a standard deviation of 15.

To calibrate the friendship network generated, experiments are conducted on scenarios with different values for large and small social reach. Since the maximum size of personal friendship network is 76 and the minimum size is not 0 (Wang & Wellman, 2010), both social reach values can be adjusted from 5 to 75, with a 5 incensement in each scenario. Totally there are 15*15 scenarios, but only those in which the value for large reach is larger than that for small reach are possible. As a result, there are 105 possible scenarios. 10 experiments are repeated for each scenario, and it is found that a large social reach of 65 and a small social reach of 10 can produce the best results. The mean, median and standard deviation of the distribution of degree of connectivity in this scenario are 11, 4 and 15, respectively.

Another assumption made on friendship network is that it is static, with all connections remaining constant over time. This assumption is made provided that the turnover of a friendship connection is slow relative to the timescale of a pandemic and therefore can be ignored in the context (Keeling & Eames, 2005). Also, the population of agents is constant during the simulation. Even if they have acquired immunity against some epidemic, they are not removed from the population. The only exception is that, when some node dies, this node and all its connections are removed. Table 7 shows the difference in friendship network between Hamill and Gilbert's model and the dissertation model.

Table 7. *Differences in Friendship Network between Hamill and Gilbert's Model and Dissertation Model*

Model	Parameter values		Network characteristics			
	Large reach	Small reach	Stability	Distribution of degree of connectivity		
				Mean	Median	Standard deviation
Hamill & Gilbert's	35	10	Dynamic	6	4	5
Dissertation	65	10	Static	11	4	15

For modeling, the friendship network is set up at the beginning of the simulation, in a similar way as it is in Hamill and Gilbert's studies (2008, 2009, 2010). Certain amount of agents is randomly placed over a space to achieve a population density of 1%. 25% of all agents are allocated with large social reach while the rest with small one. Personal networks and the whole large friendship network are formulated based on the rule specified by social reach and reciprocity. For each node, the size of its personal friendship network is the number of friends it has. The nodes connected to it are called its friend nodes, and the rest nodes stranger nodes. During the simulation, the friendship network remains stable. When some node dies, this node and all its friendship connections are removed from the community; the rest part of the friendship network remains unchanged. Figure 5 shows the friendship network created by the model.

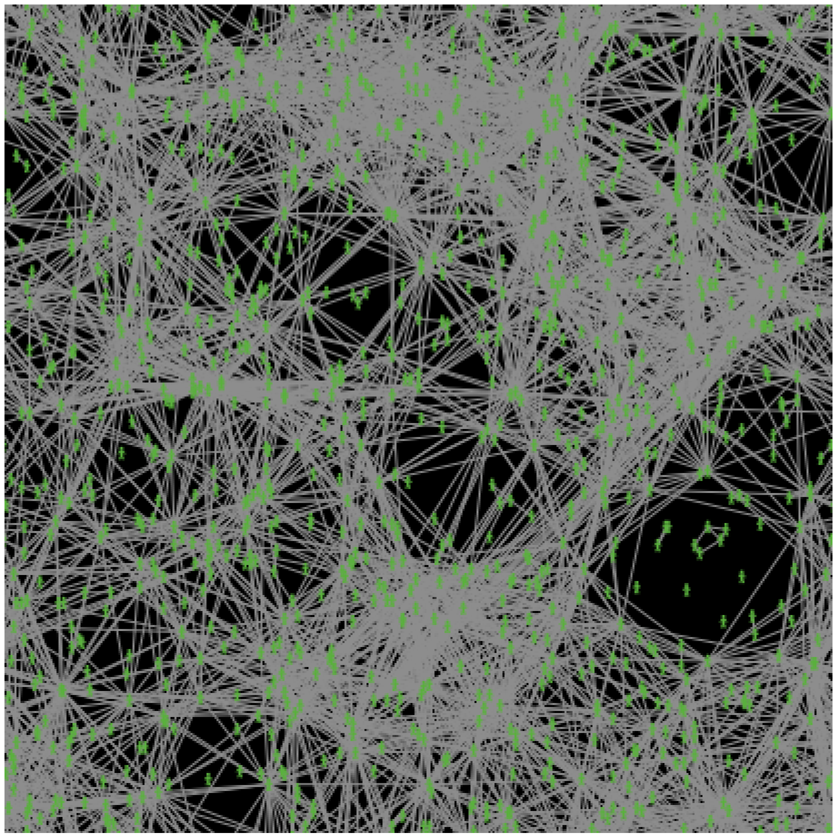

Figure 5. Community as a friendship network

Agents. Two types of agents are created in the model. One represents public sector, and the other residents or individuals in the community. The public sector is responsible for devising public risk communication strategy and sending risk information to residents accordingly. Individuals are mainly characterized by their contact pattern, health status and responsive behavior to the risk information received. Interactions between public sector and individuals through risk communication and interactions between individuals through both their contacts and information exchange generate the pandemic impacts at the community level.

Action rules. Action rules in an agent-based model define how agents behave or interact with one another at each time step. In this model, the action rule of public sector is simpler than that of individuals. At each time step, the public sector sends risk information to individuals according to certain communication strategy. The communication strategy is indicated by five indicators: the number and type of channel used for sending risk information, the frequency of each channel used for sending risk information (use frequency), the percent of population who use each channel for receiving risk information (percent of channel user), and the percent of population who consider the information from each channel credible (percent of channel believer).[11] For example, public sector can send risk information to the community using local television every one or two days.

Individual agents' behavior includes both their daily contact pattern and the biological process involved in the pandemic influenza infection. When they receive risk information, they also go through a responsive process. The following part would explain each type of individual behavior in detail.

Individual daily contact. Individual contact pattern refers to a description of who have been contacted by an individual and how (Mikolajczyk & Kretzschmar, 2008). Usually it has two indicators: the number of contacts an individual has

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[11] Why the first three indicators are selected to represent risk communication strategy has been explained before. The user and believer percent are related to but not exactly sender factors as defined in literature. The user percent could mediate the influence of sender factors, since it decides the number of individuals who receive information from and are therefore affected by characteristics of some channel. The believer percent is related to channel credibility. In addition, both indicators may be manipulated by emergency managers to some extent.

within a time unit, which is defined as contact rate, and the type of those contacts, namely, whether the contact is repeated interaction or one-time encounter (Mikolajczyk et al., 2008). In this study, one day is chosen as one time unit. The contact rate is actually daily contact rate.

Before summarizing previous findings on the characteristics of individual daily contact pattern and explaining how it is simulated, the concept of contact used in the model is first clarified.

Contact vs. at-risk contact. A closeness of contacts is usually required for the transmission of airborne infections (Mikolajczyk & Kretzschmar, 2008). For pandemic influenza, most transmissions occur within 3 feet of the source, which making close-proximity interactions highly relevant for its spread (Glass & Glass, 2008; Salathe et al., 2010). As a result, not all contacts are disease-causing contacts. Here an at-risk contact or effective contact is used to refer to an interaction that is likely to result in infection transmission. At-risk contacts are distinguished from actual contacts, which include all interactions an individual has. Unless specified otherwise a contact in this study refers to an at-risk contact.

For operaionalization purpose, it is further assumed in the model that an individual makes an at-risk contact with another individual if at least one two-way conversation has been held between them. Such a definition of effective contact for pandemic influenza transmission is first proposed by Edmunds et al (1997) and then adopted by many later studies (e.g., Beutels et al., 2006; Mossong et al., 2008). Such a definition is practical and general. It is easier for respondents to recall the number of a two-way conversation they have within some time unit and therefore easier for researchers to collect accurate empirical data. It is also comprehensive in that other common pandemic influenza transmission mechanisms can be included in this definition, such as any sort of physical touching (Mikolajczyk & Kretzschmar, 2008). Edmunds et al (1997) also provided a detailed explanation for what is a two-way conversation. It is a situation "(at a distance which did not require raising the voice) in which at least two words were spoken by each party and in which there was no physical barrier between the two parties (such as security screens)" (Edmunds et al., 1997, p.950). The length of each conversation is not considered in this concept. Nor is the number of conversation between the same pair of individuals. In other words, multiple times of conversation an individual had with the same other individual within one time unit are recorded as one at-risk contact for each party. The contact rate used in the model actually indicates the number of different individuals an individual has conversations with per day.

Characteristics of individual daily contact pattern. In current literature empirical findings on individual contact pattern for the spread of airborne infectious disease are scare, because of the difficulty in comprehensively defining an at-risk contact and the considerable work to collect relevant data (Beutels et al., 2006; Salathe & Jones, 2010). Just a small number of studies have provided some quantitative descriptions of individual daily contact rate and contact type for airborne epidemic transmission (e.g., Edmunds et al., 1997; Edmunds et al., 2006). Findings in these studies are summarized in Table 8.

Table 8. *Findings on Individual Daily Contact Pattern in Previous Studies*

Author (year)	Distribution of individual daily contact rate			Ratio between repeated to random contacts	Survey sample[12]
	Mean	Standard deviation	Range		
Salathe & Jones (2010)	10	/	/	/	A random sample from an American high school
Mikolajczyk & Kretzschmar (2008)	10	/	/	/	A small convenience sample of students from an university in Germany
Mossong et al. (2008)	13.4	10.6	/	/	A population-based prospective survey in eight European countries
Read et al. (2008)	/	/	/	1:8	A convenience sample of 49 adults in UK
Beutels et al. (2006)	16[13]	/	/	1:3	A convenience sample of 73 students and personnel from an university in Belgian
Edmunds et al. (2006)	11	/	/	1:3	A convenience sample of 29 undergraduate students from an UK university
Glass & Glass (2006)	/	/	/	1:3	A convenience sample of 249 students from an elementary, middle and high-school in US
Edmunds et al. (1997)	16.8	8	0-40	/	A convenience sample of 92 students and their families and friends from an university in Britain

[12] The limitation of using the survey results from these studies would be discussed in Chapter 6.

[13] Beutels et al (2006) found that each individual averagely had 18 contacts in weekdays, and 12 at weekends. 16 is the weighted mean of daily contact rate in any day of a week.

For example, Salathe and Jones (2010) found that the average individual daily contact rate for airborne infection transmission is about 10. This finding is line with several other studies (e.g., Edmunds et al., 2006; Mikolajczyk & Kretzschmar, 2008). There are also studies which reported a high average daily contact rate. Both Edmunds et al (1997) and Beutels et al (2006) found an average daily contact of 16 or higher. Besides the mean, the variability in the number of daily contacts among individuals is also explored. According to Edmunds et al (1997), the number of daily contacts was approximately a normal distribution, with a standard deviation of 8, and a range from 0 to 40. Mossong et al (2008) reported a standard deviation of 10.6. Based on these findings, individual daily contact rate when simulated in the model should follow a truncated normal distribution, with a mean larger than 10 but less than 17, a standard deviation between 8 and 11, a minimum value of 0 and a maximum value of 40.

Regarding contact type, previous studies provided three important findings. First, casual encounters are predominantly random and irregular; mostly they are first-time and non-physical contact, with very short duration (Mossong et al., 2008; Read et al., 2008). Second, contacts of daily frequency often involve physical interactions and are of long duration; those contacts usually occur between individuals who are familiar with each other (Mossong et al., 2008; Read et al., 2008). Three, the number of casual encounters within a day is significantly greater than the number of repeated contacts which typically occur on a daily basis; the ratio of the former to the latter reported by several studies is about 3:1 (e.g., Beutels et al., 2006; Edmunds et al., 2006; Glass & Glass, 2008). Some studies even found a much higher ratio (e.g., Read et al., 2008). Based on the three findings, it is assumed in this study that there are two types of contacts occurring per day for each individual: random encounter which is changed every day and stable contact which is constantly repeated over time. The ratio of random encounters to stable contacts among an individual's daily total contacts is at least 3:1. In other words, at least 75% of the people an individual contacts per day are randomly selected from the population while at most 25% repeatedly contacted each day. Such an assumption supports previous findings that interpersonal interactions have a hierarchical structure; there are more daily random encounters than stable contacts (Glass & Glass, 2008; Grabowskia & Kosinskia, 2005). It also corresponds to the call from previous studies that the transmission routine for infection in epidemic models should include both random encounters and repeated contacts (Mikolajczyk & Kretzschmar, 2008; Read et al., 2008).

Personal & community contact network. The opportunities for an epidemic to spread within a community are given by its contact network. In this network, the nodes represent individuals in the community, and the edges between nodes the contacts between two connected individuals along which an infection is possibly transmitted. All edges are symmetrical, which means infection can be transmitted in either direction (Grabowskia & Kosinskia, 2005). Edges are also unweighted, which means all contacts transit an infection with the same probability (Salathe & Jones, 2010). Therefore, community contact network for potential transmission of pandemic influenza is abstracted as a non-directed and unweighted graph.

Within the network, each node has its own personal or egocentric contact network. An egocentric network consists of a focus node, other nodes this node connects with, and the connection between the focus node and other nodes. The focus node is called “ego” and other nodes connected “alters”. The set of alters of this node is its “neighborhood”. The size of this neighborhood is the node’s degree of connectivity.

A node’s personal contact network comprises the ego node, the nodes it contacts with per day, and the contact connection between the ego and alter nodes. The characteristics of a node’s contact network are determined by its contact pattern. The contact rate specifies the size of its neighborhood size. Regarding the contact type, since an node’s ego-centric network is its daily transmission routine, it should include both random encounters and stable contacts. At least 75% of alters in individual contact network are changed every day; they are people an individual randomly comes across. The rest 25% alters, at most, remain the same group of people the individual constantly contacts.

Individual contact and friendship network may partially overlap given previous findings that daily stable contacts occur between individuals and people they are familiar with (Spoors 1995; Wasserman & Faust, 1994). In this study, it is assumed that those people a node repeatedly contacts over time are its friends.

At the macro level, the community contact network emerges from all individuals’ personal contact networks. Because of the turnover of partial individual contact networks, the community contact network would also be dynamically changing every time unit.

Simulation setup. To simulate individual daily contact, the value for the parameter of "contact capacity" is first decided for each node at the beginning of the simulation. The value is randomly selected from a truncated normal distribution, with a mean of 10, a standard deviation of 10.6, a minimum value of 0 and a maximum value of 40. Contact capacity represents the number of people a node can contact per day. It is distinguished from the parameter of "contact rate", which represents the number of people each node actually contacts on some day. The former may be larger than the latter since the community size may constrain the number of people a node can actually meet. Furthermore, nodes may reduce their daily contact rates in a pandemic situation for self-protection.

The initial personal contact network is set up for each node according to its contact capacity and the ratio between random and stable contacts. A parameter of "stable contact capacity" is used to represent the number of stable contacts each node can have daily. Its value equals to the product of contact capacity and 0.25. If the product is not an integer, the value equals to the next integer that is larger than the product. Similarly, a parameter of "random contact capacity" is used to represent the number of random contacts each node can have daily, and its value equals to the difference between contact capacity and stable contact capacity.

To set up a node's personal contact network, a number of stable contact capacity of nodes are randomly selected from this node's personal friendship network. A connection is then created between this node and each selected friend node. These selected friend nodes represent the individuals this node repeatedly meets every day. The connection between the node and each selected node represents stable contact. Two situations need attention when stable contacts are created. First, if the size of personal friendship network is larger than the stable contact capacity, the value for stable contact capacity is set to the value for the number of this node's friends. All friends in this situation would be the node's stable contacts, and the value for random contact capacity increased. Second, only one stable contact can be created between two nodes and only when the stable contact capacities of both ends have not been achieved. If there are already stable-contact connections connected to the node before it starts to create its stable contacts, the number of stable contact created by itself should not be stable contact capacity but the difference between the stable contact capacity and the number of stable-contact connections that have been connected to it. For nodes whose stable contact capacity has been achieved, no stable-contact connection can further be created for it. Therefore, when the stable contact capacity of one selected friend node has been achieved, another friend node that has not been selected should be randomly selected. If none of the friend nodes can be selected for connection, the stable contact capacity of the node would not be achieved. The value for random contact capacity would not be changed as well. Aimed at this case, the model uses a parameter of "stable contact rate" to represent the number of stable contacts a node has per day.

For random contacts, a number of random contact capacity of nodes are randomly selected from all stranger nodes, and then connected with the node. These selected stranger nodes represent those individuals the node randomly encounters on some day, and the connections random contacts on that day. The special situations when random contacts are created are similar as those when stable contacts are created, and are handled by the model in the same way. A parameter of “random contact rate” is created to represent the number of random contacts a node has per day. Its value is not necessarily equal to the random contact capacity.

The community contact network emerges when all nodes set up their personal contact networks. At the beginning of simulation, the distribution of degree of connectivity in the formulated community contact network follows a truncated normal distribution, with a mean of 13, a standard deviation of 8, a minimum value of 0, and a maximum value of 40.[14] Such a distribution corresponds to what has been proposed by previous studies.

For each individual node, the model creates a dynamic and hierarchical structure for its personal contact network. Both stable and random contacts exist in the network. During the simulation, the stable-contact connection remains constant till either end dies. When a node dies, it is removed from the community, as well as all of its contact connections. The random-contact connection is updated per time unit; namely, all random-contact connections are removed for each node at the end of each time step, and then recreated at the beginning of the next time step.

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[14] The distribution of degree of connectivity in the formulated community contact network is not necessarily the same as the distribution used to decide each node’s contact capacity, since the former is decided by each node’s contact rate, which is not necessarily the same as its contact capacity.

Individual biological process involved in pandemic influenza infection. The most common or basic epidemic contagion consists of a transmitter, receiver, and transmission channel (Brodie, 1996; Comellas, Ozon, & Peters, 2000). For pandemic influenza, transmitters are infectious individuals. Receivers are susceptible individuals who have contacted with transmitters. The transmission channel is the contact between them. Given the definition of a contact, the only transmission channel in the model is the direct contact between a susceptible and an infectious individual. As a result, the pandemic influenza is transmitted in the model from individual to individual via a contact network.

Meanwhile, Standard compartment models, although limited in providing insights for epidemic control, build the basis for previous studies using social network or massive agent-based models to simulate the unconscious biological process after susceptible individuals get infected. In this model, the disease progression of the pandemic influenza is modeled as an SEIR infection.[15]

The standard Susceptible-Exposed-Infected-Removed (SEIR) four-compartment model, as shown in Figure 6, successfully captures the disease progression process of certain type of influenza. Particularly, it considers the "exposed" status individuals enter after they get infected (Li et al., 1999; Rost &

[15] The methodological framework developed here would be later implemented in a specific case, to simulate the spread dynamics of 2009 H1N1 influenza in a community of Arizona. The infection progress of this pandemic influenza has been modeled by previous studies based on SEIR model (e.g., Balcan et al., 2009; Halder, Kelso, & Milne, 2010). That is why SEIR model is explained here among all other types of compartment models. If the framework is used in another case, the infection progress may be conceptualized based upon another compartment model, depending upon the epidemiologic features of the epidemic simulated.

Wu, 2008). Differential equations defining the transition rates between compartments in the model are presented as follows:

$$\frac{dS}{dt} = -\alpha\beta S\frac{E' + I}{N}$$

$$\frac{dE}{dt} = \alpha\beta S\frac{E' + I}{N} - \sigma E$$

$$\frac{dI}{dt} = \sigma E - (\gamma + \mu)I$$

$$\frac{dRe}{dt} = \gamma I$$

$$\frac{dD}{dt} = \mu I$$

Similar as in the SIR model, the first compartment includes people who are susceptible to the disease (S). α is the infection rate and β is the contact rate. Once infected, the susceptible transit into the exposed status (E), during which individuals may be infectious but not yet show any disease symptom. E' in the equations above represents the number of exposed people who have become infectious. σ represents the progression rate from E to I; its reciprocal (σ^{-1}) is the latent period, the time period between exposure to the disease and the time point the disease becomes apparent through symptoms (Perez & Dragicevic, 2009). After the latent period ends, the exposed become infected people (I) who are both infectious and symptomatic. The removed (R) compartment consists of people who either recover (Re) from the disease after the infection period (γ^{-1}) or die (D) when they are in the infected status. γ is the recovery rate, and μ is the mortality rate among infected people. Generally the recovered is assumed to acquire full immunity to subsequent infection so that these individuals never re-enter the susceptible population (Chow et al., 2008; Bootsma & Ferguson, 2007). N is the total number of people in the system, excluding those who died.

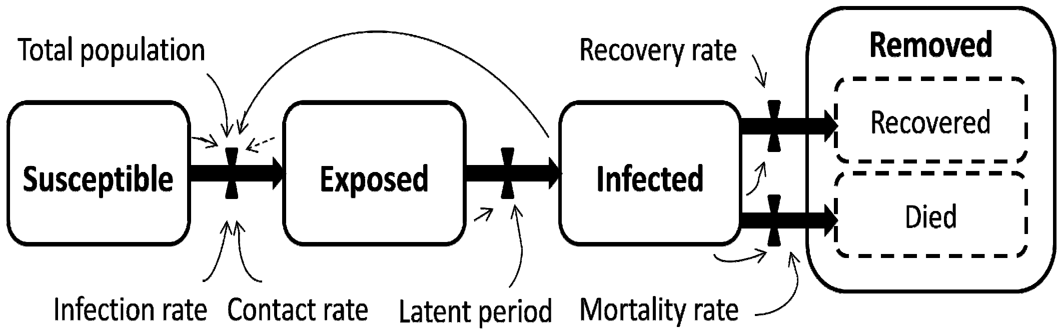

Figure 6. SEIR model of an epidemic infection progress

Simulation setup. Using the state transfer concept of SEIR model, the individual biological progress involved in the influenza infection is simulated as shown in Figure 7. Each individual node in the model could have one of five potential health states: susceptible (S), exposed (E), infected (I), recovered (Re) and died (D). Definitions of these statuses are defined as below.

- Susceptible: the node is healthy, but susceptible to infection from its contacts
- Exposed: the node has been exposed to infection, but not yet showed any symptom. It may be infectious, transmitting the influenza virus to its contacts
- Infected: the node is both infectious and symptomatic
- Recovered: the node has experienced the infection, and recovered from it. It acquires lifetime immunity, and no longer poses a threat to its contacts.
- Died: the node has been killed by the infection. It will be removed from the community, as well as all of its friendship and contact connections.

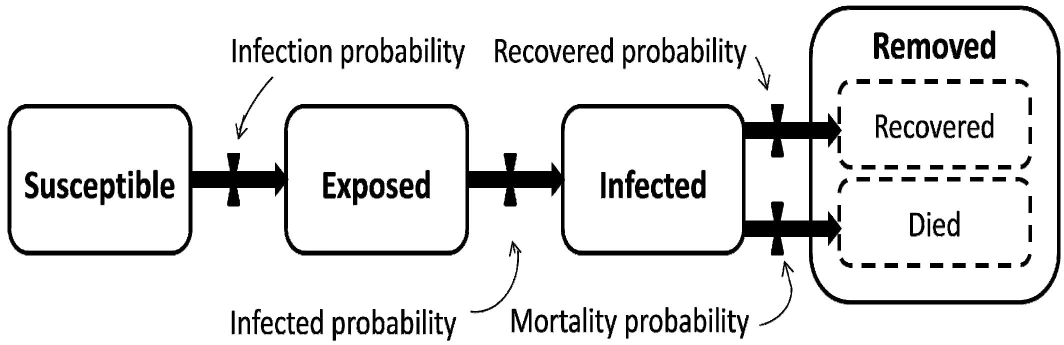

Figure 7. Individual biological progress after being infected

Over time, individual nodes' health statuses evolve along the direction showed by the arrow in Figure 7. Transition probabilities between two adjacent states at each time step are decided by different parameters. For the status transition from susceptible to exposed, this study adopts the following formula developed by previous studies (Eidelson & Lustick, 2004; Salathe & Jones, 2010), to calculate the probability (P_{SE}) for a susceptible node to get infected and enter the exposed status at each time step:

where P_{SE} is a susceptible node's infection probability. α is the infection rate, which represents the probability for a susceptible node to get infected through a contact with a infectious node. β' is the infectious contact rate; it represents the number of nodes among a node's daily contacts who are infectious. While the value for α is decided by the contagiousness of the influenza and shared by all susceptible nodes, values for β' vary among nodes, depending upon the number of their daily contacts in normal conditions, whether they are taking protective behavior, and the health status and protective behavior of the nodes they contacted. Previous studies often make assumptions about how the infection rate varies among different types of contacts, for example, contacts with different duration, frequency, occurrence time, and social and spatial proximity (Cauchemeza et al., 2011). However, according to Newman (2002), the variance in infection rate does not influence the statistical properties of an epidemic outbreak. It would spread in the population as if all contacts present an equal chance for infection. In this study, the infection rate is set to one constant value. This assumption also corresponds to the assumption of symmetric and un-weighted edges in the contact network.

The concept of infection probability essentially represents the probability for a susceptible node to get infected after it has disease-causing contacts with infectious individuals within one time step. It reflects the fact that at-risk contacts do not guarantee an infection (Jones & Adida, 2011). It also enables the model to include the heterogeneity in individuals' vulnerability and resistance to the disease (Huang, Sun, & Lin, 2005). Nodes in the model with the same infection probability at the same time do not necessarily all become infected, which reflects some people are more susceptible than others.

