Is Crisis and Emergency Risk Communication as Effective as Vaccination for Preventing Virus Diffusion? Measuring the Impacts of Failure in CERC with MERS-CoV Outbreak in South Korea

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This study measured the impacts of failure in Crisis and Emergency Risk Communication (CERC) during the outbreak of a contagious Corona viral disease. The study measured the impacts by the number of individuals and hospitals exposed to the virus. The 2015 Middle East Respiratory Syndrome (MERS) outbreak in South Korea was used to investigate the consequences of CERC failure, where the names of hospitals exposed to MERS-CoV were withheld from the public during the early stage of virus diffusion. Empirical data analyses and simulated model tests were conducted. The findings of analyses and tests show that an early announcement of the hospital names and publicizing the necessary preventive measures could have reduced the rate of infection by approximately 85% and the number of contaminated healthcare facilities by 39% at maximum. This level of reduction is comparable to that of vaccination and of social distancing.

KEY WORDS: Coronavirus; crisis & emergency risk communication; early warning; individual-based model; MERS-CoV

1. INTRODUCTION

A large-scale outbreak of a novel infectious disease always begins with a small-scale spread of new infections, but these infections are often diagnosed and considered to be familiar viral infections. This is particularly true for novel coronavirus diseases affecting the human respiratory system, whose initial symptoms appear to be of an ordinary flu. Thus, the risk of a novel virus is often underplayed at the initial stage of the outbreak; a pandemic caused by the novel virus is treated as seasonal flu and a manageable risk until it becomes clear that the disease has infected a massive number of people, rendering them severely ill and leading to deaths in a wide range of areas. This has been repeatedly observed in the history of the influenza pandemic (Dunning, Thwaites, & Openshaw, 2020; Martini, Gazzaniga, Bragazzi, & Barberis, 2019).

From the viewpoint of risk management, the development process of a pandemic makes it difficult to implement required disease-control measures. Risk management entails defining, assessing, and controlling associated risks (Aven, 2011; 2012). At the initial stage of the pandemic, however, it is a challenging task to define and assess the risks associated with the new infectious virus. The identification of a novel virus and its timing of infection—for example, whether the novel virus can spread without symptom
onset—cannot be predicted due to the paucity of information at the start of the outbreak (Cox, Trock, & Burke, 2014; Seeger, 2002). Later, even after the gap in risk knowledge is filled, risk management continues to remain a difficult problem, as pandemic risk control is not merely a biological treatment or control but a dynamic and complex social process (Kasperson et al., 1988). The combination of risk-related knowledge about the novel infectious disease and social coordination is significant to building a social risk management system, which is the key to achieving a successful risk management system. The social risk management system includes reducing the possibility of infections with personal preventive measures, unlinking the transmission chains of virus diffusion from person to person by controlling their behaviors, and isolating and treating infected people. Both preventive and reactive information need to be provided to citizens to construct collective responsibility in a society (Saliou, 1994).

Thus, it is not surprising that rapid communicative response and transparent information provision are standard procedures in risk communication for disease control (Center for Disease Control, 2014; World Health Organization, 2005). Recent cases of infectious diseases, such as Ebola, MERS-CoV, and COVID-19, have taught us that information transparency facilitates rapid response and collaboration between government agencies and citizens at the societal level, and this, in turn, can effectively prevent contagious virus diffusion in a given population (Kim, Yoon, & Jung, 2017). For example, in the case of the spread of COVID-19, South Korea demonstrated a successful “social response system” comprised of “trace,” “test,” and “treat,” combined with social distancing (Bicker, 2020; Perez, 2020). From the initial stage of the pandemic, South Korean government leaders and health officials have announced messages about the danger of a novel strain of coronavirus, COVID-19, as well as the effectiveness of wearing a mask and social distancing. Meanwhile, the United States and United Kingdom government officials gave mixed messages to the public (Cathey, 2020; Grey & MacAskill, 2020; Madhani, 2020; Mason & Sample, 2020). Although not all consequences are attributable to the message effects, the result has been a vast difference between South Korea and the United States and the United Kingdom regarding the number of people who were infected with and died due to COVID-19. For example, the United State and South Korea each reported their first laboratory-confirmed case of the infection on the same date, January 20, 2020. As of February 13, 2021, however, the number of infected cases and deaths per 100,000 people were 8,376 and 147, respectively, for the United States, and the data were 161 and 3, respectively, for South Korea (Pettersson, Manley, & Hernandez, 2020). Compared to South Korea, the number of infected cases in the United States is 52 times greater and the number of deaths is 49 times higher. In South Korea’s social response system, information transparency played a central role in preventing the additional widespread diffusion of the virus among its citizens. In daily briefings, the Korea Centers for Disease Control and Prevention (KCDC) provided information on where and when people had recently been infected and the locations that people should avoid due to the virus exposure (KCDC, 2020). This policy avoided additional infections and unneeded social damage caused by the fear and confusion that often follows a contagious disease outbreak.

However, South Korea has not always been successful in controlling the risk associated in the spread of a contagious virus. In the past, they had critically failed to assess the risk of a novel virus diffusion and had mismanaged crucial public information delivery. During the 2015 MERS-CoV outbreak, the KCDC withheld information on which hospitals had been contaminated with the MER-CoV virus. KCDC’s Crisis and Emergency Risk Communication (CERC) announcements featured worthless knowledge that was out of context, as well as directions that people could not utilize and follow. The result was unnecessary infections and deaths, including economic loss and social costs. South Korea learned from this experience that a consistent message and information transparency in the early stage of virus diffusion are critical components of CERC for building an effective social response system.