For the transition from exposed to infected status, previous literature has employed two ways to set the value for latent period in epidemic models: the constant-length method with all exposed individuals having the same value for their latent period (e.g., Haber et al., 2007; Longini et al., 2005), and the random-length method where all exposed individuals have the same progression rate from exposed to infected status (Dunham, 2005; Easley & Kleinberg, 2010). In the second way, the progression rate is usually calculated as the reciprocal of the average length of the latent period found in empirical data. Each exposed node is randomly decided whether to have status transition based on the progression rate. Variety in the length of latent period therefore can be created. In this study, the model uses the second way to consider the latent period, given the heterogeneity found in empirical data in individuals' latent period after they get infected by a pandemic influenza (CDC, 2009a). A parameter called infected probability (P_{EI}) is used to represent the probability for each exposed node to transit to the infected status at each time step. Its value equals to the reciprocal of the average latent period empirically found for a pandemic influenza.

Similarly, previous studies also provide a constant-length way and a random-length way to simulate the infected period (e.g., Haber et al., 2007). Considering the variety empirically found in the infected period for a pandemic influenza (CDC, 2009a), the model also chooses to model the infected period as random in length, by assuming that all infected nodes have the same probability to recover from the influenza at each time step. This probability is called recovered probability (P_{IR}). Its value is equal to the reciprocal of the average length of infected period empirically found for a specific influenza (Germann et al., 2006; Mathews et al., 2007).

Besides recovering from the disease, infected nodes can also be killed by the disease. The probability for them to die at each time step is defined as mortality probability. Its value is equal to the value for mortality rate found in empirical data for a pandemic influenza.

The above staged process reflects the rule that governs the disease progress for all nodes at each time step in the model. For susceptible nodes, they get infected based on the probability decided by the contagiousness of the disease and their daily contact and protective behavior. Once a node is exposed, it remains in the status for its own length of latent period and then enters the infected status. For infected nodes, they may be killed by the disease with a probability of mortality probability at each time step. If they survive the step, they have a probability of recovery probability to recover from the influenza. Furthermore, a recovered node would have lifelong immunity on recovery to the influenza.

***Individual response process to risk information*.** The response process of individuals to risk information is simulated based on the individual warning response model developed by Quarantelli (1983). As shown in Figure 8, the response process begins with the receipt of risk information, which is greatly influenced by the communication strategy employed by the public sector. After receiving the information, individuals go through a reaction process. This process consists of a set of sequential stages, including initial risk perception, social confirmation, and situational definition. Individuals first attach their own meaning to the information, and then develop an initial perception in terms of whether the risk being communicated exists and how severe it is.[16] Public risk communication here has considerable influence on individuals' risk perception. After that, people ask or observe their friends regarding how they perceive or respond to the risk. Individuals define their situation based on both their initial risk perception and

[16] The stages of understanding and initial risk perception are combined by Quarantelli (1983) into one stage: initial risk perception.

their observation during the social confirmation stage. Quarantelli (1983) defines the situational definition as whether individuals believe they are personally endangered. It is different from the initial risk perception, since the latter refers to whether individuals believe the general public or others are in danger. Individuals' responsive behavior is represented by whether they would take protective actions. Situational definition is an important determinant of individual responsive behavior, while there are also other influential factors. Furthermore, it is clear that in the model public risk communication affects individuals' response to risk information through influencing their warning receipt and initial risk perception.

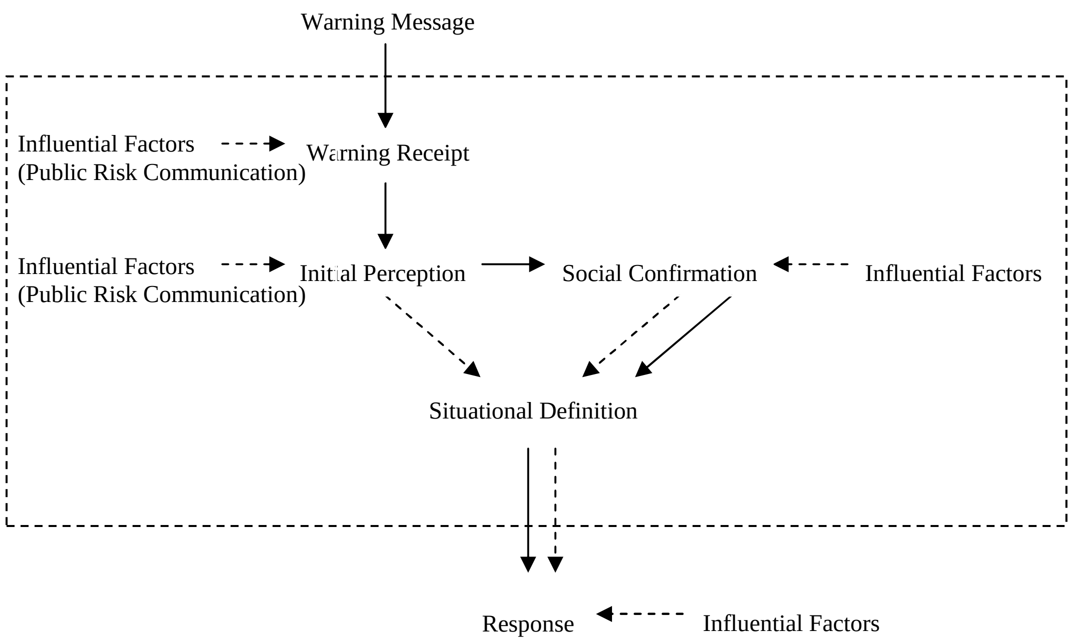

Figure 8. Quarantelli model of individual emergency warning

There are also other well-established models explaining individual response to emergency risk information, for example, Lindell & Perry model (Lindell et al., 2005; Lindell & Perry, 1992, 2004), Mileti model (Mileti & Sorensen, 1990) and Donner Model (Donner, 2007). Most of them can be considered as an extension, or more accurately specification, of the Quarantelli model. Considering Quarantelli's model is more general and inclusive, it is included in the agent-based model to simulate individuals' response to risk information.

Simulation setup. In the model, each type of channel sends risk information with a certain frequency. Several types of channel can be used simultaneously, with each sending information according to their own frequency. Here channel frequency is defined as how regularly certain channel is used; it is measured in once per number of time steps or number of days. When some channel is sending information, certain percent of agents is randomly selected as channel users according to this channel's user percent, and then certain percent of agents as channel believers according to the believer percent. The same individual can be selected to use or believe several types of channel at the same time step.

After individuals receive risk information, it is assumed that they understand what information attempts to convey, and formulate their initial risk perception. The initial risk perception here is defined as the probability for an individual to have a high level of risk perception, namely to believe that the pandemic influenza poses great danger for the general public (P_I). Such a probability in the agent-based model is influenced by the number and type of channel the individual uses to receive risk information, and whether the individual believes each channel is credible. The way in which the probability is influenced depends upon the specific research context.

Difficulties to simulate the responsive process lie in the stage of social confirmation and situational definition. Previous literature has been ambiguous about what type of information is collected by individuals at the confirmation stage and how they use all information received and collected to make decisions on the adoption of protective behavior. To address those limitations, this dissertation uses the innovation diffusion model created by Delre, Jager, and Janssen (2007) to simulate how individuals behave during the two stages.

Delre et al's innovation diffusion model is created to simulate how the aggregate level of penetration of a new product emerges from individuation decision on adopting the product. This model is also a network-based ABM. The nodes of the network in the model are individual agents and links between two nodes represent friendship relation. The adoption decision of an individual agent is described as the probability to use the new product and calculated at each time step as

$$P_i = fx_i + (1 - f)y_i$$

where P_i is the adoption probability of individual i. y_i is individual preference, which reflects the mass media influence. x_i is the local social influence. f weights these two forces and presents how strong the local influence affects the probability. The value for f is between 0 and 1.

Concerning the local social influence, it is from a node's personal friendship network and due to word-of-mouth process with its friends (neighbors in its personal friendship network). The model assumes that agents are involved in such a process if and only if they receive a message from some friend that the friend has already adopted the product. When the number of times of the node's involvement in the process exceeds certain threshold, the social influence emerges and influences its own adoption probability. Delre used a parameter of H_i to represent the personal threshold which decides a node's susceptibility to its friends' behavior. If the fraction of adopters among a node's friends is higher than H_i, the node feels the social influence. The value for x_i in this case is 1; otherwise, the value is 0.

There are two reasons why Delre et al's model can be used in this research context. First, the mechanism of the target social process is similar. Both models aim to simulate the spread of some subject, a new product or protective action, over a network through modeling individual decision making process. The decision is about whether or not to take some action to protect or improve their benefits, and it is simultaneously influenced by two communication processes. For the model created by Delre et al (2007), the rationale of the formalization of individual adoption decision is rooted in social influence theory, particularly the work of Bass (Delra et al., 2007). Bass formalizes the decision of a consumer to adopt a new product as a probability. The probability is determined by two processes of communication: external influence via advertising from mass media and internal influence via word-of-mouth (Delra et al., 2007). Consumers form their own preference for the product after receiving advertising information. Then they observe their friends' behavior or receive messages from their friends about whether their friends have adopted the product. Such a process is very similar as the individual decision making process on responsive behavior after receiving risk information: individuals' decision on taking protective action depends on their initial risk perception which is formulated by the external risk communication effort from public sector and on the internal influence that they receive from their friends. Second, a network-based ABM is used in both studies to simulate the target process, and a friendship network is included in both models as the underlying network to simulate how the product or action spread over it.

However, Delre et al's model is still unclear about how individual preference is formulated by external communication. Here research findings from previous literature on emergency risk communication are used to simulate this missing part, as discussed before.

Based on the innovation diffusion model, it is assumed in the model that Individual responsive decision is defined as the probability to take protective action. It is made based on both external and internal influences at the stage of situational definition. The risk information individuals receive from the public sector is the external influence; it formulates individuals' initial perception. The internal influence comes from the information individuals collect from some of their friends during the social confirmation stage. The internal influence does not always exist. Its existence depends upon whether the percent of a node's friends selected for information collection who take protective action among all friends selected for information collection exceeds certain threshold.

Specifically, at the social confirmation stage, an individual node selects some nodes from its personal friendship network to observe or ask whether they are taking protective behavior. The number of friend nodes selected is represented by the parameter of "confirmation attempts", and is randomly chosen from 1, 2, 3 and 4 (Lindell & Perry, 2004). The sequence of asking is based on the closeness of this node to its friend nodes. It first asks its closest friend, the node among its friends nodes which locates the nearest to it in the social space, and then its second closest friend, till the value for confirmative attempts is achieved. If the value for confirmative attempts is larger than a node's number of friends alive, the former would be set equal to the latter. If a node has no friends, no social confirmation occurs; the node's responsive decision is solely influenced by its initial risk perception. Furthermore, a moderate assumption is made on the personal threshold for internal influence to occur, since no relevant research findings have been found. A parameter called "internal influence threshold" is created. It is assumed that when 50% or more of a node's friends who are selected among all friends for information collection have taken protective action, there would be an internal influence affecting the responsive decision made in the following stage.

At the stage of situational definition, the responsive decision, described as action probability, is calculated as

$$P_A = fF_{IN} + P_I(1 - f)$$

where P_A represents individual responsive decision. f represents the strength of friends' influence on the decision. A moderate assumption is made on the value for this parameter. Both influences have the same weights in influencing the responsive decision, and f is equal to 50%. P_I is a node's initial risk perception. F_{IN} represents whether internal influence occurs. The value for this parameter is 1 when the internal influence threshold is exceeded and 0 otherwise.

Based on the action probability calculated above, individuals in the model are randomly selected to take protection action. The higher the action probability, the more likely a node takes protective action. For example, if a node's action probability is 60% at time step t, then it has a 60% possibility to take action and 40% chance not to do so at this time step. Furthermore individuals with the same action probability do not necessarily have the same responsive behavior. The way the model simulates the occurrence of protective action corresponds with what has been found in previous literature. Individual decision on responsive behavior is a key factor determining their actual responsive behavior; the more necessary an individual considers protective action, the more likely the action would be taken. Meanwhile, the decision is not the only influential factor.

In the model, the protective action individuals take is assumed to be non-pharmaceutical measure against influenza infection. That is because pharmaceutical measures—vaccine and antivirals—against a novel influenza are normally in absence when it starts to spread among a population. Individuals adopting these non-pharmaceutical measures typically reduce their contacts with other people to decrease their probability of being infected. Such measures are also called in current literature avoidance action or avoidance behavior (Lau et al., 2010; Yoo, Kasajima, & Bhattacharya, 2010). Avoidance behavior in the simulation is assumed to influence the contact pattern. It does not influence the values for other parameters; for example, the latent and infected periods remain the same regardless of whether exposed or infected people engage in avoidance behavior. For daily contact rate, previous researchers estimate that the effective contact rate, which is the product of the infection rate and the contact rate, could be reduced by 30-90% through the early implementation of non-pharmaceutical pandemic mitigation measures (Larson & Nigmatulina, 2009; Jefferson et al., 2008). The infection rate could be regarded a constant representing the biological features of the disease. So it can be inferred that avoidance behavior could reduce people's contact rate by 30-90%. In the model, a parameter of avoidance behavior effect (φ) is set to represent the reduction in contact rate due to avoidance behavior. The value for this parameter is randomly selected among 30%, 40%, 50%, 60%, 70%, 80%, and 90%, and it is updated for each node each time step when it responds to risk information by taking avoidance behavior.

For the type of individual daily contacts, no findings have been found on how it is influenced by avoidance behavior. This model assumes that the structure of individual daily contact would be sustained, despite their response to risk message. The number of stable and random contacts would be reduced by the same degree by avoidance behavior. For example, if a node has a normal daily contact rate of 24, and its avoidance behavior effect is randomly selected to 50% at some time step when it takes the behavior, then its stable daily contacts would be reduced to 3 (24 * 0.25 * 0.5), and random daily contacts to 9 (24 * 0.75 * 0.5). 3 out of the 6 original stable-contact nodes would be selected as the current stable-contact nodes, and 9 stranger nodes randomly selected as the current random-contact nodes.

Individual responsive process is initiated every time when a node receives risk information, despite whether it has received risk information or taken responsive behavior before.

Summary. The simulation flowchart in the model is shown in Figure 9. Before the simulation starts, the friendship and contact network are set up, with each node having its own personal friendship and contact network. During the simulation, at the beginning of each time step, first infected and then exposed nodes go through the biological process of the disease, as shown Figure 10. A parameter called "recovering?" is created to represent whether infected nodes should enter the recovered status at the beginning of each time step. For those nodes, if their recovering? is true, they would recover from the disease. If their recovering? is false, they remain infected status. For those who are still in infected status, they have the probability of mortality probability to die from the diseases at this time step. If they stay alive, they have the probability of recovery probability to have their recovering? set true (its default value is false), which means they would recover from the disease at the beginning of next time step.

For exposed individuals, a parameter called "infectious?" is used to represent whether they have been infectious. If its value is true, exposed nodes have been infectious since the beginning of previous time step, and should become infected this time step.[17] If the value is false, no status change occurs for these nodes. As shown in Figure 10, at the beginning of each time step, exposed nodes with a true value for infectious? enter the infected status. Exposed nodes with a false value for infections? remain their status, and have a probability of infected probability to set their value for infectious? true (its default value is false), which means they can spread the virus through contact to susceptible nodes within this time step.

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[17] Explanation would be provided later for why there is one day for exposed nodes to be infectious.

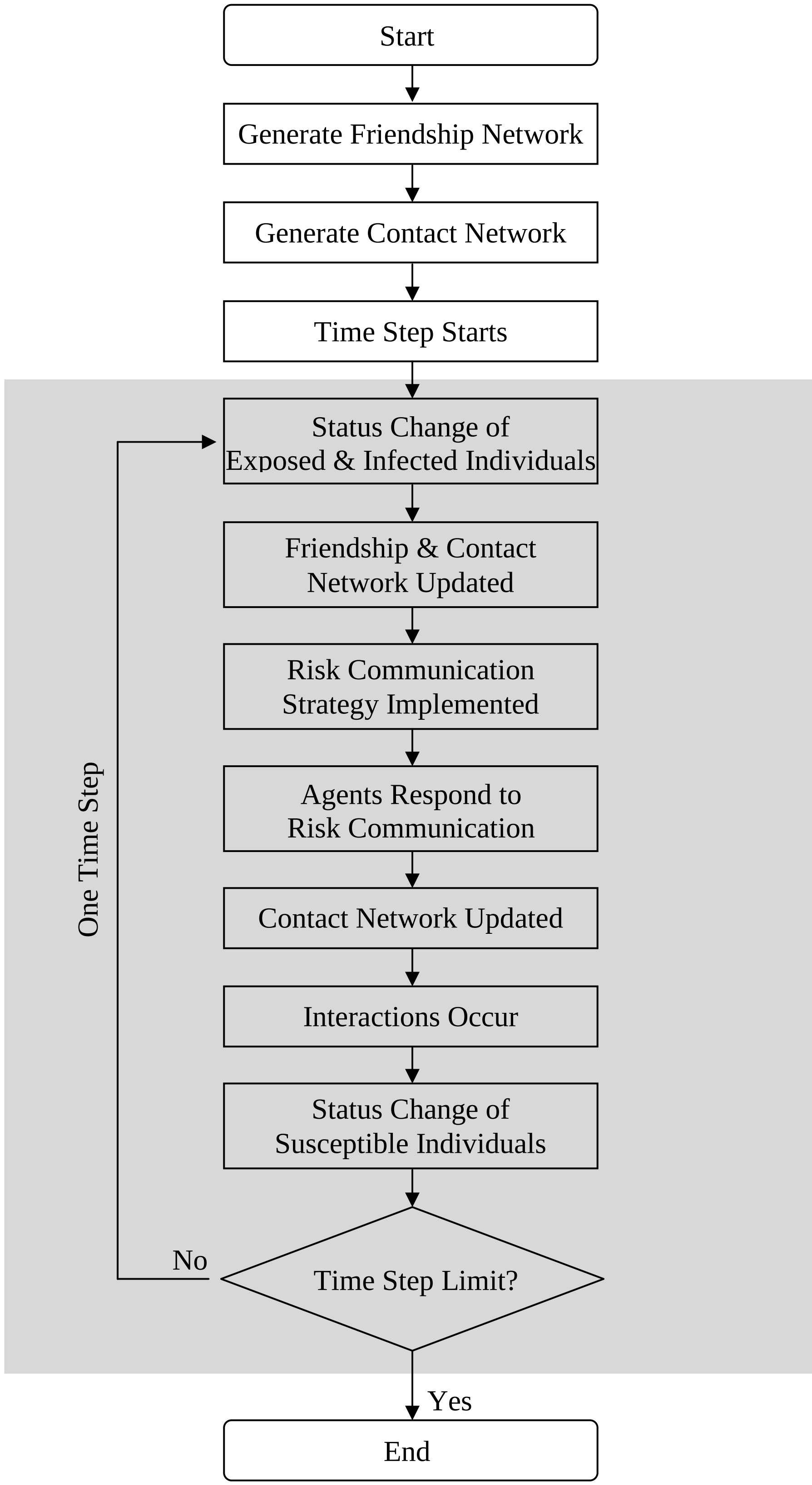

Figure 9. Simulation flowchart of the model

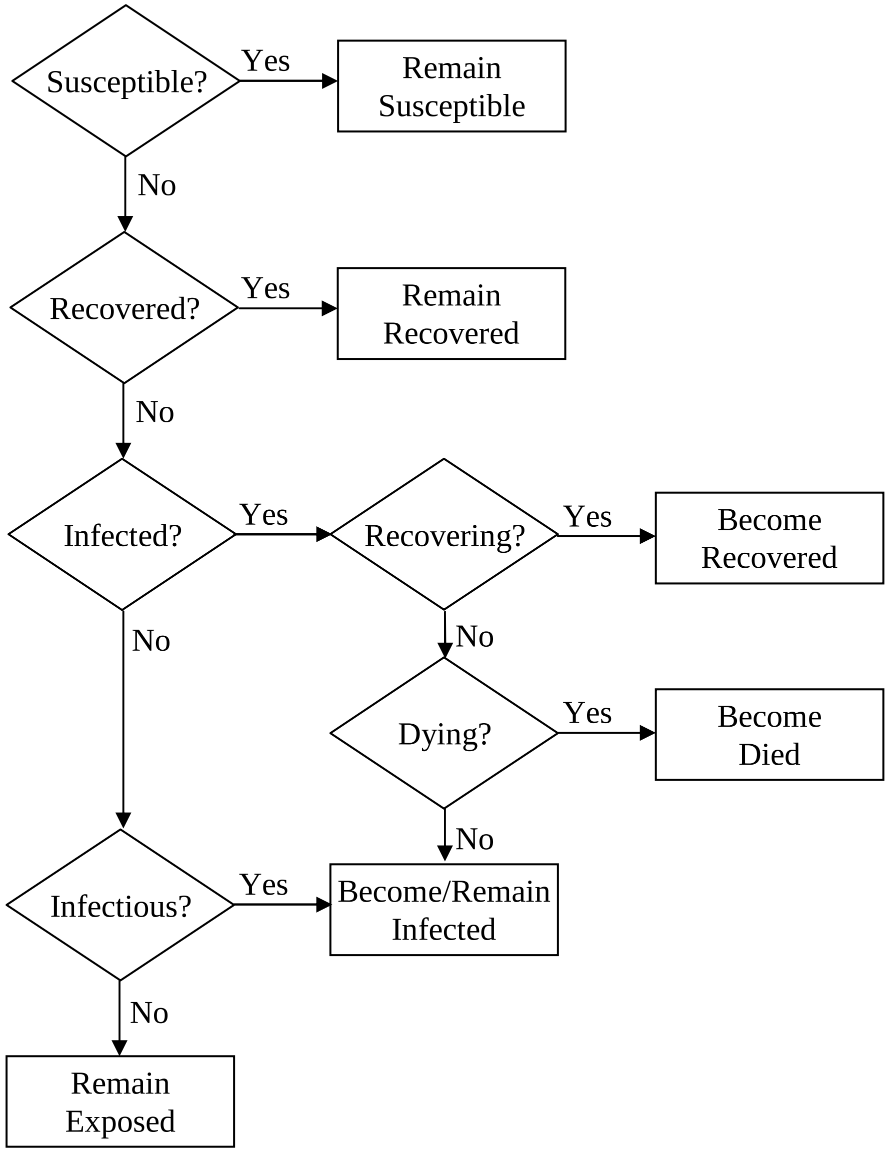

Figure 10. Biological progress of infected and exposed individuals at the beginning of each time step

The health status progress of some nodes from infected to died may lead to changes in both friendship and contact network. The friendship network and the stable component of contact network are static. But they need to remove the nodes that have died and all their connections, both friendship and contact ones. The rest part of the two networks remains unchanged. Therefore, after infected and exposed nodes finish their biological progresses, the friendship network and the stable part of the contact network are updated to keep all nodes within them alive.

The risk communication strategy is then implemented in the community. Public sector can change the five policy indicators as implementing different strategies. At each time step, whether some type of channel is sending risk information is decided by its use frequency. If it is being used, certain percent of nodes are selected among the population as the user and believer of this channel. The same node can be the user or believer of several types of channel which all send risk information at the same time step.

The receipt of risk information initiates a node's responsive process, if its health status is susceptible, exposed, or infected. These nodes have the potential to perceive the risk and take avoidance behavior for self-protection or preventing themselves from spreading the virus. For recovered nodes, they can be neither a transmitter nor a receiver. Previous literature has not provided insights in terms of how individuals respond to risk information when the potential risk constitutes no threat to them. The model assumes that recovered nodes have no response to the risk information; they will ignore the information and continue with their normal activities. If a node has not received any information, it will also act in normal.

Risk information influences individual responsive behavior by formulating their initial risk perception. In the model, a node's initial risk perception is decided by the five risk communication indictors. But how the former is formulated by the latter depends upon the specific research context. After the initial risk perception is formulated, a node sequentially goes through the stage of social confirmation, situational definition and response, as described before. The final result from the responsive process is a node's responsive behavior, and it is represented by whether or not the node takes avoidance behavior.

After all nodes have finished their responsive process, they update their contact network according to their responsive behavior. If a node takes avoidance behavior, its personal contact network is recreated in the way as described before. If it does not take the behavior, its stable contacts remain unchanged, while its random contacts recreated. This new personal contact network represents the contact routine of this node at this time step. The new contact network of the community emerges after all nodes establish their new personal contact networks.

Agents then interact with each other along their contact network just updated. After all nodes have interacted with their neighbors in their personal contact network, susceptible nodes begin their process of biological progress. An infection probability is calculated for each susceptible node, and a status change is randomly determined based on the probability. A susceptible node has a probability of infection probability to get infected and enter exposed status; otherwise, it is still susceptible to the disease.

The above process is repeated each time step after the simulation starts till the time limit.

Description of parameters. Key parameters used in the model can be categorized into four groups. They are the environment parameters, epidemiologic parameters, personal parameters, and policy parameters. A detailed description of these key parameters is as follows.

Table 9 shows those parameters which characterize the community simulated. The first four parameters define the size and shape of the community. The population-related parameters define the total population and the number of people in each health status. The rest environment parameters are used to set up the friendship and contact network.