The stark contrast between the South Korean government’s response to MERS-CoV and COVID-19 highlights the question of how to assess and evaluate the impacts of effective CERC that is properly carried out. Is it possible to quantify a reduction in the risk of infection in the case of CERC with information transparency? Is it possible to calculate the impact of CERC failure by tracking all infected people, which has been rarely done?

To answer these questions, this study examined the impacts of the KCDC’s CERC failure during an infectious viral disease outbreak. Here, the impacts refer to the number of people and hospitals
exposed to a virus. Taking the case of the 2015 MERS-CoV outbreak in South Korea, this study analyzed the number of people and hospitals that might have avoided MERS-CoV virus exposure if the South Korean government had followed the standard CERC procedure designed and prepared for the outbreak of infectious diseases.

Three aspects of this case are particularly important. First, during the MERS outbreak, the government withheld the names of MERS-CoV-infected hospitals until the media began to publish them. Thus, this case presents a unique opportunity to examine how withholding sensitive hospital information does not stop the spread of a virus but instead may even contribute to it. Second, the way KCDC implemented CERC went against every set of CERC standard procedure in globally renowned manuals prepared for the outbreak of infectious diseases (Fung, Tse, Chan, & Fu, 2015; Nature, 2015). Hence, this case provides a unique opportunity to investigate the effectiveness of the manuals and the impacts of poor CERC implementation. Lastly, a unique aspect of this case is that every infected person's transmission channel was tracked and recorded; thus, the influence of failure can be directly analyzed, both with empirical data and Individual-Based Model (IBM) simulations. In many cases of viral spread, it is difficult to pinpoint the precise points when people were infected, such as the exposure location, additional people exposed at the location, where the infected and exposed people travelled to, and who they contacted after their exposure. The lack of this information frequently precludes the creation of a simulation model that presents an empirical case based on people's behaviors, and in turn, that addresses the outcome of properly implemented CERC compared to a poorly managed one. However, the MERS-CoV case in South Korea has all tracked records for each infected person, allowing us to precisely assess the consequences of CERC failure: the exact number of people infected and exposed to the virus.

This study employed two methods to measure the impact of CERC failure, as mentioned earlier. The first method was an analysis of the empirical data. This study revisited the spread timeline of the virus, using data regarding the people and hospitals exposed to MERS-CoV. Subsequently, it examined the number of people who would not have been infected by MERS-CoV if the government adopted an open policy stance and provided hospital information at the initial stage of viral diffusion. The government’s failure to pursue the standard CERC strategy was also reviewed. The second method employed in this study included building IBM simulation models that use a configuration of parameters for the rules that individual agents follow in an artificial society setting. The model comparison of two distinct scenarios was carried out using an empirical case but following a more parsimonious model to assess the direct impact of CERC failure. These scenarios, which differed only in the timing of the announcement of sensitive hospital information, guided us to assess and evaluate the effectiveness of transparent CERC.

2. LITERATURE REVIEW

2.1. Standard CERC Response Strategy for an Infectious Disease Outbreak

One of the most important methods to manage an unanticipated and uncontrollable risk is to use CERCs effectively (CDC, 2014; WHO, 2017). CERC seeks “to inform the public and change behavior in ways that protect and improve the public health and safety” (Reynolds & Seeger, 2005, p 45). CERC emphasizes delivering messages that perform the following functions: informing the public about effective self-protection steps, guiding them in their application, publishing and updating risk information, dispelling rumors, and minimizing the disease’s damage and costs (Vaughan & Tinker, 2009, p. S324). Information-sharing strategies and the promotion of appropriate behavior, including the integration of risk communication and crisis communication, are essential parts of contingency management.

The internationally renowned standard CERC guidelines lay out the following principles of effective CERC strategy: timely delivery of information, gaining information credibility from the public, gaining public trust as a credible information source, and providing the public information they need and want to know (CDC, 2014; WHO, 2017). This strategy aims to provide information to change people’s beliefs and induce behavioral changes (Brewer, 2011). While it is difficult to presume that everyone would respond in the same way to a particular CERC message, CERC
provides an opportunity to citizens to assess and evaluate the risk associated during an outbreak to make informed decisions. This opportunity makes the risk management process beneficial not only for individuals but also for governmental agencies in resolving risk issues (Society for Risk Analysis, 2018). Indeed, numerous productive studies on information sharing and promoting specific behaviors have been conducted. A review of previous studies, for example, discovered that trust in CERC messengers plays a crucial role in shaping the public’s risk perception about disease severity, information-seeking behavior, and willingness to comply with government interventions (Balog-Way, McComas, & Besley, 2020). It has also been found that CERC transparency and openness are critical to building public trust (Anderson, Omenn, & Turnham, 2020; Balog-Way et al., 2020). Transparency encourages the relationship between voluntary cooperation and risk management cultures (Palenchar & Heath, 2007). For infectious diseases, the timely dissemination of transparent information can substantially flatten the diffusion curve of viral infections. As the relationship between risk perception and protective behaviors is well documented (Siegrist & Árvai, 2020; Van der Pligt, 1996), people use the delivered messages and available information to reason about the perceived severity of the disease and find possible options to prevent negative health consequences arising from the disease (Agüero, Adell, Giménez, Medina, & Continente, 2011; Rubin, Amlôt, Page, & Wessely, 2009). In this process, trust mediates the relationship between risk perception and the acceptance of preventive measures (Siegrist et al., 2021).

However, the impact of the CERC strategy failure, particularly related to information nondisclosure, has received less attention. The lack of research on the effects of CERC failure was partly due to the separation of risk communication and crisis communications in the past. The literature on crisis communication is primarily concerned with crisis management messages about the status or conditions of an event, whereas the risk communication literature engages with the understanding of scientific facts and the dynamics between the sender and receiver of information for known risk probabilities (Holmes, 2008; Reynolds & Seeger, 2005). The efforts to integrate risk communication and crisis communication have not piqued interest in measuring the impacts of CERC failure. Instead, the emphasis has been on the “process view” of risk and crisis development (Reynolds & Seeger, 2005, p. 49). Furthermore, the focus on CERC success stories rather than on failure hampered the assessment of CERC failure (c.f. Coombs & Holladay, 2017; Lundgren & McMakin, 2018). Indeed, many studies focus on how CERC is to be conducted and how coordination between the involved parties can be made more effective (Comfort, 2007). Finally, there are technical and ethical challenges involved in the research because it is hard to measure failure using human participants in a controlled environment. As a result, the topic of quantifying the effects of CERC failure has received less attention.

In this sense, this study offers a one-of-a-kind research opportunity. It investigates a case where a government withheld crucial information from the public for a significant length of time, only to release it later when the sensitive hospital information exposed to an infectious virus became available to the public via media channels.

### 2.2. Modeling Infectious Disease: From Parameter Modeling to Behavior Modeling

Mathematical epidemic modeling often uses a differential equation model based on changes in infection status (Daley & Gani, 1999; Hethcote, 2000). The popular approach to simulate epidemics is the compartment model known as the SEIR model, which builds its model on the interaction between four population groups: the susceptible (S), the exposed (E), the infectious (I), and the recovered (R) (Linka, Peirlinck, & Kuhl, 2020). The SEIR model uses three transition rate parameters between states: the transition rates (i) from the susceptible to the exposed, (ii) from the exposed to the infected, (iii) from the infected to the recovered. In other words, the reproduction ratio $R$—the average number of secondary infections produced by one infected person—is estimated using population characteristics (e.g., age structure and proportion of vaccinated people) and infectious disease characteristics (e.g., latency in disease transmission and probability of infection after exposure) (Hethcote, 2000). If $R > 1$, the disease will spread over time. This is a macro level modeling strategy to discern the trend in contagious disease diffusion.

Although mathematical modeling is an excellent tool to estimate infectious disease risk, it assumes that individual responses to an infectious disease in a given population are homogeneous across individuals. Therefore, the mathematical specification of the simulation model usually relies on the generic
structure of parameters that do not distinguish individuals’ heterogeneous behaviors in a given simulated population (Daley & Gani, 1999; Hunter, Namee, & Kelleher, 2018). For instance, some infected individuals may stay home after symptom onset, while others may remain in contact with susceptible people. These variations may result in a differentiated rate of disease diffusion by individuals; however, such a difference is muted in mathematical modeling as the aggregated parameters of homogeneous individual behaviors. To put it another way, mathematical modeling has disadvantages in modeling heterogeneous individual behaviors (Bobashev, Goedecke, Yu, & Epstein, 2007; Cuevas, 2020). A possible solution for this issue requires continuous changes in the model parameters following a certain statistical distribution (e.g., Linka et al., 2020). By averaging the individual impacts, this dynamic modeling method may be able to address the issue. Nevertheless, it is incapable of capturing human interactions and their heterogeneous mixing (Hunter et al., 2018).

In contrast to mathematical modeling of epidemics, an epidemic IBM is based on direct interaction between individual agents and can model heterogeneous behaviors and interactions between different groups of individuals in the given modeling environment (Burke et al., 2006; Hunter et al., 2018). Unlike the mathematical model, the equation-based modeling approach that infers a causal relationship between variable parameters (Cederman, 2005), IBM specifies individual agents’ behaviors in the form of rules that agents follow. It tests whether the micro specification of individual behaviors is sufficient to generate the aggregated macro-outcome (Epstein, 1999).

One of the most famous models of the relationship between IBM and an infectious disease is the study model built to identify an effective strategy for infectious disease containment (Burke et al., 2006; Epstein, 2004). This model distinguishes three groups of people (ordinary workers, children, healthcare workers) interacting in four different places (homes, workplaces, schools, and hospitals) across three different geographical town/district structures (uniform, ring, and hub/spike shape). Although historical data, such as epidemic transmission per contact and contact rates based on town/district structure, are utilized for model parameter calibration, the model does not rely on causal loop equations between the macrolevel number of population dynamics. If mathematical modeling had been employed for the study, the model would have been too complex to construct, and it would require too many parameters to be assumed. For example, suppose a mathematical model for the IBM mentioned above was built. In that case, one needs to know who meets whom, where, and how frequently. In order to calculate infection statistics, the likelihood of their infection, as well as transmission and contact rates, must be known. Conversely, an IBM needs no less than the rates mentioned (transmission and contact rates) and behavioral rules that set up the model. The modeling result is generated by a stochastic process when people encounter a person who follows the rules set.