Table 9. *Environment Parameters in the Model*

Parameter	**Description**
XMIN	Minimum x coordinate of the simulation space
XMAX	Maximum x coordinate of the simulation space
YMIN	Minimum y coordinate of the simulation pace
YMAX	Maximum y coordinate of the simulation space
%-large-reach	The percent of agents who have large reach among community population
Large-reach	The radius of the large social circle; it is used to create friendship network
Small-reach	The radius of the small social circle; it is used to create friendship network
Mean-of-daily-contact-capacity	The average daily contact capacity among community population
Std-of-daily-contact-capacity	The standard deviation of the distribution of individual daily contact capacity in the community
Max-of-daily-contact-capacity	The maximum daily contact capacity among community population
Min-of-daily-contact-capacity	The minimum daily contact capacity among community population
%-of-stable-contact	The average percent of stable contact capacity among individual daily contact capacity in the community
Population	The number of individual agents in the community
%-susceptible-population	The percent of agents susceptible to the disease among community population
%-exposed-population	The percent of agents in exposed status among community population
%-infected-population	The percent of agents in infected status among community population; it is also called morbidity
%-recovered-population	The percent of agents in recovered status among community population
%-died-population	The percent of agents who have died from the disease among community population

The second set of parameters is related to the disease being modeled. For an epidemic which can be simulated through the status transfer concept of SEIR, infection rate, latent period, infected period, and mortality rate are needed to specify the individual status progress involved in the epidemic, as shown in Table 10. Values for these parameters depend on the biological characteristics of the epidemic, and can be inferred from scientific literature, from research experience, or from data results collected from the field (Bagni, Berchi, & Cariello, 2002).

Table 10. *Epidemiologic Parameters in the Model*

Parameter	Description
Infection-rate	The probability for a susceptible individual to get infected after a contact with an infectious individual
Latent-period	The period of time between exposure to the disease and the time the disease becomes apparent through symptoms
Period-of-exposed-being-infectious	The period of time during which exposed individuals can spread the virus to others
Infected-period	The period of time between the moment an individual becomes symptomatic and the moment the individual recovers from the disease
Mortality-rate	The probability for an infected individual to die from the disease at each time step

The third set of parameters is related to individual agents' characteristics and behaviors (Table 11). The values for most of these parameters are updated each time step for each agent alive, to reflect its current daily contact pattern, its health status, and whether it is taking avoidance behavior.

Table 11. *Personal Parameters in the Model*

Parameter	Description
Social-reach	The radius of an agent's social circle for friendship network setup; it is either a large or a small reach
Number-of-friends	The number of friend agents an agent has; it is the size of the agent's personal friendship network

Contact-capacity	The number of agents an agent can contact per time step
Contact-rate	The number of agents an agent contacts at each time step; it is the size of the agent's personal contact network
%-of-stable-contacts	The percent of stable contacts an agent has per time step among its daily contacts
Stable-contact-capacity	The number of stable contacts an agent can have per time step; its value equals to the product of contact capacity and %-of-stable-contacts
Stable-contact-rate	The number of stable contacts an agent has at each time step
Random-contact-capacity	The number of random contacts an agent can have per time step; its value equals to the difference between contact capacity and stable contact capacity
Random-contact-rate	The number of random contacts an agent has at each time step
Health-status	The health status of an agent relative to the disease
Infection-probability	The probability for a susceptible agent to become exposed at each time step
Infected-probability	The probability for an exposed agent to become infected at each time step; it is decided by the latent period
Recovered-probability	The probability for an infected agent to recover from the disease at each time step; it is decided by the infected period
Mortality-probability	The probability for an infected agent to die from the disease at each time step
Infections?	Whether an exposed agent is infectious at each time step
Recovering?	Whether an infected agent would recover from the disease next time step
New-info?	Whether an agent receives any risk information at each time step
Channel-user?	Whether an agent is using some channel for risk information at each time step
Channel-believer?	Whether an agent believes the risk information from some channel is credible
Initial-risk-perception	The probability for an agent to believe the general public is greatly endangered
Confirmation-attempts	The number of friends an agent asks during the social confirmation stage
Responsive-decision	The probability for an agent to take avoidance behavior at each time step
Action?	Whether an agent takes avoidance behavior at each time step
Action-effect	The reduction in an agent's daily contact rate due to the adoption of avoidance behavior at each time step
Social-influence-threshold	The threshold for social influence to occur during the situational definition stage
Social-influence-effect	The percent of responsive decision which is decided by social influence

The final set of parameters is policy indicators, which specify the communication strategy employed by public sector. The number and type of channel in use determine which types of channel are used to send risk information. The rest three parameters in Table 12 decide the characteristics of each channel in use, including the percent of people among the community population who use and believe the credibility of the channel, and its use frequency.

Table 12. *Policy Parameters in the Model*

Parameter	**Description**
Number-of-channel-in-use	The number of different types of channels used by the public sector to send risk information at each time step
Channel-type	The type of channel being used
%-channel-user	The percent of agents who use some channel to receive risk information among community population
%-channel-believer	The percent of agents who believe risk information from some channel is credible among community population
Channel-frequency	How regular some channel is used to send risk information

Model implementation in Netlogo. In this dissertation, the agent-based model created is implemented in Netlogo. Netlogo is a multi-agent programmable modeling environment. It is developed based on the Logo programming language and can serve as the basis for a variety of multi-agent simulation models. The user interface of the model after implemented in Netlogo is presented in Appendix A, and the source code to implement the model in Netlogo in Appendix B.

Chapter 5

Computational Simulation Results

Research Context: 2009 H1N1 Influenza Outbreak in Arizona

2009 H1N1 influenza emerged as a new pandemic strain of influenza in April 2009. As the first global influenza pandemic in over 40 years, it caused a substantial number of illnesses, hospitalizations, and deaths (CDC, 2010a). On June 11, 2009, WHO declared that a pandemic of 2009 H1N1 influenza was underway (CDC, 2010b). The United States experienced its first wave of outbreak in the spring and summer months of 2009. A public health emergency was declared by the U.S. government on April 26. By June 19, all states in the U.S. had reported cases of 2009 H1N1 infection. The second wave occurred in the fall of 2009, with most of the nation experiencing the influenza outbreak from October to early December 2009 (Ross et al., 2010).

In Arizona, the first case of 2009 H1N1 infection was confirmed on April 29, 2009 (Shanks, 2009). The Arizona Department of Health Services (ADHS) has been reporting the number of newly infected and deceased cases each week since August 30, 2009. By early October 2009, a total of 2,243 people had been infected by and 30 people had died from the influenza in Arizona (ADHS, 2009a). New infections continued to emerge till May 2010. By early October 2010, 5,620 people in Arizona had been infected, and the total number of deceased cases was 122. The solid part of the curve in Figure 11 shows how the number of newly infected cases in Arizona changed each week during the 2009-2010 influenza season, namely, from October 4, 2009 to October 2, 2010 (ADHS, 2009b).

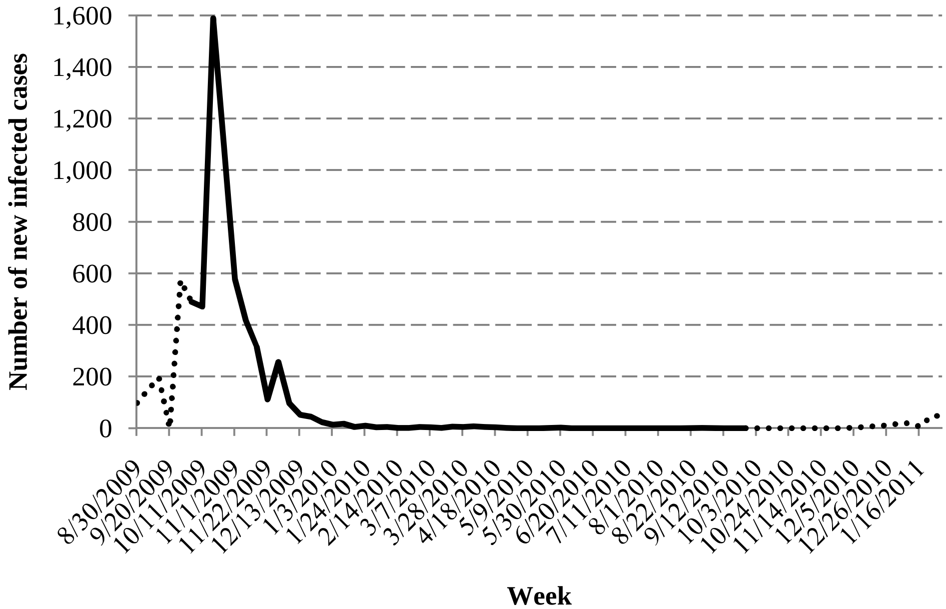

Figure 11. Epidemiological curve for 2009 H1N1 influenza weekly newly infected cases in Arizona[18]

To reduce the impacts of an influenza pandemic, ADHS has been emphasizing the use of non-pharmaceutical interventions in the absence of effective vaccine when facing a new influenza strain (ADHS, 2006, 2009c). When the second wave of 2009 H1N1 influenza outbreak occurred in October, effective vaccination against this influenza was still unavailable (ADHS, 2009d); but risk communication plans and strategies had been made before it. A Joint Information Center (JIC) and a coordinated statewide messaging system had been established and used to disseminate pandemic-related information to encourage the public to take non-pharmaceutical protective actions within the following influenza season (ADHS, 2009c). This situation provides a proper context to empirically answer the research question of this study.

[18] In this chart, only the solid curve represents the 2009-2010 influenza season.

This chapter first introduces how the computational model developed before is implemented in this specific setting. Experiments are then conducted to explore the spread dynamics of 2009 H1H1 influenza in an Arizona community during the 2009-2010 influenza season, without any policy intervention and with different risk communication strategies. Experiment results are summarized for policy and management insights.

Data Sources

First, the agent-based model needs to be parameterized for this specific research context. Table 13 summarizes the parameters used at the beginning of simulation, their default values, and the sources of these values.

Table 13. *Parameters, Values and Data Sources for Model Initialization*

Parameters	Default Value	Data Sources
Environment parameters		
XMIN	326 cell side	Hamill & Gilbert (2008, 2009, 2010)
XMAX	326 cell side	Same as above
YMIN	326 cell side	Same as above
YMAX	326 cell side	Same as above
%-large-reach	25%	Same as above
%-small-reach	75%	Same as above
Large-reach	65 cell side	Boase (2008), Wang & Wellman (2010)
Small-reach	25 cell side	Same as above
Mean-of-daily-contact-capacity	10	Salathe & Jones (2010), Mikolajczyk & Kretzschmar (2008)
Std-of-daily-contact-capacity	10.6	Mossong et al. (2008)
Max-of-daily-contact-capacity	40	Edmunds et al. (1997)
Min-of-daily-contact-capacity	0	Same as above
Ave-%-of-stable-contacts	25%	Beutels et al. (2006), Edmunds et al. (2006), Glass & Glass (2008)

Population	1,000	Perez & Dragicevic (2009)
%-of-susceptible-population	98%	Assumption of this dissertation
%-of-exposed-population	0%	Assumption of this dissertation
%-of-infected-population	2%	Assumption of this dissertation
%-of-recovered-population	0%	Assumption of this dissertation
%-of-died-population	0%	Assumption of this dissertation
Epidemiologic parameters		
Infection-rate	1.4%	Coburn, Wagner, & Blower (2009), Yang et al. (2009)
Average-latent-period	2 days	CDC (2009a)
Period-of-exposed-being-infectious	1 day	Same as above
Average-infected-period	5 days	Same as above
Mortality-rate	0.3%	Donaldson et al. (2009), Tuite et al. (2010)
Personal parameters		
Infected-probability	50%	CDC (2009a)
Revered-probability	20%	Same as above
Mortality-probability	0.3%	Donaldson et al. (2009), Tuite et al. (2010)
Confirmation-attempts	[1, 2, 3, 4]	Lindell & Perry (1992)
Action-effect	[30%, 40%, 50%, 60%, 70%, 80%, 90%]	Jefferson et al. (2008), Larson & Nigmatulina (2009)
Social-influence-threshold	50%	Assumption of this dissertation
Social-influence-effect	50%	Assumption of this dissertation
Policy parameters		
Number-of-channels-in-use	[0, 1, 2, 3]	Assumption of this dissertation ASU/ADHS Influenza Survey (2009)
Channel-type	Local TV, National TV, Radio	ASU/ADHS Influenza Survey (2009)
Channel-frequency	[1, 3, 7] days	Assumption of this dissertation

Local TV		
%-channel-user	[10%, 50%, 70%*, 90%]	Assumption of this dissertation ASU/ADHS Influenza Survey (2009)
%-channel-believer	[10%, 50%, 60%*, 90%]	Same as above
National TV		
%-channel-user	[10%, 26%*, 50%, 90%]	Assumption of this dissertation ASU/ADHS Influenza Survey (2009)
%-channel-believer	[10%, 50%, 55%*, 90%]	Same as above
Radio		
%-channel-user	[10%, 11%*, 50%, 90%]	Assumption of this dissertation ASU/ADHS Influenza Survey (2009)

Note. “[]” in this table means that any value for a parameter in the square bracket could be selected for simulation. Value with * is the empirical value for a parameter.

The target social system simulated in the model is a medium-size community in Arizona. Such a choice is made for two reasons. First, the entire population of the state or a large city cannot be taken into consideration due to limited computational capacity. Second, this study is interested in pandemic influenza spread in a social network via individual interaction. The focus on a medium-size community allows a more comprehensive understanding of the interactions at the local level (Eidelson & Lustick, 2004). Furthermore, inferences can still be made on larger groups from the analysis (Eidelson & Lustick, 2004).

Population size of the community in the model is set to 1000, the number used by previous studies for a medium-size community (e.g., Perez & Dragicevic, 2009). The population density and the shape of the community are the same as those in Hamill and Gilbert’s study (2008, 2009, 2010), to ensure the friendship networks set up have the same characteristics. 1,000 agents are randomly placed over a 100,000-cell unbounded and square space with a population density of 1%.

Parameters related to the friendship network include the percent of agents who have large and small social reach, and large and small social reach. Proper values for these parameters have been discussed before and are summarized in Table 13. Values for those parameters needed to set up a structurally hierarchical contact network for agents are also from previous studies, as discussed before.

For an epidemic to diffuse over a network, a certain number of nodes need to be infectious at the beginning of the spread process (Delre et al., 2007). In the model created, 2009 H1N1 influenza dies out within a short time period when the simulation is initialized with less than 2% nodes being infectious. The influenza in this case cannot become a public concern. To simulate the influenza outbreak as a public emergency, the model starts the simulation with 2% nodes chosen at random to have infected health status; all other nodes are initially set susceptible.[19] Over time the initial infection can spread the disease through the network. Figure 12 shows an example of how an infection unfolds within a simple contact network through successive time steps. Beginning with one infected node which is shaded at the center at time step t, the disease spreads to some but not all of the remaining non-shaded susceptible nodes. Over time more susceptible nodes are infected through their connections with infected nodes.

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[19] No common approach has been found in previous studies to decide the percent of simulated population in each health status at the beginning of pandemic influenza simulation. But the population is usually categorized into two groups: people who are infected and infectious, and people who are susceptible to the influenza (e.g., Kenah et al., 2011).

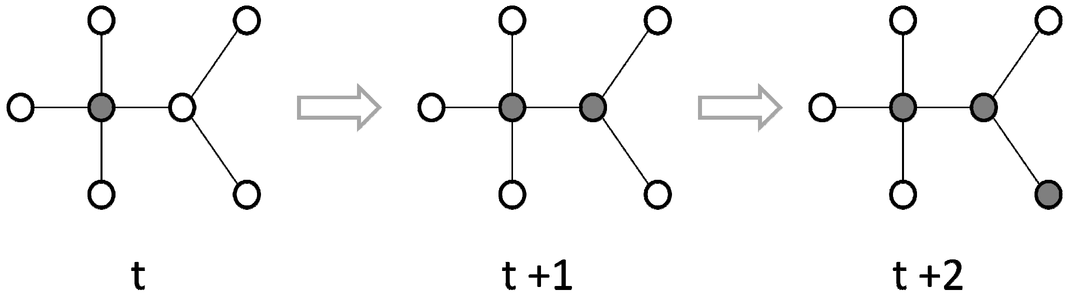

Figure 12. The spread course of an SEIR epidemic in a simple contact network

For epidemiologic parameters, their values were collected from CDC reports and earlier studies. According to CDC, "the incubation period for influenza is estimated to range from 1 to 4 days with an average of 2 days" and "influenza virus shedding (the time during which a person might be infectious to another person) begins the day before illness onset and can persist for 5 to 7 days" (CDC, 2009a). The simulation model assumes an average latent period of 2 days and an average infected period of 5 days. Another implication from the CDC's statement is that exposed individuals are not infectious at all times; they only begin to transmit the virus from the last day of their latent period (CDC, 2009a).

The infection rate can be estimated based on previous findings on the basic reproduction number (R_0), which is the number of secondary infections caused by a single infectious case introduced into the susceptible population. Considering the assumption that people can only die when they are in infected status, R_0 is equal to the product of the average contact rate, the infection rate and the average infectious period (Keeling & Rohani, 2008).[20] This model uses a value of 1.4 for

[20] The infectious period is the time period during which an individual is infectious. In the model, individuals after exposed to the influenza have an average infectious period of 6 days. It is composed of the average infected period and the last day of latent period.

the infection rate, which is based on the value of the estimated basic reproduction number from the study of Coburn et al (2009) and Yang et al (2009), and the value for the average contact rate and average infectious period. The mortality rate for 2009 H1N1 influenza was estimated to be approximately 0.3% (Donaldson et al., 2009; Tuite et al., 2010).

Values for personal parameters related to daily contact pattern are set at the beginning of simulation based upon the characteristics of community contact network. Each node's daily contact capacity is randomly selected from the truncated normal distribution of community contact network's degree of connectivity. Its ratio between stable and random contact capacity is set to 1:3. Personal parameters related to individual biological progress are determined by epidemiologic parameters. The infected-probability is the reciprocal of average latent period, and the recovered-probability the reciprocal of average infected period. Meanwhile, the parameter of infectious? is used to help simulate the last day of latent period. Its value is randomly decided based on the infected-probability for each exposed node at the beginning of each time step. If the value is true, the node becomes infectious at this time step, and infected at next time step. Otherwise, the node remains exposed and noninfectious. Appropriate values for personal parameters related to individual responsive process to risk information have been discussed before, for example, confirmation-attempts, action-effect, social-influence-threshold, and social-influence effect.

Characteristics of public risk communication strategy came from the 2009 ASU/ADHS Influenza Survey (Jehn et al., 2011). It was a random-digit telephone survey of representative households in Arizona. The survey was designed to elicit responses from the adult in the household who was the primary health-related decision-maker. It was conducted by trained interviewers using a structured questionnaire. Interviews were performed between 8:00 am and 9:00 pm including weekdays and weekends from October 1-30, 2009. A translated survey questionnaire was used for respondents speaking only Spanish.

A total of 945 available telephone numbers were identified for potential interviews, with 727 households completing the survey for a 77% final survey sample response rate. Sampling was designed around a 95% confidence interval and together with the response rate resulted in a ±3.64% margin of error. The survey contained 53 main questions, and related sub-questions, on respondents' demographics, what they knew about the 2009 H1N1 influenza, how they received relevant information and perceived the risk, and whether they were taking avoidance actions to reduce their risk of getting infected by the influenza (Jehn et al., 2011).

In the model, components of public risk communication strategy influence individual responsive behavior through formulating their initial risk perception. Given the rare empirical findings on how the former influences the latter, information collected from the survey is used to specify the relationship. Among survey respondents, 49.24% believed that it was very easy for people to get the influenza, or that the influenza situation was very urgent at that time. These respondents are considered those who have a high level of initial risk perception.

Regarding risk communication strategies, the survey included items related to channel type, and the use and perceived importance of each type of channel. Survey respondents were asked to identify the type of channel through which they obtained 2009 H1N1 flu information during the survey month. The choices were local TV, national TV, local newspaper, national newspaper, Internet, radio, magazine, friend, school, work, doctor, and other. Respondents could choose multiple types of channel and are defined as a channel user of all types of channel they used. Meanwhile, those who indicated that some type of channel they used to obtain information was "very important" or "somewhat important" were considered the believer of this channel.[21]

Logit regression was run on the survey, using whether having a high-level initial risk perception as dependent variable. Independent variables are shown in Table 14, which include whether respondents use each type of channel to receive 2009 H1N1 influenza information, whether they consider the channel important, and their demographical characteristics which previous studies found influential on individuals' risk perception of a pandemic influenza (Sjoberg, 2000).

The regression formula is showed as below.

$$\mathrm{logit}(\mathrm{P_{rp}}) = \beta_0 + \sum_{n=1}^{12}(\beta_{1n} * \mathrm{Channel_n} + \beta_{2n} * \mathrm{Channel_n} * \mathrm{Channel\_Imp_n}) + \sum_{m=1}^{9}(\beta_{3m} * \mathrm{Demo_m})$$

[21] The perceived importance of a channel is different from its perceived credibility. But the former is the only available item in the research context that is related to the latter. So here, in this specific research context, perceived importance is considered the same as perceived credibility.

Table 14. *Variable Definitions in the Logit Regression*

Variable	Definition	Possible Value
Dependant variable		
High-initial-risk-perception?	Whether a respondent has a high-level initial risk perception	1 (Yes) 0 (No)
Independent variable		
$Channel_n$	Whether a respondent uses Channel n to receive risk information	1 (Yes) 0 (No)
$Channel\_Imp_n$	Whether a respondent believes the information from Channel n is important	1 (Yes) 0 (No)
Age	Which age group a respondent is in	1 (18-34) 2 (35-65) 3 (65+)
Gender	Whether a respondent is female or male	1 (Female) 0 (Male)
Race	Whether a respondent is while or not	1 (White) 0 (Non-White)
Ethnicity	Whether a respondent is Hispanic or not	1 (Hispanic) 0 (Non-Hispanic)
Kid	Whether a respondent has kids	1 (Yes) 0 (No)
Education	Which education group a respondent is in	1 (less than Bachelor) 2 (Bachelor or college degree) 3 (Graduate or post-college degree)
Income	Which before-tax income group a respondent is in	1 (45K or less) 2 (45K+)
Ssflu	Whether a respondent got seasonal flu during the last flu season	1 (Yes) 0 (No)
Insur	Whether a respondent has any type of medical insurance	1 (Yes) 0 (No)

Note. Channel n could be any type of channel among the channel choices in the survey.

In the formula, P_{rp} represents the probability for a respondent to perceive a high level of risk because of the influenza. $Channel_n$ represents whether this respondent uses Channel n to receive pandemic information, and $Channel_n$ *

Channel_Imp$_n$ whether this respondent as a user of Channel n believes its importance.[22] Demo$_m$ is the mth demographic characteristic. Regression result is showed in Table 15.

Table 15.
Regression Result on 2009 ASU/ADHS Influenza Survey Data

	Coef.	Std. Err.	z	P > |z|	[95% Conf. Interval]	
ltv	-1.01	0.74	-1.36	0.172	-2.46	0.44
ntv	-2.40	1.50	-1.60	0.109	-5.33	0.53
lnews	14.33	8.85	0.02	0.987	-17.21	17.49
nnews	12.23	14.20	0.01	0.993	-27.69	27.96
internet	0.86	0.60	1.43	0.152	-0.32	2.05
radio	-2.56	1.06	-2.41	0.016*	-4.64	-0.48
magazine	12.54	26.00	0.00	0.996	-50.84	51.09
friend	-0.67	1.25	-0.53	0.594	-3.12	1.79
school	13.84	18.37	0.01	0.994	-35.86	36.14
work	14.22	16.00	0.01	0.996	-50.82	51.11
doctor	14.34	26.00	0.01	0.996	-50.82	51.11
other				Omitted		
ltv_Imp	1.68	0.73	2.28	0.023*	0.23	3.08
ntv_Imp	3.04	1.53	1.99	0.047*	0.39	6.05
lnews_Imp	-13.97	8.85	-0.02	0.987	-17.49	17.21
nnews_Imp	-14.02	14.20	-0.01	0.992	-27.97	27.69
internet_Imp	-0.24	0.76	-0.31	0.756	-1.73	1.26
radio_Imp	1.58	1.12	1.42	0.157	-0.61	3.77
magazine_Imp	-13.18	26.00	-0.01	0.996	-51.09	50.83
friend_Imp	-0.79	1.32	-0.60	0.549	-3.38	1.80
school_Imp	-15.25	18.37	-0.01	0.993	-36.15	35.85
work_Imp	-14.01	26.00	-0.01	0.996	-51.10	50.82
doctor_Imp	-13.43	26.00	-0.01	0.996	-51.10	50.83
other_Imp				Omitted		
age_c_2	0.13	0.53	0.25	0.805	-0.90	0.55
age_c_3	-0.25	0.64	-0.40	0.691	-1.50	0.99
gender	0.19	0.32	0.61	0.543	-0.43	0.82
race	-0.41	0.58	-0.71	0.477	-1.55	0.72
ethnicity	0.67	0.48	1.42	0.157	-0.26	1.61
kid	-0.17	0.37	-0.47	0.639	-0.90	0.55
education	0.50	0.53	0.94	0.345	-0.54	1.54
income	-0.68	0.36	-0.33	0.061	-1.38	0.03
ssflu	-0.40	0.40	-1.01	0.314	-1.19	0.38
insur	0.24	0.60	0.39	0.696	-0.95	1.42
_cons	1.84	0.96	1.91	0.056	-0.50	3.73

Note. “ltv” represents local TV, “ntv” national TV, “lnews” local newspaper, and “nnews” national newspaper.

[22] For the perceived importance to exert influence on risk perception, certain type of channel has to be used by an individual first.