In this regard, the IBM approach is one of the most appropriate modeling strategies to measure the intervention impacts of infectious disease spread. Previous studies using this strategy have examined the effects of vaccination and changes in social distancing levels (e.g., Atti et al., 2008; Germann, Kadau, Longini, & Macken, 2006); social prevention measures, such as school closures (Milne, Kelso, Kelly, Huband, & McVernon, 2008); and, weekend extensions (Mao, 2011). While these previous studies were effective in answering their study goals, the impacts of CERC and any failure to follow CERC protocols were not the focus of any inquiry. The model developed in this study was designed to help build a social response system and show CERC’s effects on preventing or ameliorating infectious viral disease outbreak. This type of investigation has gained importance since the emergence of COVID-19, as exemplified by the fact that contradictory statements about mask-wearing caused widespread societal misunderstanding and a relatively quick transmission of the disease.

Furthermore, it is reasonable to expect that people will avoid contaminated hospitals when they have the relevant information. Such behavior may greatly reduce viral contagion. MERS-CoV is not subject to airborne contagion, and people are typically infected after exposure to an environment contaminated with the virus, typically a healthcare facility (World Health Organization, 2019). This characteristic allows us to use IBM as one of the best ways of exploring communication effects. This will be seen by adjusting the timing of disclosures concerning which hospitals have infections, which will lead to calculated differences in the number of people and hospitals experiencing infections.
3. DATA AND METHOD

3.1. Background

Patient Zero, or the first person infected, visited a clinic on May 11, 2015, and he was laboratory confirmed by the KCDC on May 20, 2015 as the first case of MERS-CoV. MERS-CoV is known to be associated with acute respiratory illness due to coronavirus. The news media immediately reported the first case. While other cases were discovered, the KCDC and the Ministry of Health and Welfare (MHW) did not reveal the names of virus-contaminated hospitals but referred to them as “A,” “B,” and “C.” On June 2, 2015, the government stated, “It is an over-reaction not to visit a hospital that a MERS-infected person has visited because of that person’s visit” (Jun, 2015). On that same day, however, an online newspaper began to leak the exact name of hospitals that were virus-contaminated, rejecting the government’s request. Many other newspapers followed suit once these names were reported. On June 4, 2015, the government dropped the nondisclosure policy, referred to the contaminated hospitals by their names, but did not fully disclose all of the hospital names. On June 7, 2015, the government finally decided to fully disclose the hospitals’ names. Approximately a month later, on July 4, 2015, MERS-CoV infections seemed to be no longer occurring, the number of laboratory-confirmed infections reached 186, and 36 people died due to the infection. A total of 16,693 people were ultimately exposed to the virus or were in the place where the MERS virus was exposed. They were quarantined, either at home (self-quarantine) or in healthcare facilities. Fig. 1 depicts the timeline of important events.

3.2. Data

The data in this study were initially collected from various sources: the official MERS portal that was maintained at the time (www.mers.go.kr) by the MHW, the WHO website on South Korea’s MERS outbreak (http://www.who.int/emergencies/mers-cov/en), searches of provincial and local government websites, and national and local newspaper news articles. The collected data were matched with an exclusive report to the National Assembly members for any discrepancy. The classification of healthcare facilities by size was drawn from the Korea Health Insurance Review and Assessment Service (https://www.hira.or.kr/main.do). According to this classification, there are three types of healthcare facilities in South Korea. Clinics are usually owned and operated by one doctor at the neighborhood level and can only treat outpatients. A hospital is a healthcare facility capable of treating at least 30 people on an inpatient basis. A general hospital can treat at least 100 people on an inpatient basis.

3.3. Method

This article reports two studies. The first study used empirical data analysis to construct the event narrative. Using descriptive statistics for the collected data and an illustrative timeline showing what occurred, the event was reconstructed, and a viral exposure analysis was conducted. Note that two assumptions are indispensable to this approach. The first assumption relates to the earliest date of MERS virus exposure. This was calculated based on the most conservative assumption that if a person en-
tered a contaminated area, that person was consid-
ered to have been exposed to the virus on the first
day of exposure if multiple entries were reported.
Using this rubric, someone who visited a contami-
nated area three days in a row would be counted as
being infected on the first day of the visit. The sec-
ond assumption is related to hospital visits. Some in-
fected healthcare workers do not have any indication
to visit healthcare facilities before being transferred
to designated hospitals for treatment and quaran-
tine. For these cases, it was assumed that they were
diagnosed and quarantined at their workplace or
were directly transferred to the designated hospi-
tals. The second study used IBM simulations. The
parameters of the IBM were set by using an em-
pirical data set. This method estimated the informa-
tion nondisclosure impacts. Details about the model
are described in the results section of study 2 and
the Appendix.

4. RESULTS

4.1. Study 1: The MERS Empirical Case

4.1.1. Exposure Analysis

To assess the impact of information nondisclo-
sure, data were reconstructed, focusing on the date
when the infected individuals were exposed to the
MERS-CoV. The reconstructed data analysis indi-
cated that June 7, the date that the government chose
to disclose the names of contaminated hospitals, was
significantly late in making the necessary announce-
ment to the public. A total of 94.1% of all infec-
tions (175 out of 186 people) had already occurred
by this time, as shown in Fig. 2. These people had al-
ready been exposed to a MERS-contaminated area
or had come into close contact with infected peo-
ple. Among these 175 people, 132 had already ex-
perienced the onset of MERS symptoms. Nonethe-
less, the reliance on laboratory-confirmed cases an-
nounced by the government at each morning’s press
conference (Fig. 2) gave a false idea of virus diffusion
to the public. When the information was released,
only 46.7% (87 people) of those ultimately infected
had laboratory-confirmed diagnoses.