Therefore, respondents' perception that there was a high risk of 2009 H1N1 influenza was dependent upon whether they receive risk information from national television (ntv), local television (ltv) and radio, and meanwhile whether they believe either TV channel is important.

$$\mathrm{logit}\left(\mathrm{P_{rp}}\right) = 3.04 * \mathrm{ntv} * \mathrm{ntv\_imp} + 1.66 * \mathrm{ltv} * \mathrm{ltv\_imp} - 2.56 * \mathrm{radio}$$

The above regression result is used in the simulation in two ways. First, public risk communication strategy in the model is represented by 8 indicators: the percent of community population who receive risk information from local TV (%-ltv-user), from national TV (%-ntv-user), and from radio (%-radio-user), the percent of population who believe in the importance of local TV (%-ltv-believer) and of national TV (%-ntv-believer), and the frequency the three types of channel are used to send risk information (f-ltv, f-ntv, and f-radio). Channel usage frequency was not included in the survey, but is considered in the model given its vague influence recurrently mentioned in previous literature. As a result, public sector in the model can employ different communication strategies by choosing which of the three types of channel to be used for sending risk information, and by changing the user and believer percent and the usage frequency of each type of channel in use. Given the possible values for these policy parameters as shown in Table 13, numerous communication strategies can be implemented in the model.

Second, based on the regression result, the probability for an individual after receiving risk information to have a high-level risk perception (P_I) at each time step is calculated as:

$$\mathrm{P_I} = \frac{1}{1 + e^{-(3.04*\mathrm{ntv}*\mathrm{ntv\_imp}+1.66*\mathrm{ltv}*\mathrm{ltv\_imp}-2.56*\mathrm{radio})}}$$

Simulation Setup

The model is initialized with the creation of the artificial community. The simulation area is set up based on the display size parameters. 1000 individual nodes are created and randomly located across the area. A population density of 1% is therefore achieved. Next, the community friendship network and contact network are created in the way as discussed before. Health status for each node is then generated. Nodes are selected at random to fill the required number of people in each health status. Other parameters are set to their values as shown in Table 13.

One time step in the mode is corresponding to one day. The first time step represents October 4, 2009. Each simulation is run 364 time steps to cover the whole 2009-2010 influenza season. Simulation outputs are captured by five aggregate statistics: the percent of population ever get infected by the end of the influenza season (epidemic size), the maximum frequency of infection during the season (peak prevalence), the number of days between season beginning and the elimination of the virus (epidemic duration), the percent of population in infected status on each day (morbidity), and the percent of population ever classified as infected by each day since season beginning (cumulative morbidity). The first three indicators are usually used to measure the impacts a pandemic caused in communities (e.g., Salathe & Jones, 2010); they are recorded by the end of each simulation. The last two indicators are recorded at each time step.

The model is experimented on two scenarios. The first scenario simulates how the pandemic influenza spreads without any public intervention. The second scenario explores how the five output indicators change with the incorporation of different public risk communication strategies. Figure 13 shows the general simulation framework in this dissertation.

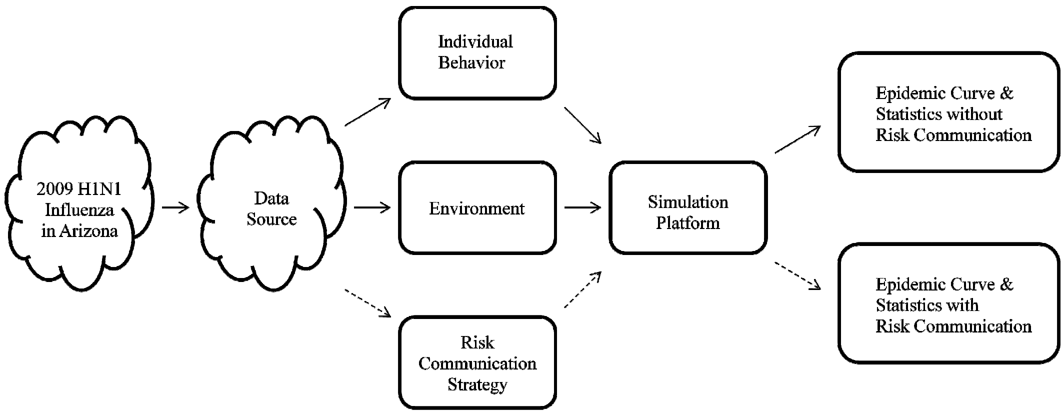

Figure 13. Simulation setup in the focused context

Experiment Results

This section summarizes and compares simulation results from the two experiment scenarios. For each simulation, the result presented below is the average results over its 20 runs.

Influenza spread dynamics without pubic intervention. Figure 14 and Figure 15 show how morbidity and cumulative morbidity change over time when there is no public intervention. Once the pandemic is initiated, there is a period of exponential growth in the morbidity. This indicator peaks on day 35 (Nov.7th, 2009), with 6.1% of community population infected within the single day; the cumulative morbidity by that day is 24.22%. After the peak, the morbidity drops exponentially. By day 112 (Jan.23rd, 2010), when there are no infectious people, 45.6% of the total population has been infected. This scenario is called the baseline scenario, in which the epidemic size is 45.6%, the peak prevalence is 6.1%, and the epidemic duration is 112 days.

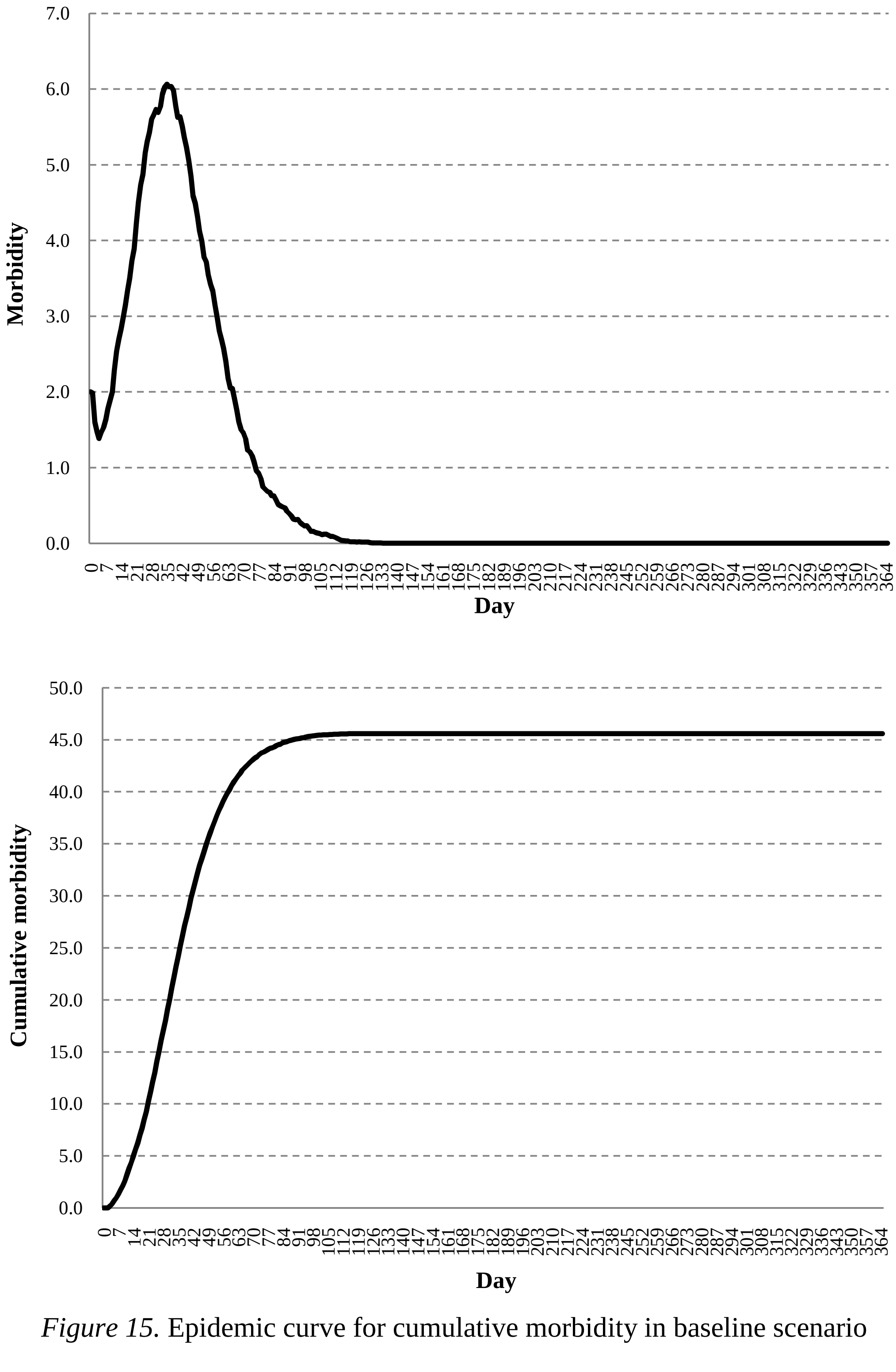

Figure 15. Epidemic curve for cumulative morbidity in baseline scenario

Influenza spread dynamics with public risk communication. In this scenario, three sets of experiment are conducted, with public sector employing one type of channel, two types of channel, and all three types of channel to send pandemic information, respectively.

One channel in use. Experiments here are conducted to explore the influenza spread dynamics when just one type of channel is used by public sector. For the strategy to use the channel, three levels of value can be selected for the user and believer percent: 10% (low), 50% (medium), and 90% (high). Channel usage frequency also has three levels of value: 7 (once per week, low), 3 (once every three days, medium), and 1 (once per day, high). As a result, 27 different strategies can be implemented in the model when one type of channel is in use.

Local TV. Table 16 summarizes the simulation results on peak prevalence, epidemic size and epidemic duration when the public sector uses different communication strategies of local TV to send risk information.

Table 16. *Pandemic Impacts with Local TV in Use Alone*

Strategy	Output	Strategy	Output	Strategy	Output
(10,10,1)	3.1; 27.3; 114;	(10,10,3)	4.9; 35.2; 114;	(10,10,7)	5.9; 41.8; 113;
(10,50,1)	2.8; 24.1; 149;	(10,50,3)	4.0; 30.6; 114;	(10,50,7)	5.7; 40.2; 113;
(10,90,1)	2.9; 19.9; 115;	(10,90,3)	3.8; 29.7; 114;	(10,90,7)	5.0; 38.6; 112;
(50,10,1)	2.3; 23.7; 163;	(50,10,3)	3.3; 27.4; 125;	(50,10,7)	3.6; 30.9; 123;
(50,50,1)	2.1; 20.3; 160;	(50,50,3)	2.1; 22.0; 161;	(50,50,7)	3.4; 27.6; 165;
(50,90,1)	2.0; 13.8; 141;	(50,90,3)	2.1; 15.8; 169;	(50,90,7)	3.0; 19.8; 133;
(90,10,1)	2.3; 24.0; 148;	(90,10,3)	2.7; 27.2; 167;	(90,10,7)	3.7; 31.0; 137;
(90,50,1)	2.0; 20.2; 179;	(90,50,3)	2.0; 20.5; 162;	(90,50,7)	2.3; 24.3; 128;
(90,90,1)	2.0; 14.7; 158;	(90,90,3)	2.0; 14.7; 178;	(90,90,7)	2.0; 16.9; 117;

Note. The strategy of how local TV is used is organized as (%-user, %-believer, use frequency); for example, (50,90,3) means the user percent, believer percent and use frequency of local TV is 50%, 90%, and once per 3 days, respectively. The output is organized as (peak prevalence; epidemic size; epidemic duration;). All tables and figures following this table in this chapter present the strategy of using some type of channel and the output for pandemic impacts in the same way.

Compared with the baseline scenario, any communication strategy using local TV can reduce the influenza impacts. As shown in Table 16 and Figure 16, the least effective strategy is (10,10,7), namely, when all three indicators are at their low levels. This strategy has little influence on peak prevalence and epidemic duration, while reducing the epidemic size by a small degree. The most effective strategy is with medium- or high-level user percent, high-level believer percent and medium- or high-level use frequency (except (50,90,3)). These strategies can not only reduce the peak prevalence by at least 67.2% and epidemic size by at least 67.5%, they can also prolong the epidemic duration, which gives public managers more time to react to the outbreak. Furthermore, most strategies can prolong the epidemic duration, while the rest have little effect on it.

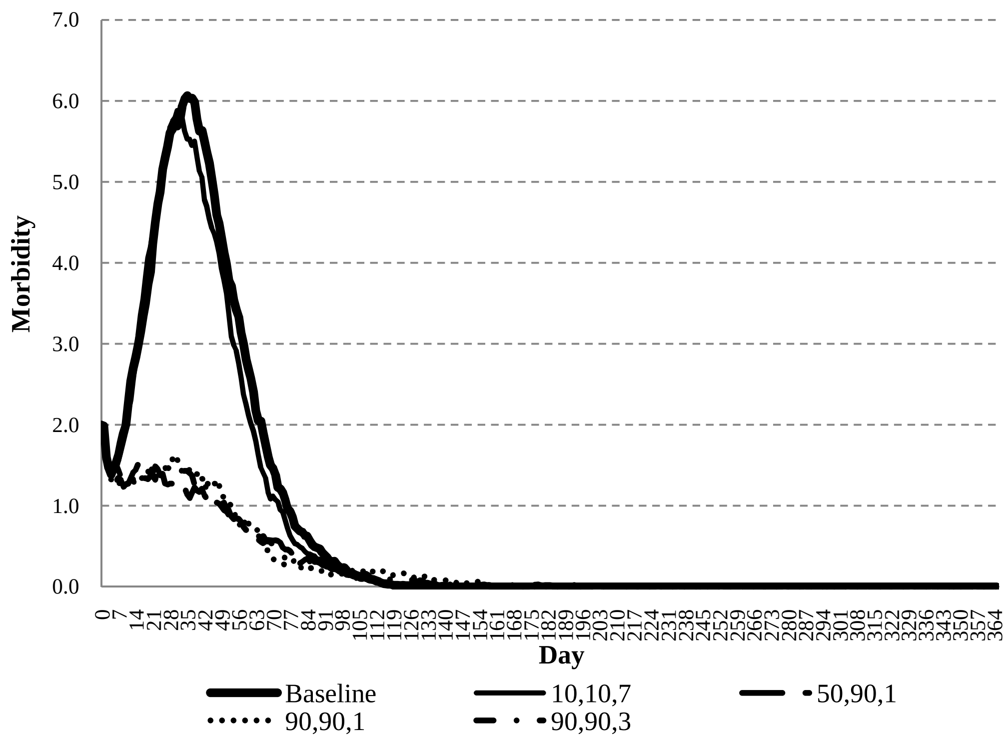

Figure 16. The most and least effective communication strategy associated with local TV

The influence of each strategy indicator can also be analyzed, with values for the other two fixed. First, local TV has a conditional threshold of 50% regarding the influence of its user percent on peak prevalence and epidemic size. When the frequency is fixed to low level, increasing the user percent can reduce the peak prevalence and epidemic size. When the frequency is fixed to medium or high level, increasing user percent after this parameter reaches 50% has little influence on the two output indicators. For epidemic duration, modifications in this parameter in both conditions change this output indicator in an inconsistent way. Such findings can be shown by Figure 17.

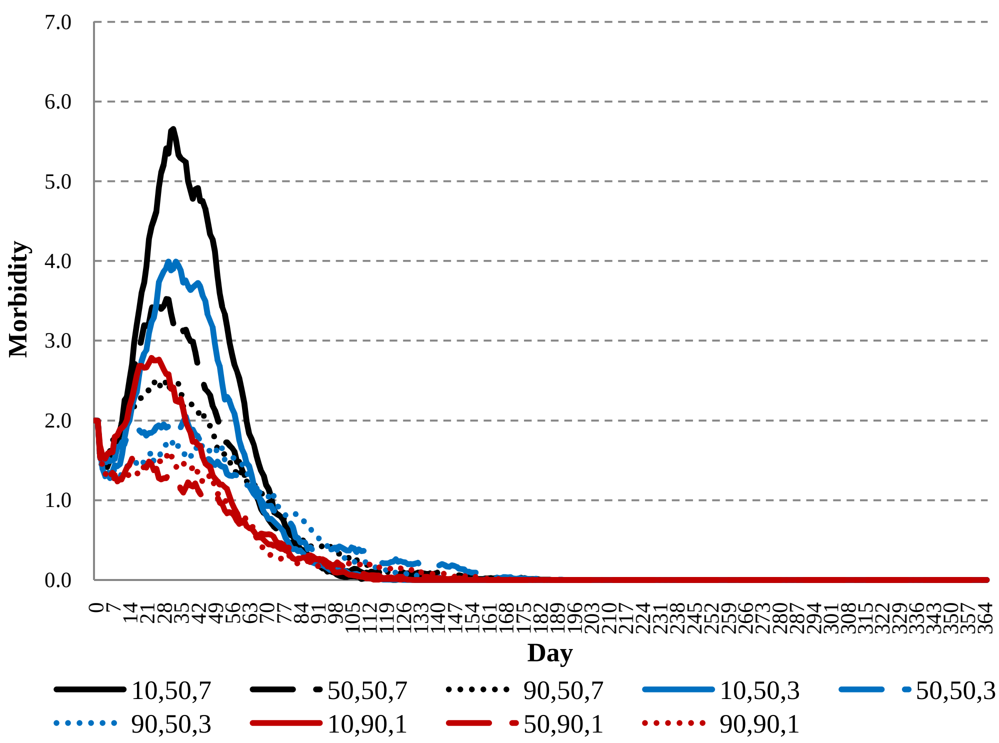

Figure 17. Influence of the user percent of local TV

For the believer percent of local TV, an increase in its value can reduce the epidemic size. For example, when the user percent is at the high level, increasing the believer percent from 50% to 90% could averagely decrease the epidemic size by 20.7%, despite the value of use frequency; increasing the percent from 50% to 90% can averagely reduce the epidemic size by 28.7%, as shown in Figure 18. Its influence on peak prevalence depends upon the value for use frequency. When the frequency is at low level, increasing believer percent can reduce peak prevalence. When the frequency is higher than the low level, increasing believer percent after it reaches 50% would have little influence. Furthermore, the believer percent exerts inconsistent influence on epidemic duration.

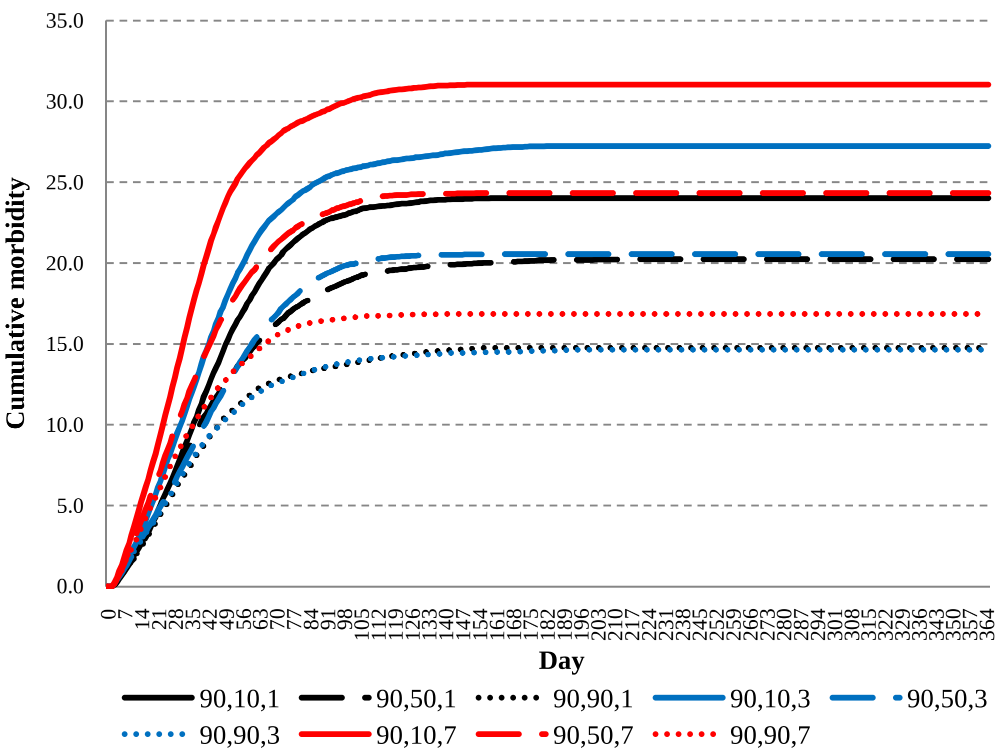

Figure 18. Influence of the believer percent of local TV

The influence of local TV' use frequency can also be summarized as being of conditional threshold. When the user and believer percent are fixed and either is less than 50%, increasing the use frequency can greatly reduce the peak prevalence and epidemic size. When both values are fixed to equal to or more than 50%, almost identical epidemic curves of the number of infected cases are produced by communication strategies with medium and high use frequency, while there is still a big difference between the influence of low-frequency strategy and medium-frequency strategy. Figure 19 partially shows such a conditional influence. Furthermore, the epidemic duration is also inconsistently influenced by changes in the use frequency.

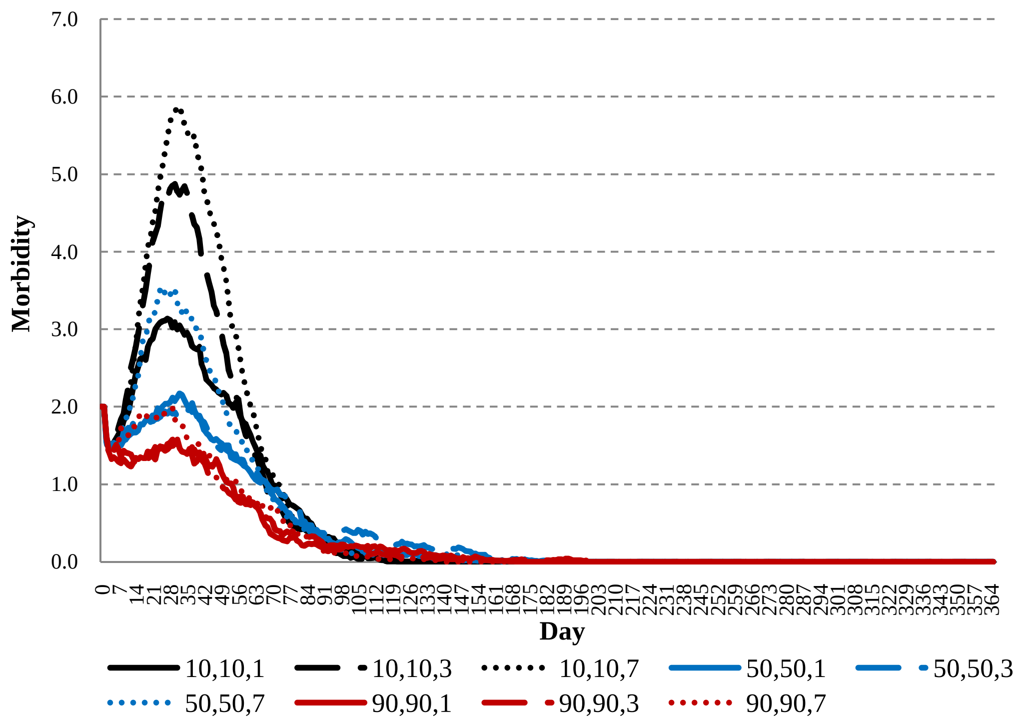

Figure 19. Influence of transmission frequency of information from local TV

National TV. Table 17 shows simulation outputs when just national TV is in use. Similar as previous situation, any communication strategy associated with the channel can reduce the peak prevalence and epidemic size. The epidemic duration is influenced inconsistently, but can be prolonged by most strategies. The least effective strategy is the one with all indicators at low level, while the most effective strategy is with all indicators at high level, as shown in Figure 20.