Additionally, it needs to be pointed out that the
public disclosure of the names of contaminated hos-
itals, by Pressian, an online newspaper, helped stop
the spread of MERS-CoV. After the newspaper dis-
covery on June 2, only 26 infected people were ex-
posed to the MERS virus out of a total 186 infected
people. Of these, 12 were healthcare workers who
were exposed when treating infected patients. This
effectively left only 14 people (7.5%) becoming in-
fected for reasons other than holding a healthcare
job. It is true that the KCDC had actively imple-
mented more intensive preventive measures such as
closing contaminated hospitals and employing cohort isolation in infected hospitals. However, these measures were mostly deployed after the disclosure of the hospital names. One of the more important facts is that after the disclosure of the contaminated hospital names, MERS patients understood that they could infect others and took greater care when visiting a hospital. For example, one infected person began to wear a mask when he visited healthcare facilities after realizing that he had been exposed to MERS-CoV, even before he was being tracked by the government (Yoo, 2015). If the information had been released on the morning of May 27, the day and time when 76 infected people were initially exposed to MERS-CoV through hospital emergency room visits, the number of people infected with the virus could have been limited at 62, which is one-third of the total reported cases.

Unfortunately, the government’s announcement of which healthcare facilities had been exposed to the MERS-CoV was far from timely. Fig. 3 shows that 72% (44 of 61) of the total number of clinics, 80% (8 of 10) of the total number of hospitals, and 83% (28 of 33) of the total number of general hospitals had been exposed to MERS-CoV by June 7. An interesting point to note in Fig. 3 is that from May 21 to June 1 (highlighted), more general hospitals were exposed to the virus than clinics, after which the number of clinics surged. This pattern indicates that, first, the hospitalized patients were transferred to general hospitals and transmitted the virus to people at those facilities. Second, those visitors of general hospitals fell ill and visited clinics, exposing a smaller number of people each time. Third, the trend continued even after the names of contaminated hospitals became known because of the leaked information. Because only 24 healthcare facilities were known to have been exposed to the MERS-CoV at the time of the leak, people continued to visit clinics to treat their symptoms, thinking that they might have simple flu. This time lag could have led to more widespread diffusion if the MERS virus had been able to infect people immediately after exposure to the virus, as is the case for COVID-19. Fortunately, the MERS virus causes contagion only after the initial symptom onset.

If the contaminated hospital information had been announced much earlier, on May 20, the outbreak might have ended with 36 people infected and seven deaths instead of 186 people infected and 37 deaths. Fig. 2 shows that 36 people had been exposed to the virus as of May 20, and only two others were exposed before May 24. Fig. 3 also shows that only
four clinics and five general hospitals had been exposed to the virus as of May 24. Thus, there was at least a four-day window to prevent the diffusion of the virus. Increased awareness of the MERS-CoV exposure, including an announcement identifying the hospitals that had received visits from infected patients, could have resulted in only 19.4% (36 of 186) of those ultimately infected being exposed as well as only 6.6% (4 of 61) of clinics, and 16.1% (5 of 31) of general hospitals. Instead, people were unaware that they were exposed to the virus at healthcare facilities, including hospital visits.

4.1.2. Government Response and Information Diffusion to the Public

Since the government concealed information regarding the names of hospitals that had been exposed to MERS-CoV, the public sought information elsewhere. Fig. 4 depicts the relative frequency of Google searches for the term “MERS hospital.” The frequency of searches for the names of the virus-exposed hospitals increased rapidly from May 28 to June 2, the date an online news outlet leaked the information. After the South Korean government revealed the names on June 7, the online search for the terms rapidly declined.

In addition to searching for information online, information about the names of the virus-exposed hospitals was circulated among the public through social media. Such messages usually incorporated a list of these hospitals as well as information sources. The sources were usually acquaintances or family members who worked in a healthcare facility. In some cases, information was inadvertently disclosed by workers at other hospitals or even at express train stations. Although there were often some erroneous details in the messages, the hospital names provided by these sources were mostly accurate (Choi, 2015).

The government focused on attenuating public fear and promoting an image of itself as being in control of the situation. For example, according to internal reports on the MERS task force, a meeting was held to change the framing of press reports. The
reports included instructions for a public relations strategy emphasizing that news articles should be framed with the number of those discharged rather than those infected (Park, 2015). In addition, the government sought to create a one-way conversation that advertised their efforts, during the period when there was an increase in the number of exposures and the degree of public questioning for details was increasing. On May 31, the government declared that it was “investing all of the nation’s resources in collaboration between the government and the private sector” (MHW, 2015a), but they were also devoting additional resources to assuaging public fears. The government held a conference on the themes of “What is MERS?” and “The Clinical Implications of MERS” on June 4 (MHW, 2015b) at a time when the virus continued to spread rapidly.

The government lost information credibility and failed to build trust in their messages to the public. MERS-CoV is known to be carried by camels before infecting humans, similar to the role of bats in COVID-19. The government’s first message contained the instruction that people should avoid close contact with camels and should not use camel oil or eat uncooked camel meat. However, all the camels in South Korea were at zoos. It is impossible to eat camel meat in any context, as it has never been imported to the country. Even the camels at that time in zoos were born and raised in South Korea, but all were quarantined after the first laboratory-confirmed case. This message sparked public ridicule (Huh, 2015).

4.2. Study 2: Individual-Based Modeling: A Simulation Study

The effects of information nondisclosure were also examined using IBM simulations. The model configuration and simulation procedures are described below.²

4.2.1. Model Configuration

An IBM has three components: individual agents, the environment, and interaction rules. The environment is where the agents interact with each other or with the environment. Rules govern these interactions. The environment is a space wherein agents are located. For simplicity, the IBM model was set up with 1,000,000 grid spaces (1,000 × 1,000 environment) and 50,000 people (agents) in it. Because the virus infected people who had visited healthcare facilities, the facilities were set as the environment’s structural setting. Three healthcare facility classes were set, differing in the maximum possible number of exposed people, which was the average maximum number of potential exposures in these facilities from empirical data (see Appendix). The total number of healthcare facilities was set at 1,000 and randomly dispersed in the grid environment. The number for each class facility in the environment followed the actual ratio in South Korea.³ In each run, people in the model randomly moved around the grid.

4.2.2. Synopsis of the Simulation Model Based on Interaction Rules

The model started with an initial setup. Then, in a model run, one agent was randomly selected as Patient Zero and visited the closest clinic, and from there, visited the closest general hospital, which simulates the actual event that happened. The person was then quarantined, and other people within the visited hospital boundary were exposed to the virus. The number of people within the hospital at the time of Patient Zero’s visits is random, but it must be less than the maximum possible number of the given facility class. In the simulation, 0.245% of the exposed people were assumed to be infected. This was 1.1% in the real-world event. However, in an artificial environment without real-world friction, maintaining this number means that the number of infections would have been highly inflated as compared to the empirical data. In addition, the model also needed to consider the time window between exposure and symptoms, which, for simplicity, was not set in the simulation model but was adjusted by the infection rate. The infection rate was adjusted similarly to match the number of infections in the real case after several model pretests.

The model assumed that the infected people would immediately visit the closest healthcare facility, exposing people there to the virus as did the Patient Zero. The infected people were quarantined after completing one of the four patterns of visiting healthcare facilities, as explained below. The process of exposure, infection, contact with others, and quar-

²The summary of IBM configuration and setting will be available in the Appendix Table A1 and Fig. A1.

³There are about 8,200 clinics, about 1,500 hospitals, and 335 general hospitals in Korea, as of 2014.
antine was repeated as a basic routine until the model halted.

Three crucial rules were applied. First, four visiting patterns observed in the real-world data were applied to the IBM. According to the MERS data, the ratio of virus exposure by the healthcare facility class was six clinics to one hospital to three general hospitals. Four patterns of facility visitation maintained this 6:1:3 visitation ratio, that is, visiting three clinics only; visiting a general hospital only; visiting two clinics and then visiting a general hospital; lastly, visiting a clinic, a hospital, and a general hospital in a sequence. The difference in the pattern was due to the difference in the patients' risk perception and awareness of the infection. Some people were unaware that they were infected by MERS-CoV and went to the first-level healthcare facility clinics, while others decided to go to third-level healthcare facilities for being treated with special care. The model was set with these four patterns, maintaining the 6:1:3 visitation ratio.

Second, the completion of one pattern was counted as one day, and the sequence of the patterns was randomized. In other words, the completion of the four patterns as one set was considered in four days. The introduction of a randomized sequence is because a run with one specific pattern before the other patterns may distort the number relative to other patterns. For example, visits to three clinics tend to expose a smaller number of people than visits to all three classes of healthcare facilities.

Third, it was assumed that, upon the publication of the names of all virus-contaminated healthcare facilities, clinics were the only facilities that gained novel exposure to the virus, as seen in the actual data. This implies that the publicized facilities were closed, and those who were infected within them were quarantined. Indeed, the facilities of hospital class and general-hospital class operated triage rooms for screening infected people, and no further outside contamination was found. The reported cases were healthcare workers exposed to infected patients.

4.2.3. Reporting of the IBM Simulation

The report of the simulation result is based on the average number of 500 runs of the model using two different model types: the full model that pursues a similar result to the actual case and an early warning model that disclosed the names of contaminated hospitals much earlier. The purpose of multiple runs is to obtain a robust result for the model using the randomized sequence of the four patterns mentioned earlier. The two model types are compared to calculate and measure the impacts of failure in CERC.

Both models started on May 27 when the virus began to cause infections outside a few hospitals’ limited boundaries. At this point, there was a golden window when the government would have been able to release information on which hospitals had been infected to prevent viral spread throughout the country. The end date of the model was set June 7 when the South Korean government decided to release the hospital information after an online newspaper’s report. The number of people infected on June 7 was compared between the two models.

The first model is a simulation case in which the sensitive information is released on June 2, and the infected healthcare facilities are then closed until June 7. The second early warning model assumes that the sensitive information is released on May 27, and all affected healthcare facilities are closed to prevent further infection and cannot be visited until June 7. This allowed a comparison between the number of people and hospitals exposed to the virus between the simulated model with the actual setting and the hypothetical setting of early warning. The final note about the modeling strategy is that all the models tested their sensitivity by changing information disclosure dates. This is presented in the graphical depiction of the results.