Table 17. *Pandemic Impacts with National TV in Use Alone*

Strategy	Output	Strategy	Output	Strategy	Output
(10,10,1)	3.6; 29.4; 154;	(10,10,3)	4.7; 36.4; 111;	(10,10,7)	5.6; 40.5; 112;
(10,50,1)	2.9; 23.2; 156;	(10,50,3)	4.5; 32.3; 115;	(10,50,7)	5.8; 39.1; 112;
(10,90,1)	2.7; 19.5; 248;	(10,90,3)	4.5; 30.8; 155;	(10,90,7)	4.8; 35.3; 129;
(50,10,1)	2.7; 24.8; 142;	(50,10,3)	3.0; 28.5; 150;	(50,10,7)	4.0; 31.5; 135;
(50,50,1)	2.0; 18.3; 165;	(50,50,3)	2.1; 19.1; 144;	(50,50,7)	3.4; 25.8; 139;
(50,90,1)	2.0; 10.3; 112;	(50,90,3)	2.0; 11.2; 120;	(50,90,7)	2.6; 19.1; 108;
(90,10,1)	2.6; 25.0; 129;	(90,10,3)	2.9; 27.4; 123;	(90,10,7)	3.3; 27.9; 122;
(90,50,1)	2.0; 19.0; 145;	(90,50,3)	2.0; 19.4; 164;	(90,50,7)	2.5; 20.2; 132;
(90,90,1)	2.0; 9.5; 159;	(90,90,3)	2.0; 10.2; 143;	(90,90,7)	2.0; 17.2; 118;

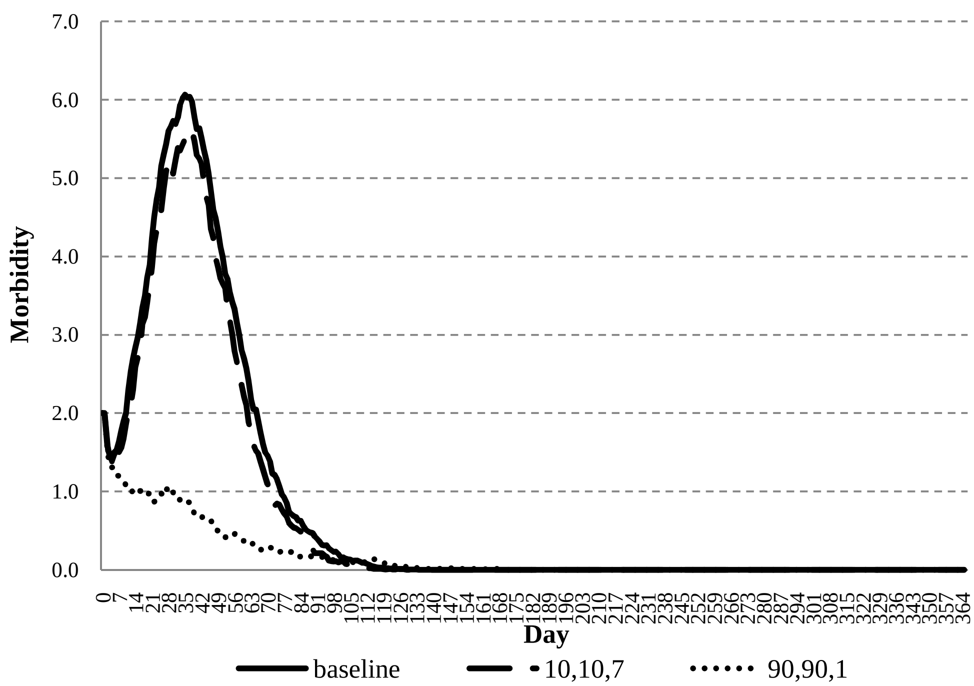

Figure 20. The most and least effective communication strategy associated with national TV

The influence of each strategy indicator on pandemic impacts with national TV used alone is similar as that with the separation usage of local TV. With fixed values for the believer percent and use frequency, there is a conditional threshold of 50% for the influence of user percent to reduce peak prevalence and epidemic size. The existence of this threshold depends upon whether the use frequency is at low level. As an example, Figure 21 shows the almost identical influences communication strategies exert on cumulative morbidity over time after their user percent reaches 50% and their use frequency is medium or high. Besides, the epidemic duration is influenced inconsistently by changes in the user percent.

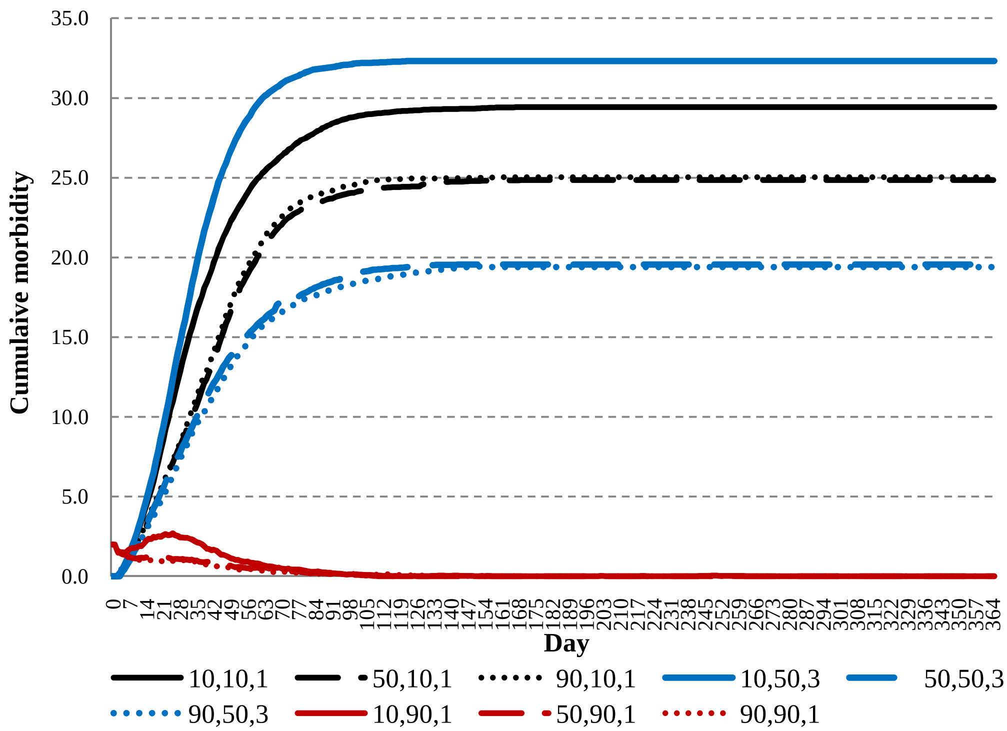

Figure 21. Influence of the user percent of national TV[23]

[23] One set of number in the legend represents one strategy to use national TV. For example, (90,50,1) means the user percent, believer percent and use frequency of national TV is 90%, 50%, and once per day, respectively.

The influence of national TV's believer percent also depends on its use frequency. When the frequency is at low level, increasing believer percent can reduce both peak prevalence and epidemic size. When the frequency is medium or high, increase the percent can only reduce the epidemic size while have small influence on the peak prevalence. Figure 22 shows an example of such an influence of believer percent. In addition, the epidemic duration is also inconsistently influenced by changes in the believer percent.

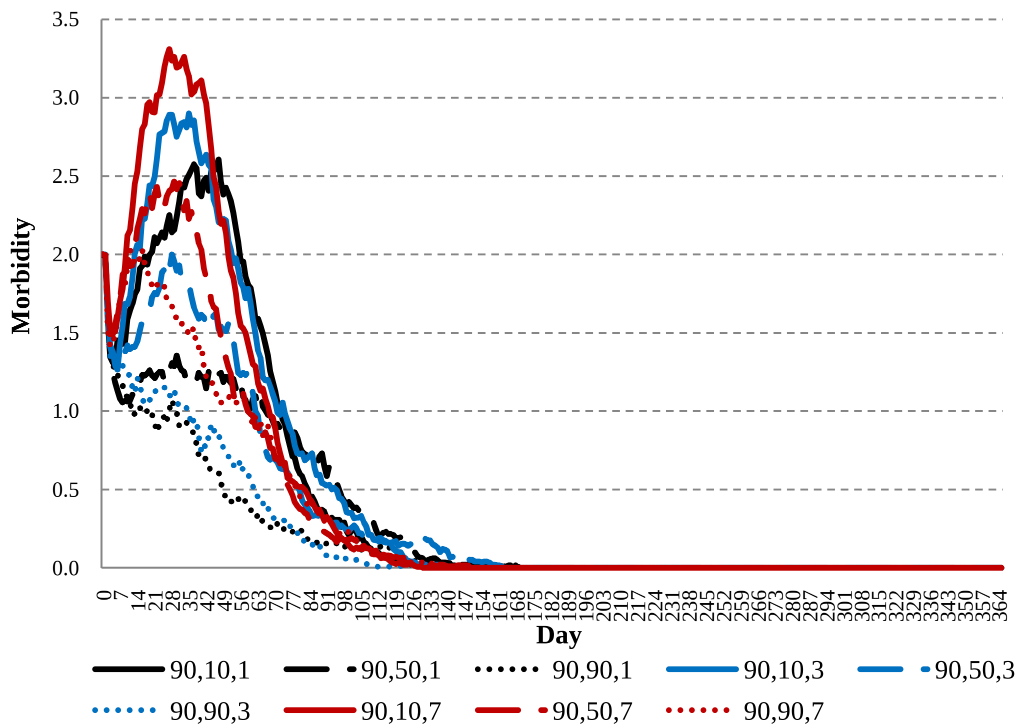

Figure 22. Influence of the believer percent of national TV

For the influence of use frequency, Figure 23, as an example, shows its conditional threshold of once per 3 days, the existence of which depends upon the level of user and believer percent. When both percents are equal to or higher than 50%, sending risk information more frequently after the frequency reaches the medium level achieves little to reduce the peak prevalence or epidemic size.

Otherwise, increasing the frequency is an effective way to decrease the number of infected cases at some time point or over time. Furthermore, no consistent pattern has been found regarding the relationship between the use frequency and the epidemic duration, as in the situation when local TV is used alone.

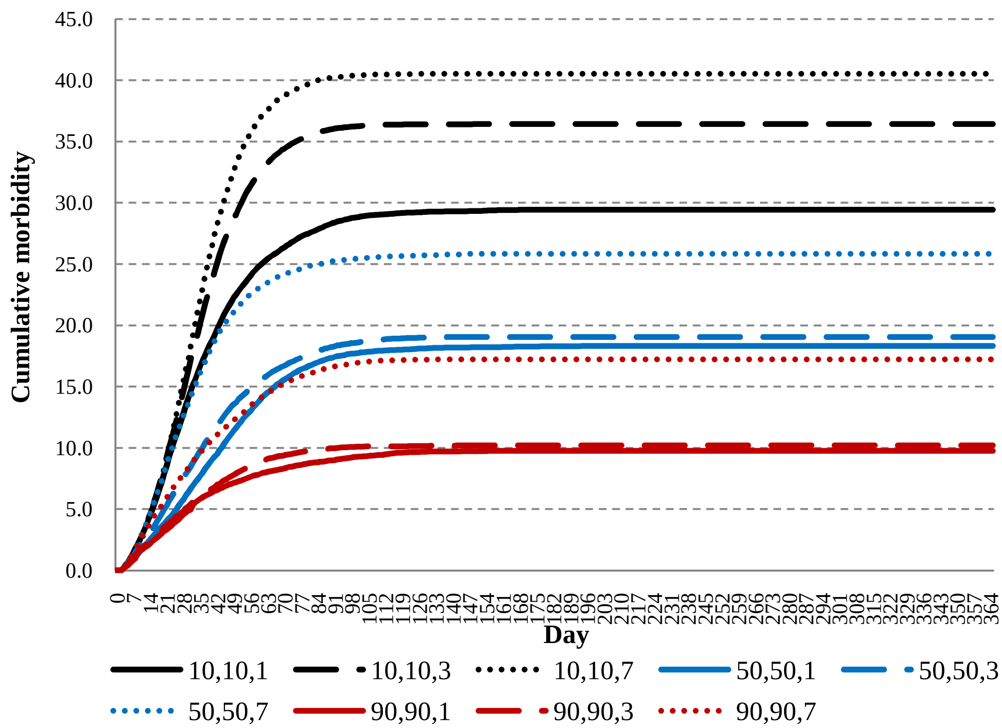

Figure 23. Influence of information transmission frequency of national TV

Local TV vs. national TV. The effects of these two TV channels are similar in terms of how each strategy indicator influences the pandemic impacts. Such similarity may be caused by their similar influences on individual initial risk perception. On the other hand, no consistent results have been found regarding which TV channel with the same strategy indicators is more effective to reduce pandemic impacts. Although national TV seems more influential on individual initial risk perception and therefore pandemic impacts, local TV could be of equal or more effects in some situations, as shown in Figure 24.

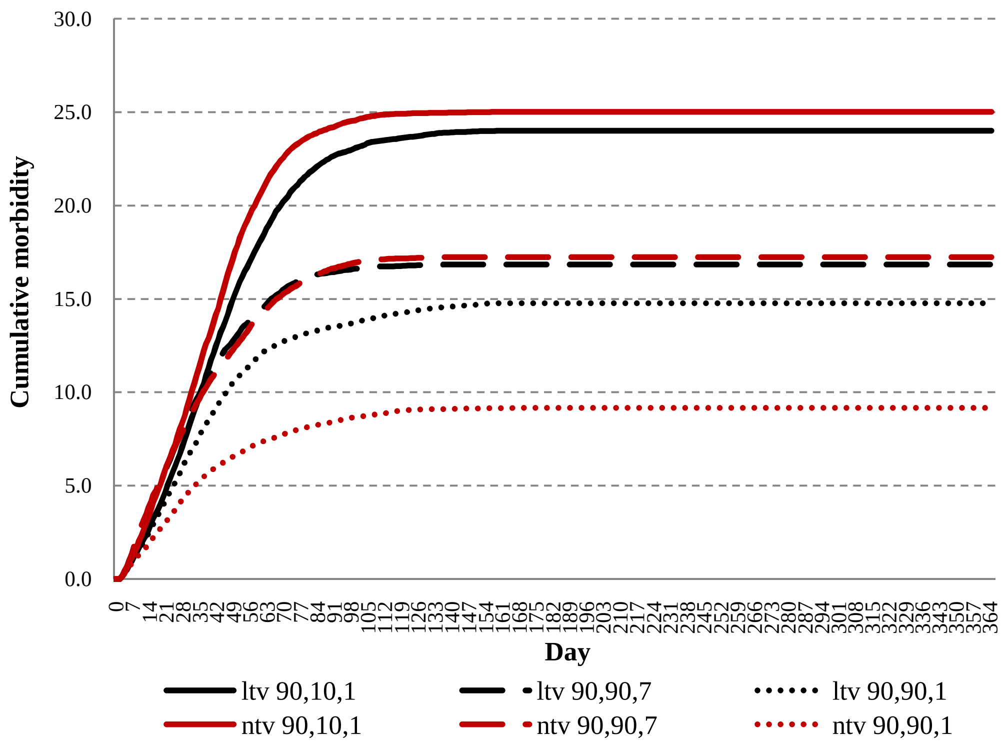

Figure 24. Comparison of the influence of local and national TV with each used alone

Radio. When radio is used alone to send risk information, no communication strategies can effectively reduce the pandemic impacts. As shown in Table 18, even the most effective strategy with 50% user and 1-day frequency can only reduce the peak prevalence by 6.5% and the epidemic size by 4.8%, and delay the epidemic duration by one week. The least effective strategy is with 10% user and 7-day frequency. This strategy has no influence on peak prevalence and epidemic size, but prolong the epidemic duration.

Table 18. *Pandemic Impacts with Radio in Use Alone*

Strategy	Output	Strategy	Output	Strategy	Output
(10,1)	5.8; 45.0; 120;	(10,3)	6.0; 43.6; 112;	(10,7)	6.1; 45.6; 124;
(50,1)	5.7; 43.4; 119;	(50,3)	5.6; 44.8; 128;	(50,7)	6.1; 44.8; 115;
(90,1)	6.1; 45.4; 110;	(90,3)	5.7; 44.1; 124;	(90,7)	6.0; 45.0; 114;

Figure 25 shows the epidemic curve of cumulative morbidity in the baseline scenario and the situation with each communication strategy associated with radio used. All these epidemic curves are very close to each other, which indicates the little role radio can play in impact mitigation in the community. Furthermore, no consistent pattern has been found in terms of how changes in any strategy indicator of radio influence the pandemic impacts.

Summary. When public sector just uses one type of channel to send risk information, local or national TV should be preferred to radio in order to mitigate pandemic impacts. Public managers can manipulate the three strategy indicators of either TV channel to change the peak prevalence and epidemic size in their expected direction. For epidemic duration, although its direction of change is hard to be anticipated, it would be either delayed (in most cases) or influenced slightly.

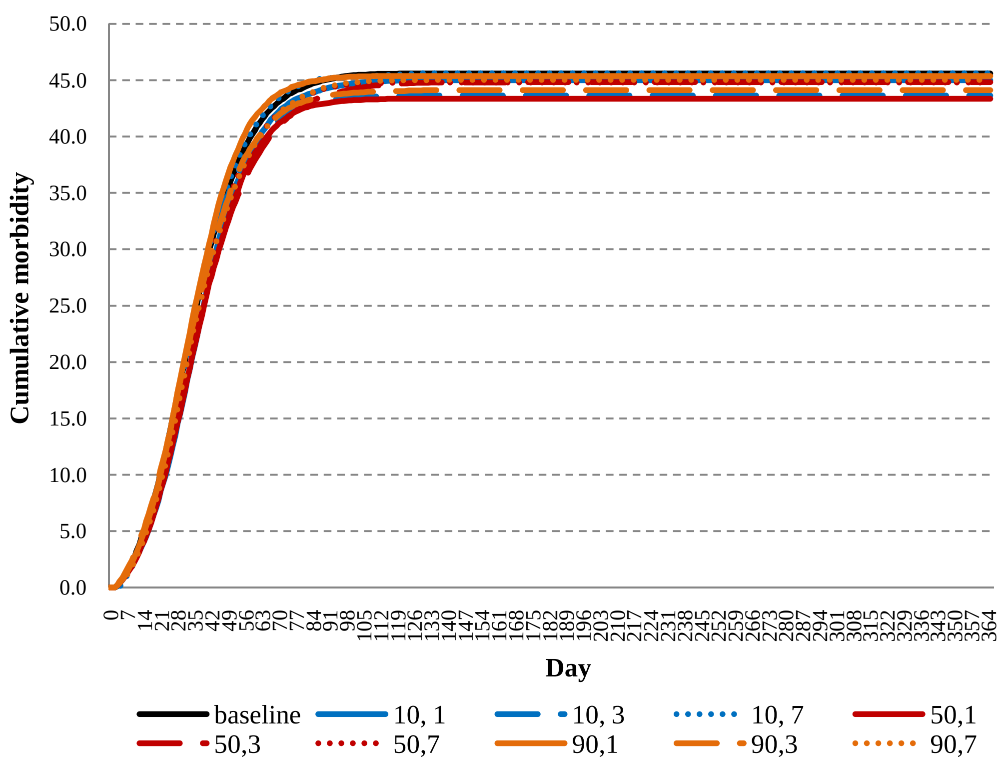

Figure 25. Influence of communication strategies associated with radio

Two channels in use. The three types of channel can be used singly or in combination. This set of experiment simulates pandemic impacts with two types of channel used simultaneously to send risk information. Different combinations of two types of channel include local TV and national TV, local TV and radio, national TV and radio. Given the extensive number of possible communication strategies associated with two types of channel, the experiment here fixes the strategy indicators of one type of channel to their empirical values found in this specific context, and explores how changes made in the indicators of the other type of channel from their empirical values influence the pandemic impacts.

According to ASU/ADHS influenza survey, the percent of respondents who use the channel for 2009 H1N1 influenza news and believe its importance for local TV is 70% and 60%, and for national TV 26% and 55%. Approximately 11% of respondents receive pandemic information from radio. No information on use frequency has been provided in the survey. This dissertation assumes that, the local TV was empirically used in the context to send pandemic information on a daily basis. The other two types of channel were used with a smaller frequency. The empirical values for the three indicators for local TV, national TV, and radio are (70%, 60%, 1), (26%, 55%, 3), and (11%, 3), respectively.

Local TV & national TV. When local TV is used alone and with a medium or high frequency, there is a 50% threshold in terms the influence of its user or believer percent on peak prevalence. When local TV is used with both user and believer percent at medium or high level, increasing its frequency after it reaches medium level also has little influence on the peak prevalence and epidemic size.

Considering that all indicators of local TV are empirically higher than the medium level, the first question here is whether and how further increasing the user or believer percent of local TV or reducing its use frequency, when indicators of national TV are fixed at their empirical values, influences pandemic impacts.

Table 19 summarizes the simulation results on three output indicators from this experiment situation. Figure 26 shows the epidemic curve for cumulative morbidity in this situation. The black solid line represents the baseline scenario, and the black dashed line the situation with national TV used alone at its empirical level. The blue solid line represents the situation when indicators of both TV channels are at their empirical levels. All other dashed lines are generated when one (blue dashed lines) or two (red dashed lines) indicators of local TV are changed from their empirical value.

Based on the simulation results, public sector in the community can greatly reduce the pandemic impacts by separately using the existing communication strategy for national TV. The peak prevalence is reduced by 57.4% and epidemic size by 55.0%. The pandemic impacts can be further mitigated by including local TV. Simultaneously using both channels at their empirical levels can bring larger reduction in peak prevalence and epidemic size, and particularly could prolong the epidemic duration.

With both channels used at their empirical levels, further increasing the value for the believer percent of local TV can reduce the epidemic size, but has no influence on peak prevalence and shortens the epidemic duration. Further increasing local TV’s user percent has little influence on peak prevalence and epidemic size. This is possibly because the frequency here is at high level and the user present has already reached its 50% threshold. Furthermore, reducing the use frequency to once every three days has little influence on peak prevalence and epidemic size, which may also be explained by the conditional threshold of use frequency found in previous experiments.

Table 19. *Pandemic Impacts with Varying Strategies for Local TV and Fixed Strategy for National TV*

Strategy	Output	Strategy	Output	Strategy	Output
National TV alone	2.6; 20.5; 123;	ntv & (70,60,1)	2.0; 18.4; 157;	ntv & (90,60,1)	2.0; 18.1; 150;
ntv & (70,90,1)	2.0; 13.2; 136;	ntv & (70,60,3)	2.0; 18.4; 155;	ntv & (90,90,1)	2.0; 12.9; 124;

Note. ntv represents national TV. The strategy of how local TV is used is organized as (%-user, %-believer, use frequency). For example, (90,60,1) means the user percent, believer percent and use frequency of local TV is 90%, 60%, and once per day, respectively.

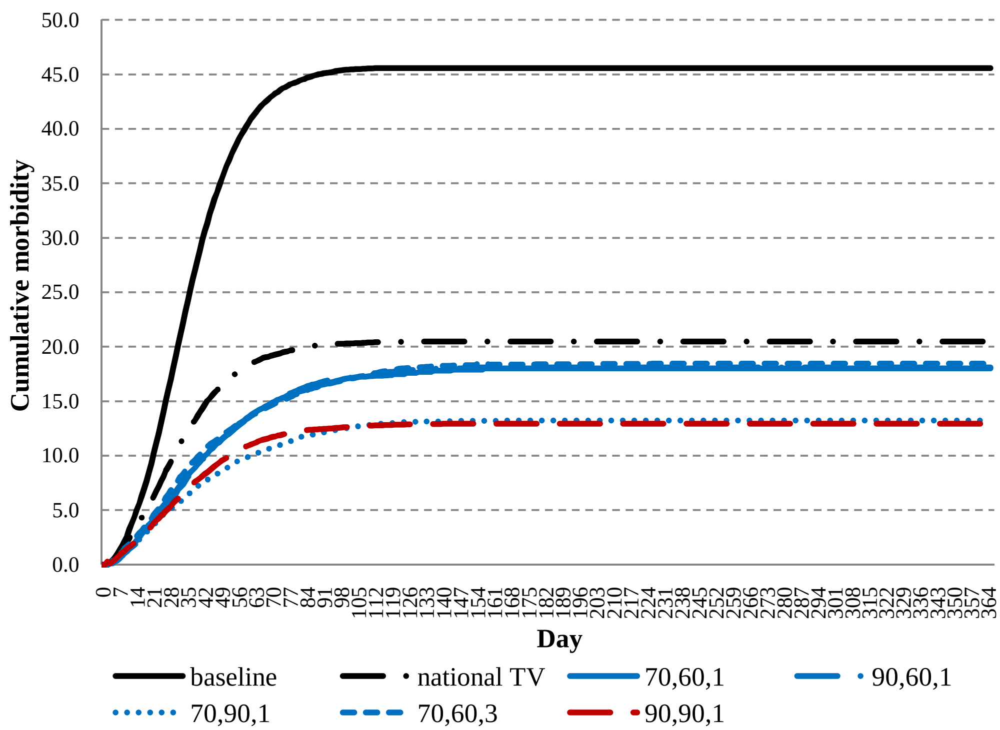

Figure 26. Influence of local TV with fixed strategy for national TV

Compared with local TV, national TV reaches a much smaller population of the community, and is used with lower frequency. So the second question concerns whether and how increases in the three indicators of national TV from their empirical values—with fixed values for local TV's indicators–influence pandemic impacts. Simulation results are summarized in Table 20 and Figure 27.

Table 20. *Pandemic Impacts with Fixed Strategy for Local TV and Varying Strategies for National TV*

Strategy	Output	Strategy	Output	Strategy	Output
Local TV alone	2.0; 18.6; 184;	ltv & (26,55,3)	2.0; 18.0; 157;	ltv & (50,55,3)	2.0; 15.6; 161;
ltv & (90,55,3)	2.0; 15.6; 162;	ltv & (26,90,3)	2.0; 17.3; 143;	ltv & (26,55,1)	2.0; 14.2; 129;
ltv & (50,90,3)	2.0; 13.0; 174;	ltv & (50,55,1)	2.0; 14.1; 149;	ltv & (26,90,1)	2.0; 13.3; 150;
ltv & (50,90,1)	2.0; 11.9; 183;				

Note. ltv represents local TV. The strategy of how national TV is used is organized as (%-user, %-believer, use frequency).

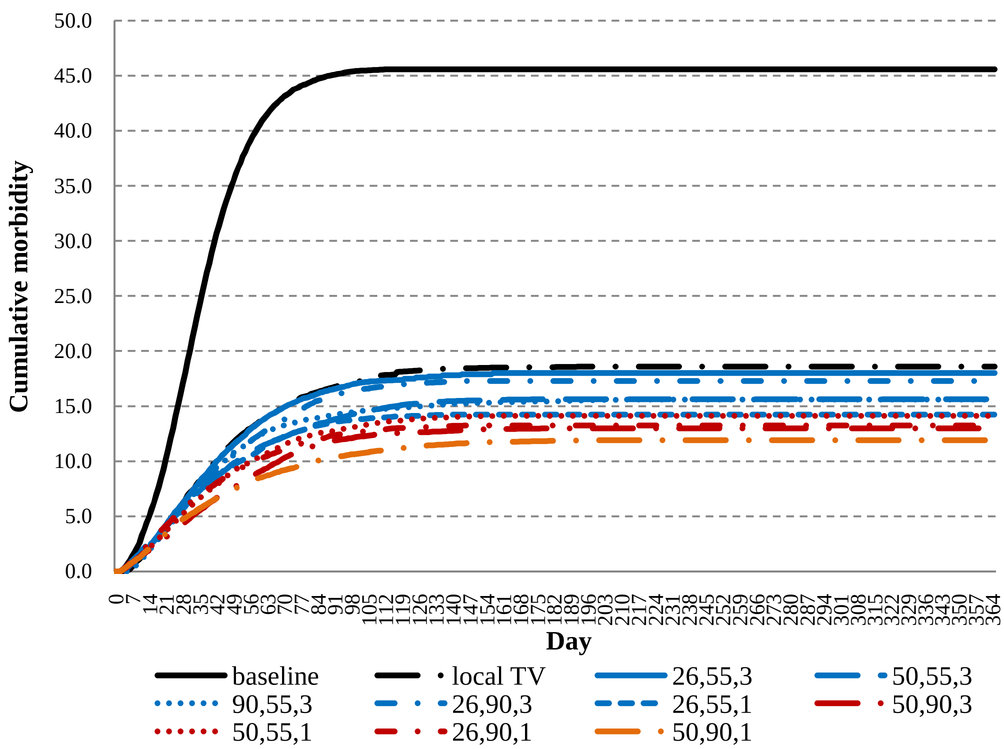

Figure 27. Influence of national TV with fixed strategy for local TV

In Figure 27, the black solid curve represents the baseline scenario, and the black dashed curve the situation with local TV used alone at its empirical level. The blue solid curve is generated when indicators of both TV channels are at their empirical levels. The blue, red and orange dashed curves represent the situation when one, two or all indicators of national TV are increased from the empirical level; indicators of local TV are fixed at their empirical levels.

Using local TV alone at its empirical level is more effective in reducing pandemic impacts than the usage of national TV alone at its empirical level. When both TV channels are used at their empirical strategy levels, public sector can further increase the value for any one, two or all three indicators of national TV to reduce the epidemic size. But no influence can be induced on peak prevalence. Also, simultaneously increasing the value for two indicators is more effective than increasing the value for one, and the largest effect comes when all three indicators are increased. Meanwhile, there is still a 50% threshold of user percent's influence. After this indicator reaches the threshold, further advancing its value alone would have small influence on pandemic impacts. For the epidemic duration, it can be prolonged by further increasing the user percent, by further increasing the believer percent with either the user percent or use frequency higher than its empirical level, and by further increasing the use frequency with the believer percent at its high level. When the user percent and use frequency are fixed at their empirical levels, further increasing believer percent actually shortens epidemic duration. The same situation occurs when the use frequency is increased with the believer percent lower than the high level.

Local TV & Radio. When the two types of channel selected are local TV and radio, experiments are still conducted to examine with the indicators of one type of channel constant at their empirical values, whether and how introducing the other type of channel and changing its indicators influence pandemic impacts.

Table 21 and Figure 28 show the simulation results with constant values for radio indicators. A communication strategy using radio alone—with its indicators at their empirical levels—would not influence the influenza spread dynamics. That can be seen through the almost identical epidemiological curves of cumulative morbidity from this situation and the baseline scenario. Incorporating local TV in the strategy is needed in this case. The pandemic impacts can be greatly mitigated when both types of channel are simultaneously used at their empirical levels. The 50% threshold of the influence of local TV's user percent on peak prevalence and epidemic size still exists, which makes further increasing this indicator alone unnecessary. But emergency managers can increase the believer percent of local TV to reduce the epidemic size, while noting the shortened epidemic duration. Reducing the use frequency of local TV to medium level has little influence on peak prevalence and epidemic size, but greatly shortens the epidemic duration.

Table 21. *Pandemic Impacts with Varying Strategies for Local TV and Fixed Strategy for Radio*

Strategy	Output	Strategy	Output	Strategy	Output
Radio alone	6.1; 45.5; 112;	Radio & (70,60,1)	2.0; 20.1; 180;	Radio & (90,60,1)	2.0; 20.0; 154;
Radio & (70,90,1)	2.0; 15.8; 139;	Radio & (70,60,3)	2.0; 20.5; 133;	Radio & (90,90,1)	2.0; 15.3; 123;

Note. The strategy of how local TV is used is organized as (%-user, %-believer, use frequency).

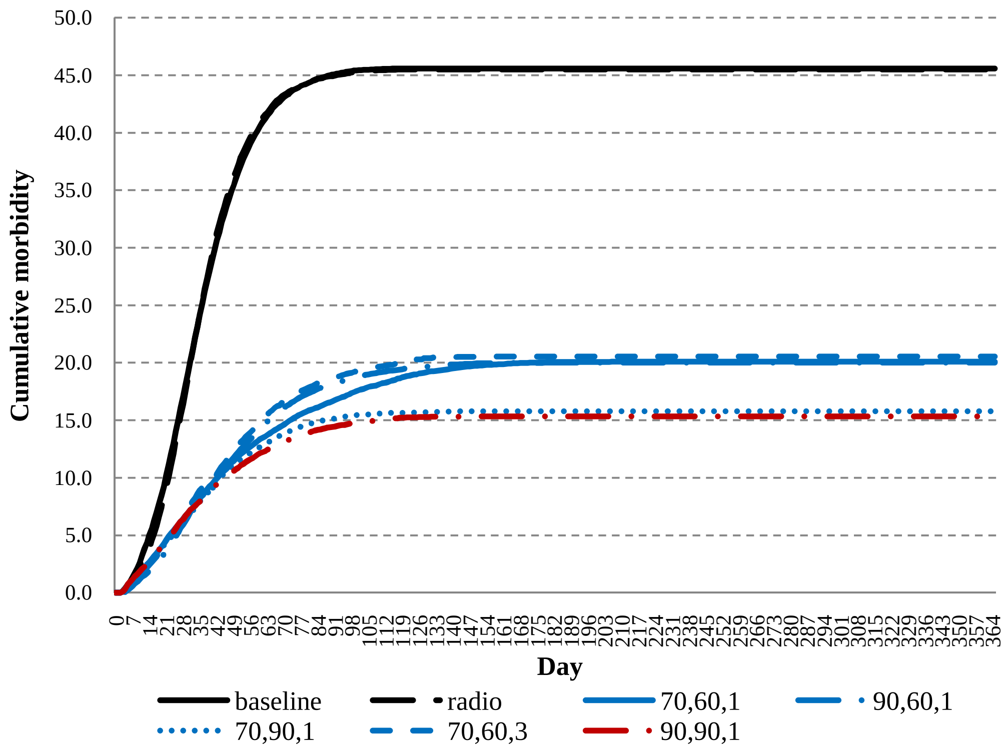

Figure 28. Influence of local TV with fixed strategy for radio

As emergency managers have already used local TV at its empirical level and are considering whether radio should be added to the strategy, Table 22 and Figure 29 should be referred to before any decision is made. The introduction of radio reduces the effectiveness of current communication strategy, despite the varying values for two radio indicators. After it is introduced, increasing its user percent increases the peak prevalence and epidemic size, and shortens the epidemic duration. The relationship between radio use frequency and epidemic impacts seems to be curvilinear. Both the increase in radio frequency from medium to high level and the decrease from medium to low level are associated with severer pandemic impacts. The frequency of once per 3 days seems to be an optimal option in current simulation.

Table 22. *Pandemic Impacts with Fixed Strategy for Local TV and Varying Strategies for Radio*

Strategy	Output	Strategy	Output	Strategy	Output
Local TV alone	2.0; 18.6; 184	ltv & (11,3)	2.0; 20.1; 180;	ltv & (50,3)	2.3; 23.3; 160;
ltv & (90,3)	3.2; 29.6; 148;	ltv & (11,1)	2.3; 24.3; 136;	ltv & (11,7)	2.0; 19.5; 141;

Note. ltv represents local TV. The strategy of how radio is used is organized as (%-user, %-believer).

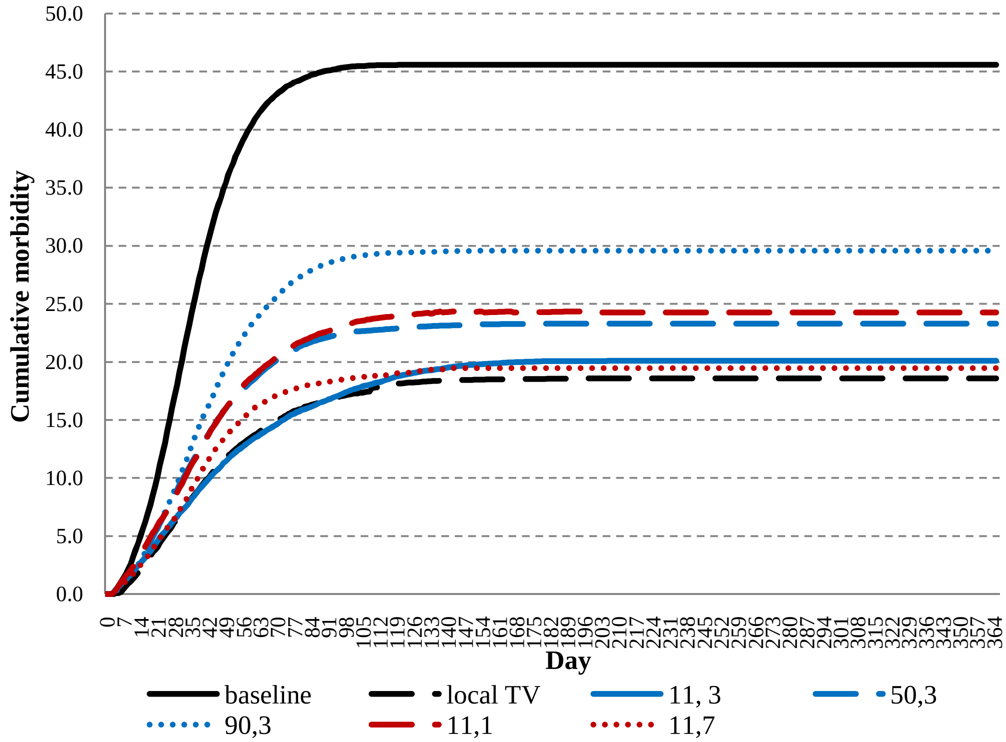

Figure 29. Influence of radio with fixed strategy for local TV

National TV & radio. The pandemic impacts when radio used alone to send risk information can also be mitigated by adding national TV in the communication strategy. As shown in Table 23 and Figure 30, the strategy of simultaneously using radio and national TV at their empirical levels could greatly reduce the impact compared with the baseline scenario, although it is not as effective as adding local TV at its empirical level to the separate usage of radio.

Table 23. *Pandemic Impacts with Varying Strategies for National TV and Fixed Strategy for Radio*

Strategy	Output	Strategy	Output	Strategy	Output
Radio alone	6.1; 45.5; 112;	Radio & (26,55,3)	3.3; 26.7; 142;	Radio & (50,55,3)	2.2; 22.8; 144;
Radio & (90,55,3)	2.0; 22.3; 145;	Radio & (26,90,3)	3.0; 26.1; 125;	Radio & (26,55,1)	2.0; 19.0; 116;
Radio & (50,90,3)	2.0; 21.1; 144;	Radio & (50,55,1)	2.0; 17.6; 121;	Radio & (26,90,1)	2.0; 14.4; 122;
Radio & (50,90,1)	2.0; 14.0; 130;				

Note. The strategy of how national is used is organized as (%-user, %-believer, use frequency).

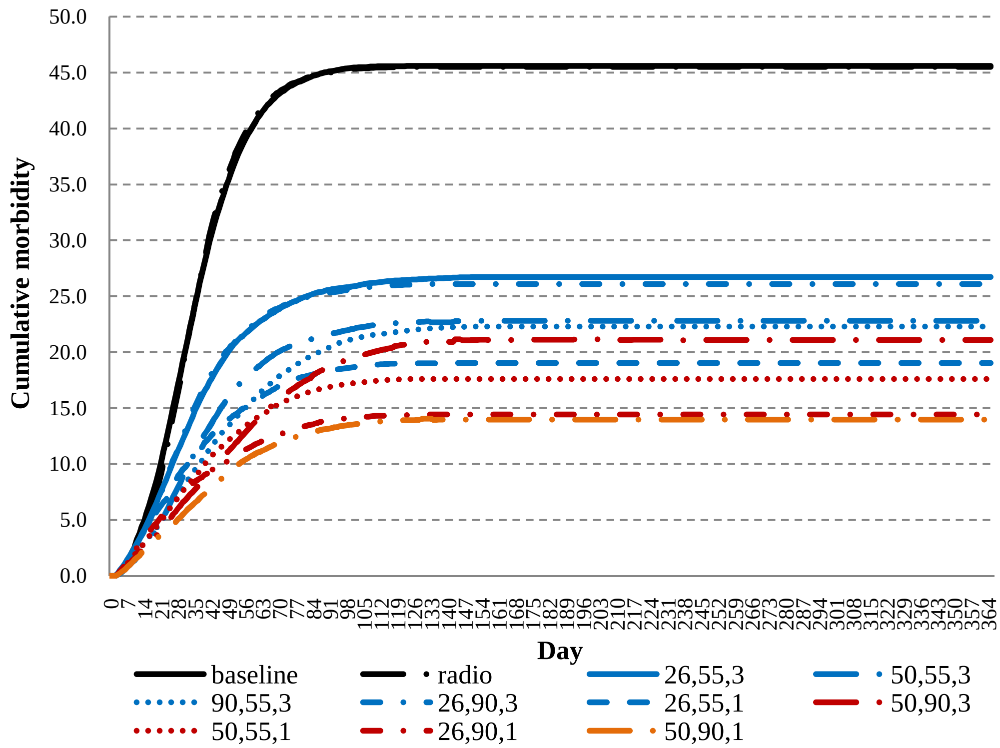

Figure 30. Influence of national TV with fixed strategy for radio

Further increasing the user percent of national TV from its empirical level—with fixed values for radio indicators—reduces the epidemic size and prolongs epidemic duration, but has small influence on peak prevalence. Such an influence can be observed till the user percent reaches 50%, after which small changes can be caused in pandemic impacts by increases in this indicator. Increasing the believer percent of national TV alone from its empirical level has similar influences on peak prevalence and epidemic size, but shortens the epidemic duration. The use frequency of national TV also plays a similar role; increasing its level alone can reduce both peak prevalence and epidemic size, but shorten the epidemic duration.

The situation in which radio is added to the strategy of using national TV alone is similar as that where radio is added to the separate usage of local TV. As shown in Table 24 and Figure 31, regardless of the value for its indicators, the introduction of radio decreases the effectiveness of previous strategy in mitigating pandemic impacts. There is a negative relationship between the user percent of radio and pandemic impacts, and a quasi-curvilinear relationship between use frequency and pandemic impacts. Emergency managers need to avoid the usage of radio, or minimize its user percent and keep its use frequency to send pandemic information at one time every 3 days.

Table 24. *Pandemic Impacts with Fixed Strategy for National TV and Varying Strategies for Radio*

Strategy	Output	Strategy	Output	Strategy	Output
National TV alone	2.6; 20.5; 123;	ntv & (11,3)	3.3; 26.7; 142;	ntv & (50,3)	4.5; 38.0; 135;
ntv & (90,3)	4.6; 41.4; 124;	ntv & (11,1)	3.6; 30.9; 133;	ntv & (11,7)	3.2; 25.9; 135

Note. ntv represents national TV. The strategy of how radio is used is organized as (%-user, %-believer).

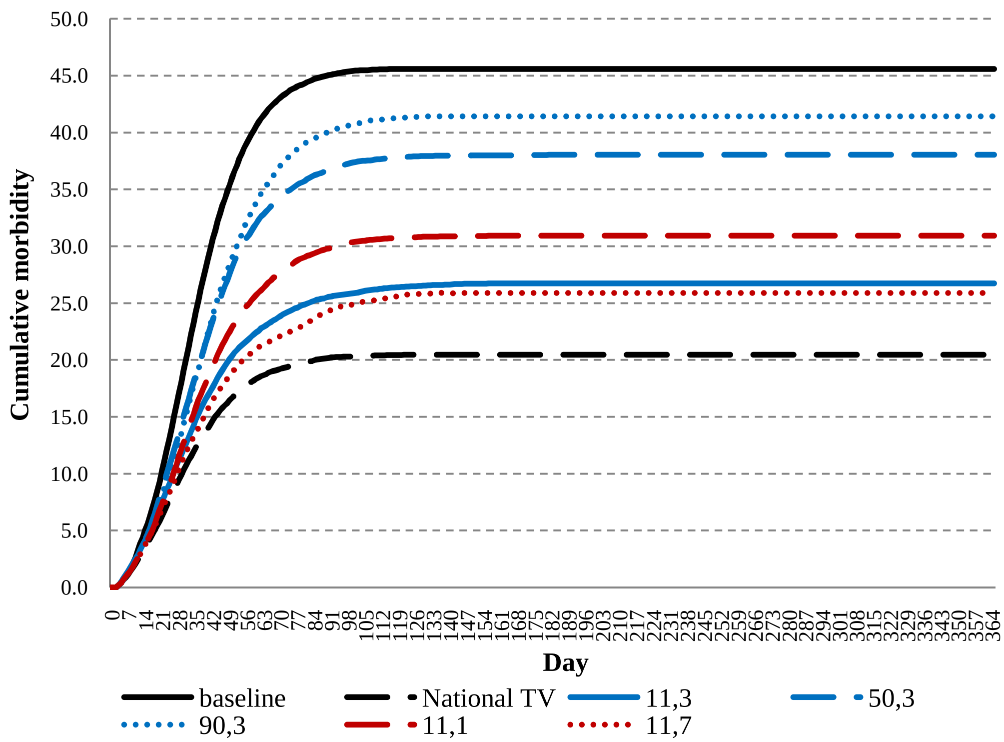

Figure 31. Influence of radio with fixed strategy for national TV

Local TV & national TV & radio. This set of experiment explores the situation where the indicator values for one type of channel are changed from their empirical values while the other two types of channels are fixed at their empirical levels. Simulations are first run to examine the influence of indicators of local TV, and results are shown in Table 25 and Figure 32. In Figure 32, the black solid curve represents the baseline scenario, and the black dashed curve the situation with national TV and radio used at their empirical levels. The blue solid curve is generated when all three types of channel are at their empirical levels, namely, when the exact empirical communication strategy in the research context is implemented. The blue and red dashed curves are produced with varying levels for local TV indicators, with national TV and radio fixed at their empirical levels.

Table 25. *Pandemic Impacts with Varying Strategies for Local TV and Fixed Strategy for National TV and Radio*

Strategy	Output	Strategy	Output	Strategy	Output
National TV & Radio	3.3; 26.7; 142;	ntv & radio & (70,60,1)	2.0; 18.6; 176;	ntv & radio & (90,60,1)	2.0; 18.4; 146;
ntv & radio & (70,90,1)	2.0; 14.4; 136;	ntv & radio & (70,60,3)	2.0; 19.5; 126;	ntv & radio & (90,90,1)	2.0; 14.3; 136;

Note. ntv represents national TV. The strategy of how local TV is used is organized as (%-user, %-believer, use frequency).

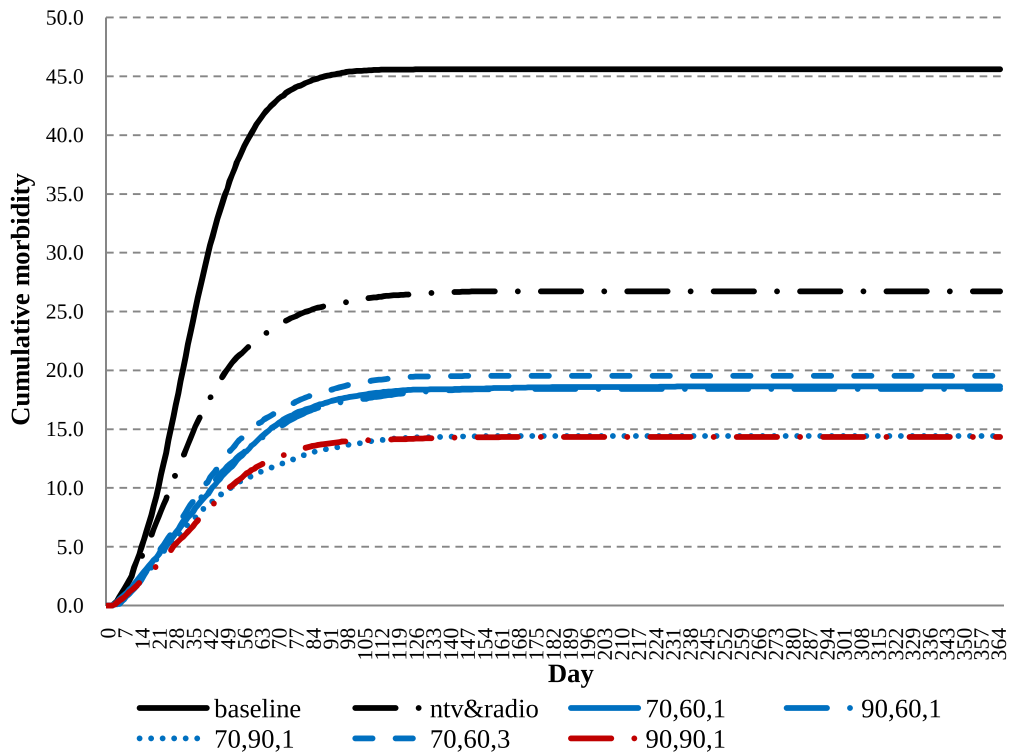

Figure 32. Influence of local TV with fixed strategy for national TV and radio

The influence of indicator changes in local TV on pandemic impacts in this case is similar as that when local TV is used with national TV or radio. Summarization therefore can be made regarding the influence of this channel when it is not used alone. Increasing its user percent alone from its empirical level or decreasing the use frequency alone from its empirical level has small effect on peak prevalence and epidemic size, but shortens epidemic duration. Increasing the believer percent alone from its empirical level has little effect on peak prevalence and shortens epidemic duration, but brings a large reduction in epidemic size. For emergency managers in the research context, no efforts seem necessary to change the user percent and use frequency of local TV in current risk communication strategy. But they can attempt to increase this channel's believer percent, based on their choices between smaller epidemic size and longer epidemic duration.

The influence of national TV when its indicators are changed from their empirical levels is shown in Table 26 and Figure 33. Such an influence is similar as that when national TV is used with local TV or radio. As a result, it can be summarized that, when national TV is used at its empirical level and with any other types of channel, increasing its user percent alone—to at most 50%—reduces the epidemic size and extends the epidemic duration while exerts no influence on peak prevalence. Increasing its believer percent or use frequency alone has similar effects on the peak prevalence and epidemic size, but shortens the epidemic duration. Emergency managers in the context therefore can modify their current risk communication strategy by increasing the user percent of national TV to 50%. They can also increase its believer percent and use frequency to reduce the epidemic size, while noting the shortened epidemic duration.

Table 26. *Pandemic Impacts with Varying Strategies for National TV and Fixed Strategy for Local TV and Radio*

Strategy	Output	Strategy	Output	Strategy	Output
Local TV & Radio	2.0; 20.1; 180;	ltv & radio & (26,55,3)	2.0; 18.6; 176;	ltv & radio & (50,55,3)	2.0; 16.4; 179;
ltv & radio & (90,55,3)	2.0; 16.2; 175;	ltv & radio & (26,90,3)	2.0; 17.6; 143;	ltv & radio & (26,55,1)	2.0; 16.9; 135;
ltv & radio & (50,90,3)	2.0; 15.6; 236;	ltv & radio & (50,55,1)	2.0; 14.8; 162;	ltv & radio & (26,90,1)	2.0; 13.4; 138;
ltv & radio & (50,90,1)	2.0; 12.7; 171;				

Note. ltv represents local TV. The strategy of how national TV is used is organized as (%-user, %-believer, use frequency).