4.2.4. IBM Simulation Result

The comparative trends in the number of people exposed in the actual case and the simulated model are exhibited in Fig. 5(a). The comparison shows that the trend of the simulated model generally followed the trends in the actual case, implying that the comparison was conducted reasonably as sensitivity tests presented in Appendix Table A2. It is important to note that the simulation model was created to be simple as possible, but that it was quite similar to the actual case in terms of the number of people exposed.

A comparison between the simulated model following the actual trend and the model projecting early warning is presented in Table I and is displayed in Fig. 5(b). In Table I, the effects of information sharing with the public are seen to have an enormous effect, reducing the number of those exposed to the virus. Compared with the simulation where the names were not released until June 2, the model with an earlier release of hospital name information showed significantly fewer people being exposed to
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**Fig 5.** Trends in virus diffusion: individually based models and the real case. (a) trends in the actual case and simulated full model. (b) trends in the simulated full model and early warning model.
Table I. Comparison Between the Real Event and IBM Simulation: Number of Exposures

| Date     | Real Event | Simulated Full Model (a) | Simulated Early Warning Model (b) | Reduction Rate |
|----------|------------|--------------------------|-----------------------------------|----------------|
| 05-27-2015 | 120        | 144.4                    | 144.8                             | -0.2           |
| 05-28-2015 | 127        | 286.4                    | 285.8                             | 0.2            |
| 05-29-2015 | 129        | 427.9                    | 388.9                             | 9.1            |
| 05-30-2015 | 468        | 623.7                    | 491.4                             | 21.2           |
| 05-31-2015 | 723        | 865.2                    | 491.7                             | 43.2           |
| 06-01-2015 | 823        | 1,140.1                  | 491.7                             | 56.9           |
| 06-02-2015 | 1,417      | 1,547.4                  | 491.8                             | 68.2           |
| 06-03-2015 | 1,732      | 1,907.0                  | 491.9                             | 74.2           |
| 06-04-2015 | 2,045      | 2,236.3                  | 492.1                             | 78.0           |
| 06-05-2015 | 2,257      | 2,567.7                  | 492.1                             | 80.8           |
| 06-06-2015 | 2,926      | 2,912.6                  | 492.2                             | 83.1           |
| 06-07-2015 | 3,096      | 3,266.7                  | 492.4                             | 84.9           |

Table II. Comparison Between the Real Event and IBM Simulations: Number of Healthcare Facility Exposures

| Date     | Clinics Simulated Full Model (a) | Hospitals Simulated Full Model (a) | General Hospitals Simulated Full Model (a) | Clinics Simulated Early Warning Model (b) | Hospitals Simulated Early Warning Model (b) | General Hospitals Simulated Early Warning Model (b) | Reduction Ratio |
|----------|-----------------------------------|-----------------------------------|--------------------------------------------|------------------------------------------|---------------------------------------------|---------------------------------------------|-----------------|
| 05-27-2015 | 1.002                             | 0.000                             | 1.000                                       | 1.000                                    | 0.000                                       | 1.000                                       | 1.000           |
| 05-28-2015 | 1.002                             | 0.000                             | 1.006                                       | 2.342                                    | 0.082                                       | 1.292                                       | 1.292           |
| 05-29-2015 | 1.004                             | 0.000                             | 1.006                                       | 2.538                                    | 0.082                                       | 1.292                                       | 1.292           |
| 05-30-2015 | 1.01                              | 0.000                             | 1.006                                       | 4.396                                    | 0.374                                       | 2.100                                       | 2.100           |
| 05-31-2015 | 1.202                             | 0.000                             | 1.162                                       | 5.184                                    | 0.430                                       | 2.500                                       | 2.500           |
| 06-01-2015 | 1.38                              | 0.000                             | 1.222                                       | 5.486                                    | 0.462                                       | 2.624                                       | 2.624           |
| 06-02-2015 | 3.438                             | 0.284                             | 1.920                                       | 5.582                                    | 0.472                                       | 2.678                                       | 2.678           |
| 06-03-2015 | 6.358                             | 0.566                             | 2.754                                       | 6.132                                    | 0.536                                       | 3.010                                       | 3.010           |
| 06-04-2015 | 8.224                             | 0.704                             | 3.172                                       | 6.502                                    | 0.572                                       | 3.198                                       | 3.198           |
| 06-05-2015 | 9.054                             | 0.726                             | 3.292                                       | 6.668                                    | 0.580                                       | 3.288                                       | 3.288           |
| 06-06-2015 | 10.976                            | 0.800                             | 3.742                                       | 7.324                                    | 0.660                                       | 3.684                                       | 3.684           |
| 06-07-2015 | 12.814                            | 0.908                             | 4.216                                       | 7.818                                    | 0.716                                       | 3.964                                       | 3.964           |
| Reduction Ratio |                        |                                    |                                             | 39.0                                      | 21.1                                        | 6.0                                         |                 |

the virus. This result indicates that, compared with the full model, on average, only 15.1% of the people are exposed to the virus (3266.7 vs. 492.4). The ratio of the rate of infection between the early warning model and the actual outbreak was 19.4% (36 out of 186). Thus, in the case of the diffusion of MERS-CoV, an early warning would have reduced the risk of virus exposure by approximately 15–20% of the actual case. Interestingly, this abrupt stopping pattern of the virus diffusion is similar to the vaccination effect (Polack et al., 2020) or social distancing (Wang et al., 2020) as in the Appendix Fig. A2. Thus, a transparent CERC message strategy combined with social distancing can significantly reduce potentially massive infections. This was exactly what happened in South Korea during the COVID-19 pandemic due to the lessons learned from the MERS experience.