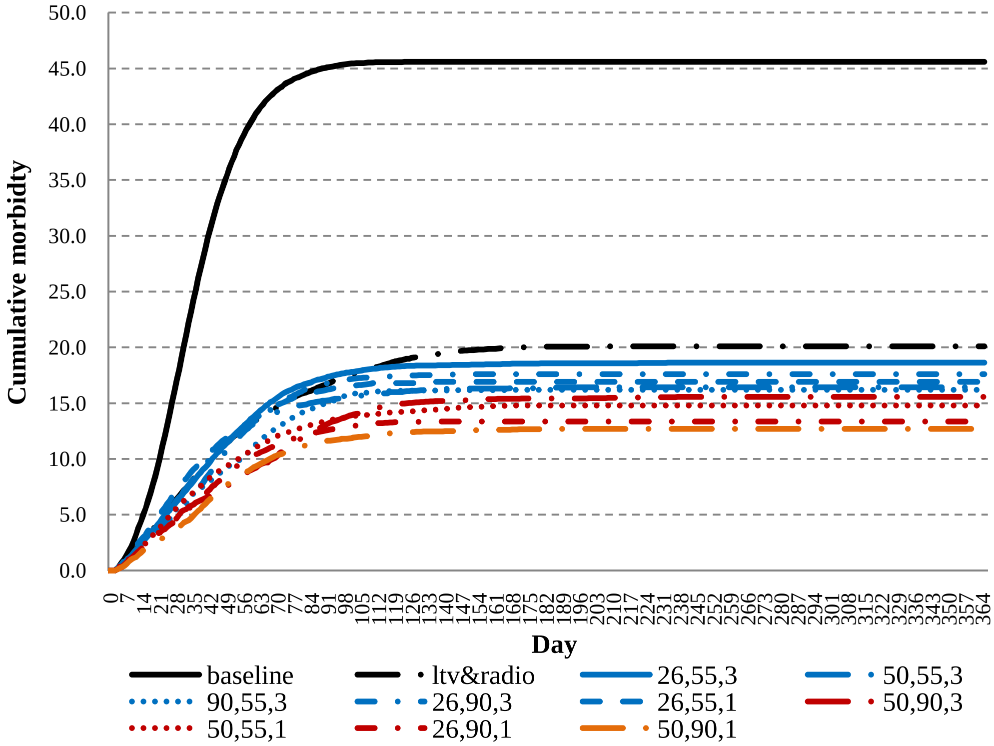

Figure 33. Influence of national TV with fixed strategy for local TV and radio

For radio, Table 27 and Figure 34 show the simulation results with varying values for its indicators when local and national TV are fixed at their empirical levels. The introduction of radio—at its empirical level—to communication strategy here cannot be simply considered counter-productive. The peak prevalence remains constant and the epidemic duration is extended by almost three weeks, while there is a small increase in the epidemic size (3.3%). After radio is included in the strategy, the influence of changing the values of its indicators is consistent with that when it is not used alone. Raising its user percent or use frequency aggravates the pandemic impacts. Reducing its use frequency brings little decrease in epidemic size, but shortens the epidemic duration.

Table 27. *Pandemic Impacts with Varying Strategies for Radio and Fixed Strategy for Local and National TV*

Strategy	Output	Strategy	Output	Strategy	Output
Local & national TV	2.0; 18.0; 157	ltv & ntv & (11,3)	2.0; 18.6; 176;	ltv & ntv & (50,3)	2.2; 22.9; 164;
ltv & ntv & (90,3)	2.4; 25.6; 154;	ltv & ntv & (11,1)	2.3; 22.0; 140;	ltv & ntv & (11,7)	2.0; 18.1; 151;

Note. ltv represents local TV, and ntv national TV. The strategy of how radio is used is organized as (%-user, %-believer).

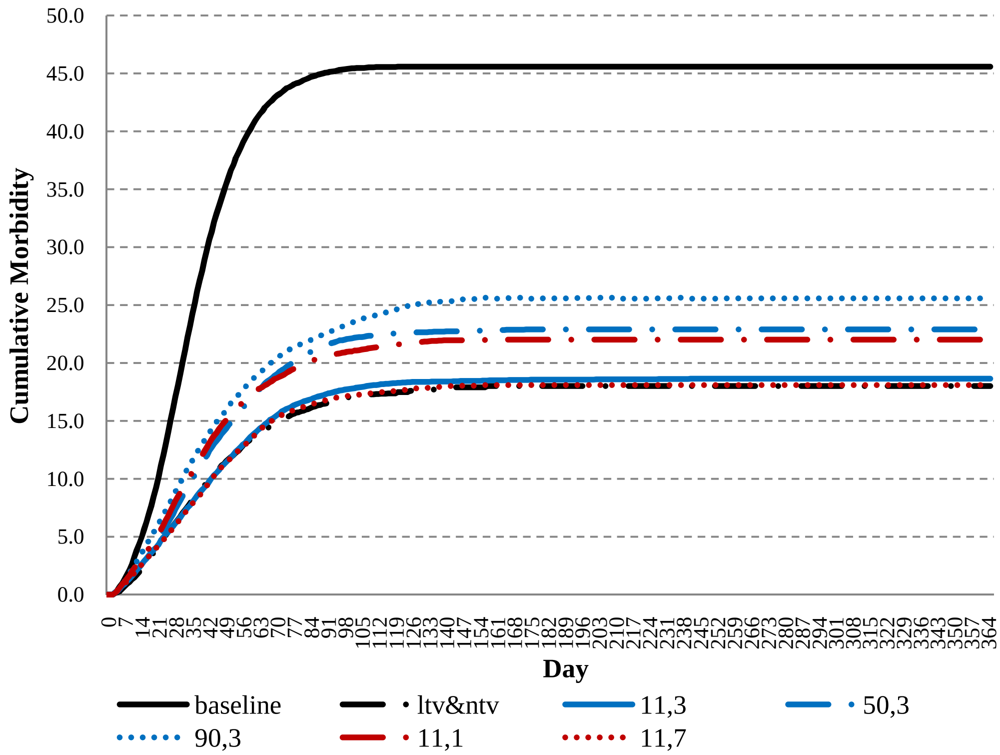

Figure 34. Influence of radio with fixed strategy for local and national TV

Chapter 6

Discussion

This dissertation addresses current limitations in the literature of public risk communication in EM filed. Four inter-related research questions are answered in the context of 2009 H1N1 influenza outbreak in an Arizona community.

First, emergency risk communication theory, social influence theory and empirical data are used to answer the first and second research question, namely how individuals make responsive decisions to risk information and what is the influence of information transmission channel on the decision. According to Quarantelli's model of individual warning response, individuals after receiving risk information go through a staged process consisting of initial risk perception, social confirmation, situational definition and response (Quarantelli, 1983, 1990). The responsive decision is the result from situational definition, which is simultaneously formulated by initial risk perception and the information collected in the social confirmation stage. Public risk communication influences individual response behavior through influencing their warning receipt and shaping their initial risk perception, which is defined as whether individuals perceive a high risk for the general public (Quarantelli, 1983, 1990).

The influence of risk communication on individual initial risk perception is specified in the specific research context by conducting logit regression on the data from 2009 ASU/ADHS Influenza Survey. The dependent variable of the regression is the probability of an individual to perceive a high risk for the general public. The independent variables include whether individuals use some type of channel to receive pandemic information, and whether they believe the channel is important. A variety types of channel are included in the regression, including local TV, national TV, local newspaper, national newspaper, Internet, radio, magazine, friend, school, work, doctor, and other. Regression results showed that, in the specific research context, individuals' initial risk perception is positively associated whether they receive pandemic information from local or national TV and meanwhile believe information from local or national TV is important. It is negatively associated with whether they receive pandemic information from radio.

The way in which the initial risk perception formulated, together with the confirmative information collected, influences individuals' responsive decision is conceptualized based on the model of Delre et al (2007). Initial risk perception and confirmative information collected have equal weight regarding influencing responsive decision. But the influence from confirmative information does not always exist; it is only present when the percent of people taking protective action among individuals' friends who are asked for confirmation exceeds certain percent. Otherwise, the responsive decision is solely decided by initial risk perception. Here responsive decision is represented by the probability for an individual to take protective actions. Responsive action—whether or not taking protective actions—is randomly decided based on this probability. Reasons for why using such a definition for responsive decision have been discussed before.

By now, a clear picture has been provided regarding individual response process to emergency risk information, as well as how characteristics of information transmission channel in the research context influence the process. To make such knowledge more insightful for emergency managers, it is integrated into an agent-based simulation framework with theories and empirical findings from epidemiology and social network theory. Two streams of interaction occur in this framework. First, in the context of influenza pandemic, interactions occur among individuals along the contact network through which the influenza virus spreads over the population. Second, individuals interact with their friends and public sector through information exchange, to decide whether to take protective action. These two streams of interaction at the individual level are inter-dependent and interactional. Together they generate the impact the pandemic causes at the community level over time, which in the context represents the public response pattern. And this is how the third research question is responded to.

The fourth research question concerns the influence characteristics of information transmission channel can induce on pandemic impacts. An information transmission channel is indicated by its type, user percent, believer percent and use frequency. Local TV, national TV and radio are included in the simulation model, since just these three types of channel influence individual initial risk perception in the context and therefore have the potential to influence emergency impacts. For each type of channel, the user percent and use frequency determine the percent of community population who receive risk information from the channel at each time step, while the believer percent decides the percent of population who believe in its importance. The spread dynamics of the pandemic influenza is simulated in two scenarios: when there is no public intervention and when there is public risk communication. In the second scenario, communication strategies can vary in the number and type of channel used and the user percent, believer percent and use frequency of each channel in use.

The results of influenza propagation simulation indicate that the pandemic can cause severe impacts in the community if no intervention measures are implemented. Since it is initiated, the influenza keeps spreading for almost four months, and over 40% of community population can get infected during the period. Public risk communication, if appropriately designed, can greatly reduce the impacts in this case. Simulation results from situations with different communication strategies and their policy insights are summarized as follows.

When only one type of channel is used to send risk information, either local TV or national TV should be selected. The introduction of either TV channel would decrease the pandemic impact, although the extent of reduction depends on the values for its three indicators. Using radio alone achieves little regarding reducing the pandemic impact. For the two TV channels, the influence of changing the value for one indicator on pandemic impacts with the other two fixed is similar. First, there is a conditional threshold of 50% regarding the influence of user percent of either TV channel. Emergency managers can decrease the peak prevalence and epidemic size by increasing the user percent when the channel is used equally to or less frequently than one time every week. When the use frequency is equal to or higher than one time every three days, increasing user percent after it reaches 50% would change little in the two impact indicators. Second, the way in which the believer percent of either TV channel influences pandemic impacts is also dependent upon its use frequency. While both peak prevalence and epidemic size can be reduced by increasing the believer percent when the use frequency is one time every week, only the latter can be influenced by the same change in believer percent when the frequency is increased to one time every three days or more frequently. Third, there is also a conditional threshold in the influence of use frequency. When the user and the believer percent are both equal to or higher than 50%, increasing the use frequency after it reaches one time every three days has little effect on peak prevalence and epidemic size; otherwise, emergency managers can mitigate the impacts by increasing the use frequency. For the epidemic duration, no consistent findings have been found in term of how it is influenced by any indicator of either TV channel. Furthermore, when emergency managers are deciding which TV channel should be used, preference should be first clarified between smaller peak prevalence and epidemic size and longer epidemic duration. With the same values for all three indicators, generally national TV is more capable of reducing peak prevalence and epidemic size while local TV prolonging the epidemic duration.

When emergency managers decide to use two types of channel for risk communication, the combination of local and national TV should be preferred. Here indicators for both channels are first set at their empirical levels. Experiments are then conducted to explore the changes in pandemic impacts brought by increases in one indicator value from its empirical level with values for others fixed. Simulation results show that, compared with the baseline scenario, using both TV channels at their empirical levels can effectively reduce peak prevalence and epidemic size and extend the epidemic duration. Further changing the strategy cannot induce influence on peak prevalence, but the epidemic size can be reduced by increasing the believer percent of local TV, or any one, two or all three indicators of national TV. Meanwhile, those changes do not necessarily lead to prolonged epidemic duration. Increasing the believer percent of local TV alone, or increasing the believer percent or use frequency of national TV alone, would actually shorten the duration. Choices need to be made in this case regarding in which dimension pandemic impacts should be mitigated. Another finding from this set of experiment is that, emergency managers can reduce local TV's use frequency to one time every three days. Such change has little influence on pandemic impacts, but may be able to save public resources.

In the empirical context, local emergency managers utilized all three types of information channel. Such empirical strategy is demonstrated by simulation very productive in reducing emergency impacts. To further advance the effectiveness of this strategy, emergency managers can increase the user percent of national TV. Notices are demanded when emergency managers are attempting to increase the believer percent or use frequency of national TV, or to increase the believer percent of local TV. These measures would shorten the epidemic duration, although they can help reduce the epidemic size. No changes should be made in the user percent and use frequency of both local TV and radio.

Contribution

This dissertation makes contributions, both theoretically and practically, in three ways. For EM, ABM is advocated as an alternative and appropriate approach to address issues. Since decades ago, EM researchers have recognized the complex nature of modern emergencies and the need for a new approach to study and manage them (Alexander, 2002; Rosenthal & Kouzmin, 1997; Rosenthal et al., 1989). This study summarizes the key features identified by previous literature for this new approach, and argues ABM simultaneously possesses these features, which theoretically makes it the approach in need. Such theoretical possibility is further exemplified by using ABM to deal with a specific EM issue of reducing influenza pandemic impacts through effective public risk communication strategy. In this example, public risk communication is framed as a dynamic process, during which individuals interact with each other and with public sector through communication. The management effectiveness in this case is measured by the extent to which pandemic impacts can be mitigated by communication strategies, which is a system-level pattern generated from all individuals' autonomous decision-makings and actions. Such a framework is also developed from an inter-disciplinary perspective; it integrates theories and empirical findings from multiple disciplines, including epidemiology, sociology, computational simulation, and emergency management.

For public risk communication, this dissertation provides a comprehensive review of related studies in the EM field over the past seven decades. People who have a preliminary interest in this area can use this review as a starting point to find out in the field of EM what public risk communication is, what practitioners believe, what previous studies have found, and what has been missed from current literature. Particularly, detailed accounts have been provided on the key component of emergency public risk communication, namely, how individuals respond to risk information during emergencies and what are the factors influencing this response process. This review can also be utilized by researchers and practitioners already in EM field to check against their knowledge and experience, which may advance the progress of the field.

Through the literature review, four limitations are found constrain the further theoretical development and practical application of emergency risk communication. Reasons for the existence of these limitations are both theoretical and methodological. This dissertation attempts to address three of these four limitations, by integrating theories from multiple disciplines and both quantitative and qualitative empirical data into a simulation framework based on ABM. In this framework, public risk communication is conceptualized as a dynamic and interactive process. How individuals make decisions and respond to risk information are appropriately assumed given social network and social influence theory and empirical data from previous emergency risk communication studies. The link between risk information transmission channel and individual response process is also made clear through combining theoretical models of explaining individual warning response and empirical data. At the community level, public response pattern, based on which emergency managers design and evaluate their strategies, is automatically generated from interactions at the individual level. This simulation framework is later implemented in a case study where communication strategies with different characteristics of information transmission channel are executed to control the spread of a pandemic influenza through influencing individual responsive behavior to risk information. The addressing of these limitations further suggests ABM an appropriate alternative to the traditional approach to emergency public risk communication which may provide more insights on effective practices.

Public risk communication is an integral component of emergency management. Understanding its dynamics is crucial for effectively managing public emergencies in communities (Drabek & Boggs, 1968; Mileti & O'Brien, 1992; Reynolds, 2005). This dissertation re-illustrates the key role public risk communication plays. In the specific research context, effective public risk communication strategies can not only greatly reduce the total number of people get infected, but also slow the pandemic influenza spread, and therefore help buy time to introduce other public interventions, particularly the production and distribution of vaccines. Although emergency managers cannot solely rely on risk communication and people's protective actions to avoid adverse social outcomes, effective risk communication could lessen the impact of a pandemic. The role of public risk communication during an emergency therefore requires more attention in public emergency management scholarship.

Using simulation, this dissertation further models the effects of different communication strategies on pandemic impacts for policy insights. Simulation results suggest that, the communication strategy local emergency managers empirically used is very effective in reducing pandemic impacts within the community. If emergency managers want to further mitigate the impacts, they may consider increasing the user percent of national TV. Increasing the believer percent or use frequency of national TV, or increasing the believer percent of local TV can help reduce the total number of people get infected, but shortens the epidemic duration. There is no need to change the user percent and use frequency of local TV; otherwise, less time would be left for local managers to deal with the emergency. For radio, it can only be used at its empirical level; changing the value for either of its indicators would be counter-productive.

For studies and practices in emergency public risk communication, the current simulation model can serve as a support tool in both research and decision-making process. More specifically it supports the identification of factors and mechanism of epidemic spread exactly during the descriptive phase, and allows the shifting of different scenarios in a reasonable rapid way. These features enable the model to carry out a comprehensive evaluation of intervention strategy choices in order to select the appropriate control measures. In this dissertation, computational experiments are not just conducted on the situations with three types of channel used to send pandemic information, as in the empirical context. The effectiveness of possible communication strategies with any one type of channel or with any two types of channel is also tested and compared. Simulation results from all these hypothetical situations provide a solid basis for emergency manager to design effective communication strategies before the emergency and to systematically evaluate and improve the strategies used during the emergency.

For epidemic simulation and control, this study develops a computational model that has the potential to more accurately anticipate the spread dynamics of a pandemic influenza and to test and compare the effectiveness of different public interventions to control it. Pandemic spread of an influenza is one of the biggest threats to society because of the potentially high mortality and high social and economic costs associated. The 20th century saw three influenza pandemics, with each causing devastating numbers of deaths (Nicholls, 2006). In 2009, an H1N1 influenza pandemic occurred, which corroborated the expectations of former CDC Director Julie Gerberding who said in April 2007 that: “We know that a pandemic will eventually occur. We always say it’s not a question of if; it’s a question of when” (Ulene, 2007). In view of the threat of a future pandemic of a highly pathogenic influenza strain, understanding the spread of pandemic influenza and engaging in pandemic preparedness and response efforts have become major public health priorities (Salathe & Jones, 2010).

One prerequisite for effective pandemic planning and intervention is to accurately anticipate the epidemic’s spread dynamics. For this purpose, different types of computational models have been developed, from the early differential equation compartment models to more recent large-scale individual-based stochastic models (Bobashev et al., 2007; Jenvald et al., 2007; Lee et al., 2009). These models have provided important insights into the understanding and control of pandemic influenza. However, most of them are criticized because of how they construct the contact network for virus transmission and of their ignorance of key social and human components for pandemic influenza simulation.

The structure of contact network is critical in determining the epidemiological pattern seen in the spread of contagious diseases, such as HIV/AIDS (Anderson, 1999) and pandemic influenza (Lloyd-Smith et al., 2005). The most appropriate way argued by current literature to construct contact network in epidemic simulation is to use the empirical data on corresponding contact pattern (Huang et al., 2004; Mikolajczyk et al., 2008). This approach has been applied to construct networks for contacts for sexually transmitted diseases (e.g., Fenton et al., 2001; Garnett et al., 1996). For pandemic influenza simulation in current literature, models tend not to be parameterized by directly analyzing empirical data on contact pattern, but often rely on priori contact assumptions with little or no empirical basis, or simply use certain type of network (e.g., Carrat et al., 2006; Glass et al., 2006; Mei et al., 2010). In addition, little effort has been devoted to empirically map the dynamic contact pattern for pandemic influenza spread in human communities, and there has not been a simple way to explore the sensitivity of epidemiological results to the deviation of certain type of network or assumed contact structure from the actual contact pattern. Simulation results from these models are therefore considered problematic and vulnerable to those questions of what if (Keeling & Eames, 2005).

Meanwhile, existing pandemic influenza simulation models usually treat the disease spread dynamics as a pure engineering or physical problem, while crucial social or human factors are not taken into account. These models often ignore human behavioral responses to potential threats. Individuals in the model are usually assumed to not change their behavior during an epidemic but continue with their regular activities as usual. Empirical studies have reported the opposite phenomena, especially in a pandemic situation (Ekberg et al., 2009; Lau et al., 2007; Lau et al., 2003). When confronted with the threat of pandemic influenza, people undertake actions to protect themselves from infection (Lau et al., 2007;

Lau et al., 2003), and keep these protective coping behaviors until the epidemic ends (Leung et al., 2003; de Zwart et al., 2010).

To address this issue, the concept of “prevalence elastic behavior” is introduced, which refers to the adaptive action people take as a reaction to epidemic prevalence (Philipson, 2000; Philipson & Posner, 1993). Later studies on pandemic-related estimation incorporate this notion into simulation models by assuming all individuals reduce their overall social activities due to a pandemic, and the reduction is based on the propagation condition of the disease (e.g., Larson & Nigmatulina, 2009; Yoo et al., 2010). Human responses are still oversimplified in these models. Emergency public risk communication literature has showed that whether people adopt self-protective actions is influenced by risk communication, and not all people would adopt such actions when facing some potential threat (Lindell & Perry, 1983; Mileti & Darlington, 1997; Nigg, 1987). Such complexities of people’s behavior call for more careful incorporation of these social dimensions in the pandemic influenza simulation.

This dissertation develops a network-based agent-based model to simulate the spread dynamics of a pandemic influenza. As discussed before, ABM is a sharp tool for pandemic influenza simulation. It allows interactions among individuals and could overcome the limitations of other modeling approaches. It permits the study of a specific aspect of epidemic spread and is capable of addressing the stochastic nature of the epidemic process. Two features distinguish the agent-based model created in this study from previous pandemic influenza simulation models, particularly the massive agent-based models and social network models incorporating ABM technique. First, the underlying contact network for virus transmission is constructed based on relevant empirical data. Second, individual protective behavior is appropriately considered in the model by including the component of public risk communication. Theories from emergency risk communication and previous empirical data are used to frame the probability for an individual to take protection action, and how this probability is influenced by communication strategies. These two features simultaneously make the current model a promising exploration instrument for researchers as well as a decision support tool for local public managers to accurately anticipate the spread dynamics of a pandemic influenza. Furthermore, both researchers and practitioners can further introduce different public interventions—beside public risk communication—into the model and use it to systematically evaluate and compare their effectiveness for pandemic containment.

Theoretically, this study underlines the importance of social and human factors in determining an epidemic's spread dynamics. Epidemic simulation therefore must not be considered as a simple engineering or medical problem. Social and behavioral aspects need to be taken into account. Besides, this study illustrates the significance of non-pharmaceutical measures in pandemic control, particularly individuals' voluntary action to reduce their own social contacts. These measures can exert great effect in reducing the pandemic impact. For example, many studies have considered the reduction of public contacts an effective means to control the 2003-2003 SARS spread (e.g., WHO, 2003). Non-pharmaceutical measures are also associated with lower social costs, particularly compared with those pharmaceutical interventions which require considerable amounts of labor and resources (Huang et al., 2004). The importance of non-pharmaceutical measures becomes even more salient when a novel pandemic strain of influenza is just found and no vaccination or antivirals against it is available. On the other hand, the public normally is reluctant to take protective actions, since such actions would change their routine activities (Quarantelli, 1983). The responsibility to encourage the public therefore rests on emergency managers to design effective strategies for public risk communication.

Limitation

There are several limitations in this dissertation. The first concerns how the contact network is set up. A contact in the model is defined as what Edmunds et al did in their study, namely, as a two-way conversion (Edmund et al., 1997). Although such a definition is easier for operationalization and measurement, there are numerous questions about the validity of such a definition, particularly regarding whether it could reflect the true picture of contacts that might lead to pandemic influenza transmission. For example, considering the exact nature of at-risk contacts is largely unknown, a contact as defined probably does not capture all potentially important routines of transmission, such as direct contact by contaminated hands and mouths, indirect fomite transmission from shared objects, or being in the same space without talking (Beutels et al., 2006). However, as Edmunds et al (1997) argued, such a definition of contact can serve as a starting point, with the advantage of being "well understood, easy to recall and record, and thus possible to collect from a study population" (Edmunds et al., 1997, p.950).

Another reason to adopt this definition is to keep consistency. Previous empirical findings used to parameterize the contact network in the model are from those studies which used the same definition of a contact for influenza transmission.

For individual daily contact rate, previous studies exploring the number of individuals' daily at-risk contacts for influenza transmission generally used convenience samples (e.g., Beutels et al., 2006; Edmunds et al., 2006; Read et al., 2008), focused on a specific group of population (e.g., Mikolajczyk & Kretzschmar, 2008; Salathe et al., 2010), or were conducted in European countries (e.g., Edmunds et al., 1997; Mikolajczyk et al., 2008; Wallinga et al., 2006). Using empirical data from those studies to parameterize the model is problematic, but there are few studies that investigated individual daily contact rate using the general U.S. population (Destefano et al., 2010). There are also other characteristics of individual daily contact pattern found in previous literature which have not been included in the model. For example, the contact rate and type may be different between weekdays and weekends (Beutels et al., 2006; Edmunds et al., 1997). Furthermore, the empirically measured daily contact data is used as a valid proxy to quantify the unobservable actual infectious contacts; it is not equivalent with the virus transmission routine.

Another limitation with this study is that, the implementation of the model requires a thorough work of parameterization. While the value of some parameters can be estimated based on previous studies (e.g., epidemiologic parameters), the value of others may not be easily determined empirically (e.g., contact pattern), or they exist only as certain range values (e.g. avoidance behavior effect). There are also some parameters whose value can only be assumed, since no specific research has been found on the parameter in the simulation context (e.g., social influence threshold and social influence effect). Despite that, the current approach provides an opportunity to identify areas and parameters for future research.

This study does not take into account other public intervention efforts for pandemic control, particularly vaccination. Researchers and practitioners often consider vaccination the best measure for preventing and controlling a pandemic influenza outbreak (Longini et al., 2004). However, when there is an outbreak of a novel pandemic strain of influenza, the time and production capacity are usually insufficient to produce and distribute enough effective vaccines to protect the general public (Mniszewski et al., 2008; Monto, 2006). The influence of public risk communication in this case needs to be understood by public managers, in order to encourage individuals to adopt non-pharmaceutical measures for self-protection. Furthermore, other public interventions are often used with the presence of public risk communication. By further including vaccination and other containment measures, the current model may provide better understanding and testing of other interventions' influence on the spread dynamics.

Public risk communication in this dissertation is a response intervention for pandemic control. It is implemented after the influenza season begins, and the public before the season is assumed not having any preparedness against the influenza. The effectiveness of public risk communication in this case may be different from that when it is used both before and throughout the influenza season or when the public is prepared to some extent for the influenza before the season. Regarding the strategies emergency managers in the research context can adopt to improve the effectiveness of public risk communication, this dissertation generally proposed improving the user percent, believer percent and use frequency of local or national TV. No recommendations have been proposed in terms of how to implement these strategies, particularly how to improve the percent of community population who use and believe the importance of either TV channel.

The spatial dimension is also not included in the model. The literature on pandemic influenza simulation has increasingly realized the important role of spatial structure in shaping the spread dynamics (Dangerfield et al., 2009; Mollison, 1995). A large body of studies has been conducted on how space-related factors affect the spread and hence influence the design of control measures (e.g., Bian, 2004; Ferguson, 2006; Germann, 2006). These studies commonly integrate network model or massive agent-based model with realistic landscapes, which represent the continuous geographic environment individuals interact with each other. Simulation models developed in such a way address the non-spatial character of compartment models, and can provide spatial implications for pandemic control (Cauchemeza et al., 2011; Dibble & Feldman, 2004). However, these models still have the same problem as their counterpart models without spatial component regarding the simulation of contact pattern. For epidemic simulation, the influence of actual geographic location and distance are usually considered secondary to that of the characteristics of contact network

(Huang et al., 2004). This dissertation focuses on the more important aspect of pandemic influenza simulation, which is also rarely explored in previous studies. Besides, the spatial dimension can be easily incorporated in the developed simulation framework.

Several researchers have emphasized the role of social media as a new type of channel for risk communication during emergencies (e.g., Kittler et al., 2004; Vaughan & Tinker, 2009). In contrast to the types of channel traditionally used, social media facilitates interactive communication and content exchange. Such two-way communication channel has already been used by individuals, organizations, and government agencies for disseminating emergency risk information (Macias, Hilyard, & Freimuth, 2009). The ASU/ADHS Influenza Survey included social media (e.g., the Internet or social media sites) as a choice respondents could select for the channel they were using to receive 2009 H1N1 flu information. However, whether using or believing the importance of this type of channel is not statistically significantly related to whether having a high-level initial risk perception. So social media is excluded from the simulation model. Given the emerging awareness about the importance of social media during an emergency, further research on its effect is needed.

Future Research

The computational model developed in this dissertation is a flexible framework, and it can be extended to accommodate several additional ideas and avenues of research.

First, the model employs a set of simplification and approximations. Although it has made the best use of available data, these simplifications and approximations can be gradually improved as future research provides more findings. For example, given the compatibility between Netlogo and GIS data, the landscape of a particular area can be easily incorporated in the model to examine disease spread dynamics within the area both temporally and spatially. But more information is needed in terms of how to set up a reasonable contact network for disease spread over geographic space, particularly when the space is broad.

Second, the model can be adjusted and applied to other contexts. It can be customized to study the spread dynamics of any other communicable disease by modifying the transmission process and epidemiologic parameters. It can also be extended to simulate the influence of various pharmaceutical and non-pharmaceutical interventions on epidemic spread dynamics, including therapeutic and prophylactic use of antivirals, vaccination, and school closures. Furthermore, it can be used for simulation in other communities. A common problem shared by all these extensions is that, the model needs re-parameterized, and the value for lots of parameters cannot be easily determined. For example, to simulate the spread dynamics of another epidemic, what the definition of an at-risk contact should be and how personal and community contact network should be set up require new discussion. If the model is used to simulate the spread dynamics of the same epidemic but within another community, current values for those parameters related to public risk communication may not be able to be generalized to the new context. For example, the perceived importance of a single type of media usually varies greatly in different communities and time periods. To accurately anticipate the disease spread dynamics and the effectiveness of certain communication strategy, researchers and public managers need to tailor the model with reasonable values for their own contexts.

Third, in this dissertation, attentions have been paid to the one way communication from public sector to the public, although it has been realized that the emergency public risk communication is a two-way communication process. Future extension of this study can modify the simulation model to include the feedback from the public to the public sector; namely, emergency managers can dynamically adjust their communication strategies based on how the public respond to the current strategy. The risk communication process then can be made interactive, and different insights may be provided from such a dynamic view. Given the efforts that have been made by this dissertation and the flexibility of ABM, such an extension is not a task impossible.

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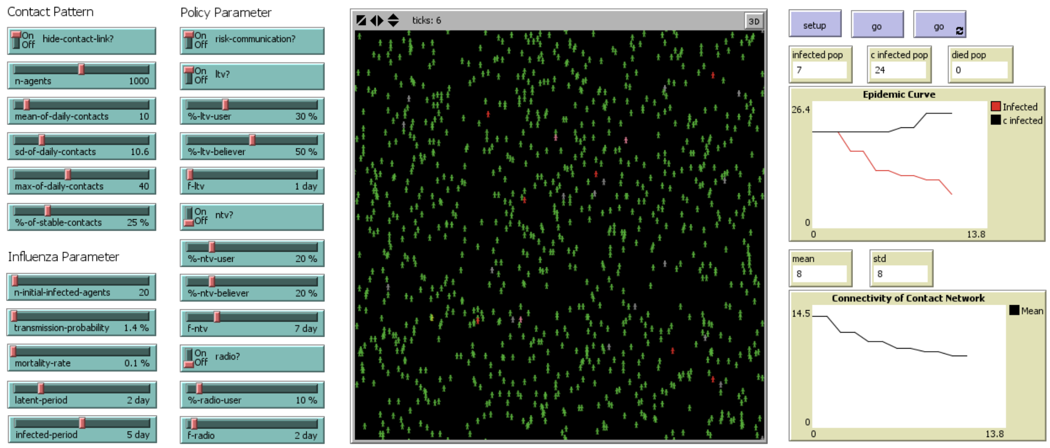
APPENDIX A

USER INTERFACE OF NETLOGO MODEL


Contact Pattern
hide-contact-link?
n-agents 1000
mean-of-daily-contacts 10
sd-of-daily-contacts 10.6
max-of-daily-contacts 40
%-of-stable-contacts 25 %
Influenza Parameter
n-initial-infected-agents 20
transmission-probability 1.4 %
mortality-rate 0.1 %
latent-period 2 day
infected-period 5 day
Policy Parameter
risk-communication?
ltv?
%-ltv-user 30 %
%-ltv-believer 50 %
f-ltv 1 day
ntv?
%-ntv-user 20 %
%-ntv-believer 20 %
f-ntv 7 day
radio?
%-radio-user 10 %
f-radio 2 day
ticks: 6
3D
setup
go
go
infected pop
7
c infected pop
24
died pop
0
Epidemic Curve
26.4
0
0
13.8
Infected
c infected
mean
8
std
8
Connectivity of Contact Network
14.5
0
0
13.8
Mean

APPENDIX B

SOURCE CODE OF NETLOGO MODEL

```
globals [ %-large-reach large-reach small-reach social-influence-effect social-
influence-threshold mean-of-contact-connectivity std-of-contact-connectivity
susceptible-population exposed-population infected-population
recovered-population died-population cumulative-infected ]

undirected-link-breed [ large-f-links large-f-link ]
undirected-link-breed [ small-f-links small-f-link ]
undirected-link-breed [ stable-links stable-link ]
undirected-link-breed [ random-links random-link ]

breed [ agents agent ]
agents-own [ alive? large-f-agent? my-f-network-size my-friends
my-friends-ordered my-strangers my-c-network-size my-contacts
my-contacts-temp stable-random-ratio my-daily-contacts
my-normal-daily-contacts stable-capacity stable-capacity-temp
number-of-stable-contacts my-stable-contacts my-stable-contacts-temp
random-capacity random-capacity-temp number-of-random-contacts
my-random-contacts epi-status infectious? recovering? my-infection-probability
new-info? ltv ntv radio ltv-cre ntv-cre initial-rp personal-rp n-conf-attempts action?
action-effect ]

;---------------set up -------------------------------

to setup
  ca

  set %-large-reach 0.25
  set large-reach 65
  set small-reach 10
  set social-influence-effect 0.5
  set social-influence-threshold 0.5

  set susceptible-population (n-agents - n-initial-infected-agents)
  set exposed-population 0
  set infected-population n-initial-infected-agents
  set recovered-population 0
  set died-population 0
  set cumulative-infected n-initial-infected-agents

  create-agents n-agents
    [ set shape "person"
      set size 5
      set large-f-agent? false
      setxy random-pxcor random-pycor
      while [ any? other turtles-here ]
```

```
  [ fd 1 ]

 set my-f-network-size 0
 set my-c-network-size 0
 set my-daily-contacts 0
 set my-normal-daily-contacts 0

 set my-friends []
 set my-friends-ordered []
 set my-strangers []
 set my-contacts []
 set my-contacts-temp []

 set stable-capacity 0
 set stable-capacity-temp 0
 set number-of-stable-contacts 0
 set my-stable-contacts []
 set my-stable-contacts-temp []
 set random-capacity 0
 set random-capacity-temp 0
 set number-of-random-contacts 0
 set my-random-contacts []
 set stable-random-ratio 0

 set alive? true
 set epi-status 0     ;0susceptible, 1exposed, 2infected, 3recovered, 4died
 set color green
 set infectious? false
 set recovering? false
 set my-infection-probability 0

 set new-info? false
 set ltv 0
 set ntv 0
 set radio 0
 set ltv-cre 0
 set ntv-cre 0
 set initial-rp 0
 set personal-rp 0
 set n-conf-attempts one-of [1 2 3 4]
 set action? false
 set action-effect 0 ]

let n-ltv-believer round (n-agents * %-ltv-believer / 100)
let n-ntv-believer round (n-agents * %-ntv-believer / 100)
```

```
    ask n-of n-ltv-believer agents [
      set ltv-cre 1 ]
    ask n-of n-ntv-believer agents [
      set ntv-cre 1 ]

    ask n-of n-initial-infected-agents agents [
      set epi-status 2
      set infectious? true
      set color red ]

  setup-friend-network
  setup-contact-network
end

to setup-friend-network
  let n-large-agents (%-large-reach * n-agents / 100)
  ask n-of n-large-agents agents
    [ set large-f-agent? true ]

  ask agents with [ large-f-agent? = true ]
    [ create-large-f-links-with other agents with [large-f-agent? = true] in-radius
large-reach
        [ hide-link ] ]
  ask agents
    [ create-small-f-links-with other agents with [large-f-agent? = false ] in-radius
small-reach
        [ hide-link ] ]

  ask agents
    [ set my-f-network-size (count link-neighbors)
      set my-friends [who] of link-neighbors
      set my-friends (shuffle my-friends)
      set my-strangers [who] of other agents with [(link-neighbor? myself) = false]
      set my-strangers (shuffle my-strangers)

      let my-friend-agents link-neighbors
      let i 0
      let j 0
      while [i < my-f-network-size]
        [ set j [who] of min-one-of my-friend-agents [distance myself]
          set my-friends-ordered (lput j my-friends-ordered)
          set my-friend-agents my-friend-agents with [who != j]
          set i (i + 1) ] ]
end
```

```
to setup-contact-network
   ask agents [
    ;decide contact network size
    set my-c-network-size round (random-normal mean-of-daily-contacts sd-of-
daily-contacts)
    while [(my-c-network-size < 0) or (my-c-network-size > max-of-daily-
contacts)]
      [ set my-c-network-size round (random-normal mean-of-daily-contacts sd-of-
daily-contacts) ]

    ;decide the capacity of stable and random contacts
    set stable-capacity round (%-of-stable-contacts * my-c-network-size / 100)
    set random-capacity (my-c-network-size - stable-capacity)
    if stable-capacity >= my-f-network-size
      [ set stable-capacity my-f-network-size
        set random-capacity (my-c-network-size - stable-capacity) ] ]

   ;setup stable and random contacts
   let i 0
   while [i < n-agents] [
     let update-id-list-stable []
     let update-id-list-random []

     ask agent i [
       if stable-capacity != 0 [
         if (number-of-stable-contacts < stable-capacity) [
           let j 0
           while [j < my-f-network-size] [
             let current-agent item j my-friends
             ifelse ([stable-capacity] of agent current-agent != 0) and ([number-of-
stable-contacts] of agent current-agent < [stable-capacity] of agent current-agent)
                    and ([stable-link-neighbor? myself] of agent current-agent = false)
               [ create-stable-link-with agent current-agent [if hide-contact-link? [hide-
link]]
                 set number-of-stable-contacts (number-of-stable-contacts + 1)
                 set my-stable-contacts lput current-agent my-stable-contacts
                 set update-id-list-stable lput current-agent update-id-list-stable
                 if number-of-stable-contacts = stable-capacity [stop]
                 set j (j + 1) ]
               [ set j (j + 1)] ] ]]]

     ask agent i [
       if (number-of-stable-contacts != stable-capacity) [set random-capacity (my-
c-network-size - number-of-stable-contacts)]]
```

```
ask agent i [
  if random-capacity != 0 [
    if (number-of-random-contacts < random-capacity) [
      let my-current-strangers my-strangers
      foreach my-friends [
        if [stable-link-neighbor? myself] of agent ? = false [
          set my-current-strangers lput ? my-current-strangers ] ]
      set my-current-strangers (shuffle my-current-strangers)

      let j 0
      while [j < length my-current-strangers] [
        let current-agent item j my-current-strangers
        ifelse ([random-capacity] of agent current-agent != 0) and ([number-of-
random-contacts] of agent current-agent < [random-capacity] of agent current-
agent)
            and ([random-link-neighbor? myself] of agent current-agent = false)
          [ create-random-link-with agent current-agent [if hide-contact-link?
[hide-link]]
            set number-of-random-contacts (number-of-random-contacts + 1)
            set my-random-contacts lput current-agent my-random-contacts
            set update-id-list-random lput current-agent update-id-list-random
            if number-of-random-contacts = random-capacity [stop]
            set j (j + 1) ]
          [set j (j + 1)]]]]]

if (empty? update-id-list-stable) = false [
  let k 0
  while [k < length update-id-list-stable] [
    let update-id item k update-id-list-stable
    ask agent update-id [
      set number-of-stable-contacts (number-of-stable-contacts + 1)
      set my-stable-contacts lput i my-stable-contacts ]
    set k k + 1 ] ]

if (empty? update-id-list-random) = false [
  let k 0
  while [k < length update-id-list-random] [
    let update-id item k update-id-list-random
    ask agent update-id [
      set number-of-random-contacts (number-of-random-contacts + 1)
      set my-random-contacts lput i my-random-contacts ]
    set k (k + 1)]]

set i (i + 1) ]
```

```
   ask agents [ ;for test
      let a other agents with [stable-link-neighbor? myself = true or random-link-
neighbor? myself = true]
      set my-contacts [who] of a
      set my-contacts-temp my-contacts
      set my-daily-contacts (count a)
      set my-normal-daily-contacts my-daily-contacts
      ifelse my-normal-daily-contacts = 0
        [set stable-random-ratio 0]
        [set stable-random-ratio (number-of-stable-contacts / my-normal-daily-
contacts) ] ]
end

;---------------go -------------------------------

to go
  report-parameter
  do-plot

  tick

  if ticks = 1 [
    ask agents [
      set random-capacity number-of-random-contacts ;here random capacity is # of
random contacts when the model is setup. it is not changed after step 1
      set stable-capacity number-of-stable-contacts ;here stable capacity is # of
stable contacts when the model is setup. it is not changed after step 1
      set stable-capacity-temp stable-capacity
      set random-capacity-temp random-capacity ] ]

  change-health-status-nonsusceptible
  update-friendship-network

  ask agents with [alive?] [
    set number-of-random-contacts 0
    set number-of-stable-contacts 0
    ask my-random-links [die]
    set my-random-contacts []
    ask my-stable-links [die]
    set my-stable-contacts-temp []

    set new-info? false
    set ltv 0
    set ntv 0
```

```
    set radio 0
    set action? false
    set action-effect 0 ]

  receive-risk-information
  response-to-risk-information
  update-contact-network
  change-health-status-susceptible

  do-plot
end

to report-parameter
  ;infection spread among population
  set susceptible-population ((count agents with [epi-status = 0]) * 100 / n-agents)
  set exposed-population ((count agents with [epi-status = 1]) * 100 / n-agents)
  set infected-population ((count agents with [epi-status = 2]) * 100 / n-agents)
  set recovered-population ((count agents with [epi-status = 3]) * 100 / n-agents)
  set died-population ((count agents with [epi-status = 4]) * 100 / n-agents)

  ;contact network characteristics
  set mean-of-contact-connectivity mean [my-daily-contacts] of agents with
[alive?]
  set std-of-contact-connectivity standard-deviation [my-daily-contacts] of agents
with [alive?]

  ;file-open (word "population.txt")
  ;file-write "step"
  ;file-write ticks
  ;file-write susceptible-population
  ;file-write exposed-population
  ;file-write infected-population
  ;file-write recovered-population
  ;file-write died-population
  ;file-write (cumulative-infected * 100 / n-agents)
  ;file-close
end

to do-plot
  set-current-plot "Epidemic Curve"
  set-current-plot-pen "Infected"
  plot (count agents with [epi-status = 2])
  set-current-plot-pen "c infected"
  plot cumulative-infected
```

```
  set-current-plot "Connectivity of Contact Network"
  set-current-plot-pen "mean"
  plot mean-of-contact-connectivity
end

to change-health-status-nonsusceptible
  ask agents with [alive?] [
    if epi-status = 2 [
      ifelse recovering? = true
        [ set epi-status 3 set color grey set infectious? false set recovering? false]
        [ ifelse (random-float 100) < mortality-rate
            [ ask my-links [die]
              set alive? false
              set epi-status 4
              set infectious? false
              set color black ]
            [ if (random-float 1) < (1 / infected-period) [set recovering? true] ] ] ]
    if epi-status = 1 [
      ifelse infectious? = true
        [set epi-status 2 set color red set cumulative-infected (cumulative-infected +
1)]
        [if (random-float 1) < (1 / latent-period) [set infectious? true set color
pink] ] ] ]
end

to update-friendship-network
  ;remove friends who has died; strangers remain the same
  ask agents with [alive?] [
    set my-friends [who] of agents with [large-f-link-neighbor? myself = true or
small-f-link-neighbor? myself = true]
    set my-f-network-size (length my-friends)
    let i 0
    while [i < length my-friends-ordered] [
      let current-agent-id item i my-friends-ordered
      if [alive?] of agent current-agent-id = false [set my-friends-ordered (remove-
item i my-friends-ordered)]
      set i (i + 1) ]

    let j 0
    while [j < length my-stable-contacts] [
      let current-agent-id item j my-stable-contacts
      if [alive?] of agent current-agent-id = false [set my-stable-contacts (remove-
item j my-stable-contacts)]
      set j (j + 1) ] ]
end
```

```
to receive-risk-information
  if risk-communication? [
    let n-agent-alive (count agents with [alive?])
    if ltv? [
      if (ticks > 0) and (ticks mod f-ltv = 0) [
        let n-agent-ltv round (n-agent-alive * %-ltv-user / 100)
        ask n-of n-agent-ltv (agents with [alive?]) [
          set new-info? true
          set ltv 1 ] ] ]
    if ntv? [
      if (ticks > 0) and (ticks mod f-ntv = 0) [
        let n-agent-ntv round (n-agent-alive * %-ntv-user / 100)
        ask n-of n-agent-ntv (agents with [alive?]) [
          set new-info? true
          set ntv 1 ] ] ]
    if radio? [
      if (ticks > 0) and (ticks mod f-radio = 0) [
        let n-agent-radio round (n-agent-alive * %-radio-user / 100)
        ask n-of n-agent-radio (agents with [alive?]) [
          set new-info? true
          set radio 1 ] ] ] ] ]
end

to response-to-risk-information
    ask agents with [alive?] [
    if epi-status != 3 [
    if new-info?
      [ let temp1 (3.04 * ntv * ntv-cre + 1.66 * ltv * ltv-cre - 2.56 * radio)
        set temp1 (0 - temp1)
        set temp1 (1 + exp temp1)
        set initial-rp (1 / temp1)

        ifelse my-f-network-size = 0
          [ set personal-rp ((100 - social-influence-effect) * initial-rp / 100) ]
          [ if n-conf-attempts > my-f-network-size [set n-conf-attempts my-f-
network-size]

            let i 0
            let n-friend-confirm 0
            let n-friend-adopt 0

            while [i < n-conf-attempts] [
              let current-id (item i my-friends-ordered)
              if [action?] of agent current-id
```

```
            [ set n-friend-adopt (n-friend-adopt + 1) ]
           set n-friend-confirm (n-friend-confirm + 1)
           set i (i + 1) ]

         ifelse (n-friend-adopt / n-friend-confirm) >= (social-influence-threshold /
100)
           [set personal-rp (social-influence-effect / 100 + (100 - social-influence-
effect) * initial-rp / 100)]
           [set personal-rp ((100 - social-influence-effect) * initial-rp / 100)] ] ]

     ifelse (random-float 1) < personal-rp
       [ set action? true ]
       [ set action? false ] ] ]

  ask agents with [alive?] [
    ifelse action?
      [ set action-effect one-of [0.3 0.4 0.5 0.6 0.7 0.8 0.9]
        set my-daily-contacts round ((1 - action-effect) * my-normal-daily-contacts)
        set stable-capacity-temp round (my-daily-contacts * stable-random-ratio)
        set random-capacity-temp (my-daily-contacts - stable-capacity-temp)
        if (random-capacity-temp > random-capacity) [set random-capacity-temp
random-capacity] ]
      [ set my-daily-contacts my-normal-daily-contacts
        set stable-capacity-temp stable-capacity
        set random-capacity-temp random-capacity ] ]
end

to update-contact-network
  let i 0
  while [i < n-agents] [
    let update-id-list-stable []
    let update-id-list-random []

    ask agent i [
      if alive? [
        ;update stable contacts
        if stable-capacity-temp != 0 [
          if number-of-stable-contacts < stable-capacity-temp [
            let j 0
            while [j < length my-stable-contacts] [
                  let current-agent-id item j my-stable-contacts
                  ifelse ([alive?] of agent current-agent-id ) and ([stable-capacity-temp]
of agent current-agent-id != 0)
                         and ([number-of-stable-contacts] of agent current-agent-id <
[stable-capacity-temp] of agent current-agent-id)
```

```
                      and ([stable-link-neighbor? myself] of agent current-agent-id =
false)
                  [create-stable-link-with agent current-agent-id [if hide-contact-link?
[hide-link] ]
                   set number-of-stable-contacts (number-of-stable-contacts + 1)
                   set my-stable-contacts-temp lput current-agent-id my-stable-
contacts-temp
                   set update-id-list-stable lput current-agent-id update-id-list-stable
                   if number-of-stable-contacts = stable-capacity-temp [stop]
                   set j (j + 1)]
                  [set j (j + 1)]]]]]]

    ask agent i [
      if alive? [
        ;update random contacts
        if random-capacity-temp != 0 [
          if (number-of-random-contacts < random-capacity-temp) [
            let my-current-strangers my-strangers
            foreach my-friends [
              if [stable-link-neighbor? myself] of agent ? = false [
                set my-current-strangers lput ? my-current-strangers ] ]
            set my-current-strangers (shuffle my-current-strangers)

            let k 0
            while [k < length my-current-strangers] [
              let current-agent-id item k my-current-strangers
              ifelse ([alive?] of agent current-agent-id) and ([random-capacity-temp] of
agent current-agent-id != 0)
                   and ([number-of-random-contacts] of agent current-agent-id <
[random-capacity-temp] of agent current-agent-id)
                   and ([random-link-neighbor? myself] of agent current-agent-id =
false)
                [create-random-link-with agent current-agent-id [if hide-contact-link?
[hide-link]]
                 set number-of-random-contacts (number-of-random-contacts + 1)
                 set my-random-contacts lput current-agent-id my-random-contacts
                 set update-id-list-random lput current-agent-id update-id-list-random
                 if number-of-random-contacts = random-capacity-temp [stop]
                 set k (k + 1)]
                [set k (k + 1)] ] ] ] ] ]

     if (empty? update-id-list-stable) = false [
       let n 0
       while [n < length update-id-list-stable] [
         let update-id item n update-id-list-stable
```

```
        ask agent update-id [
          set number-of-stable-contacts (number-of-stable-contacts + 1)
          set my-stable-contacts-temp lput i my-stable-contacts-temp ]
        set n (n + 1)] ]

    if (empty? update-id-list-random) = false [
      let m 0
      while [m < length update-id-list-random] [
        let update-id item m update-id-list-random
        ask agent update-id [
          set number-of-random-contacts (number-of-random-contacts + 1)
          set my-random-contacts lput i my-random-contacts ]
        set m (m + 1)] ]

    set i (i + 1) ]

  ask agents with [alive?] [
    let a other agents with [stable-link-neighbor? myself = true or random-link-
neighbor? myself = true]
    set my-contacts-temp [who] of a
    set my-daily-contacts (count a)]
end

to change-health-status-susceptible
  ask agents with [alive?] [
    if epi-status = 0 [
      let infectious-stable-contact (count stable-link-neighbors with [infectious? =
true])
      let infectious-random-contact (count random-link-neighbors with [infectious?
= true])
      let infectious-contact (infectious-stable-contact + infectious-random-contact)
      set my-infection-probability (1 - exp (- transmission-probability * infectious-
contact / 100))
      if (random-float 1) < my-infection-probability [ set epi-status 1 set color
yellow ] ] ]
end
```