Another interesting finding of the study is that social preventive measures, such as voluntary avoidance of healthcare facilities, were found to have greatly reduced the number of people exposed to the virus. Table II shows that, on average, 12.8 contaminated clinics appeared in the actual simulated case, but only 7.8 clinics appeared in the early warning model. This means that the early warning would have reduced the number of exposed clinics to 39.0% of the number of clinics in the simulated model without the early warning. This reduction was 21.1% and 6.0% for hospitals and general hospitals, respectively.

Unfortunately, it is not possible directly to compare the ratio based on the exposure because we do not know the number of exposed people on June 7, when the early warning would have implemented; that is the purpose of this simulation study.
respectively. Because MERS-CoV tends to spread through healthcare facilities, an early warning would have been most effective in convincing the public to avoid healthcare facilities.

5. DISCUSSION

This study shows that having extensive manuals and meticulous procedures in place does not guarantee the effectiveness of CERC and other factors need to be considered for practical implementation of CERC. South Korea government made “the standard manual for infectious diseases emergency management” in December 2014, six months before the MERS-CoV spread, as the outcome of the long effort to have the manual for infectious disease control since 2010 (Ministry of Health and Welfare, 2014). Yet, the sensitive information about which hospital had contaminated were kept hidden. The delivered information was useless and out of context. Public officials were concerned about the public panic but disregarded social costs and public confusion.

One of the reasons for ineffective communication may lie in the internal decision-making processes. In fact, during periods of infectious virus spread, internal decision-making processes among public officials frequently obstruct essential information delivery, disregarding the prepared and planned protocols. For example, the conflict between government leaders and health experts causes political tensions inside the government, which in turn undermines the credibility of information and trust in government instruction (Kim & Kreps, 2020). The top-level government officials’ assessment of economic impacts and their fear of public panic can effectively negate the efforts of health experts. However, CERC literature seems to grasp the issue of information delivery as something between the officials/experts and the public. It is undeniably important to locate “health experts at the forefront to educate the public” (Madad & Spencer, 2021, p. 965) and to use the media for two-way communication with the public (Holmes et al., 2009) for effective CERC. CERC is to provide relevant information to the public and in doing so, it helps inform decisions by individuals, stakeholders, and community for perceived risks (Reynolds & Quinn, 2008). Yet, as this study shows, CERC’s first step lies in the responsible agency’s decision-making process at the early stage of virus diffusion rather than the dissemination of public health information. In this sense, more research on how government leaders prioritize a certain risk factor among many other factors—such as public health, economy, mass panic, and public awareness—will be fruitful for future research.

The field of risk management may also benefit from future research that how CERC impacts other forms of Non-Pharmaceutical Interventions (NPIs). The NPIs has been targeted individuals and groups of people, such as community, to change their behaviors to limit the virus spread (Center for Disease Control, 2018; Reynolds & Quinn, 2008). As the MERS case in South Korea has shown, revealing the name list of the virus contaminated hospitals alone has literally flattened the infection curve because it has naturally informed people to avoid those hospitals. This means that risk communication can be directly translated into NPI. Then, it stands to reason that numerous NPIs working in tandem can greatly limit the number of people exposed to the infectious virus. By contrast, when CERC sends inconsistent information and instructs new NPI such as wearing masks, not only CERC is ineffective but also other NPIs often confront noncompliance such as social distancing due to distrust toward government. In this sense, future study needs to investigate the CERC’s role and its effectiveness as a component of the NPI portfolio, not as an independent NPI strategy.

From the modeling perspective, future IBM applications can be further developed by integrating the risk communication perspective with the current IBM applications of direct intervention strategies. Previous IBM research has concentrated on the vaccination effect, social distancing and containment strategies, contact tracing, and quarantine (Tracy, Cerdá, & Keyes, 2018). While many studies have emphasized the role of communication, particularly in these days of fake news and misinformation from social media—referring to it as “infodemic”—it is surprising to see that IBM appears to have overlooked message effects in favor of focusing on the causal mechanism of social networks. Future IBM models can contribute to the risk analysis field by developing complex models from the CERC perspective.

6. CONCLUSION

This study examines the impacts of CERC failure in an outbreak of an infectious viral disease, focusing on the number of people and hospitals exposed to the virus. The first study incorporated with the analysis of the MERS response case in South
Korea. This revealed that more than 80% of those infected by MERS-CoV would not have been infected if the information concerning which hospitals were exposed to the virus had been released at once to the public. The second study using IBM confirms the findings of the first study. Although the models used the simplest possible configuration, the results of the modeling are well aligned with the actual case. The model confirmed that transparent information delivery is vital for protecting people from exposure to an infectious virus. The simulation demonstrated that early warning could have eliminated approximately 85% of the exposure risk, almost to the extent of a vaccination effect (see Appendix). For healthcare facilities, this ranged from 6.0% to 39.0%, depending upon the facility size. In summary, this study empirically demonstrated that information nondisclosure alone could result in an enormously negative outcome and greatly increase the number of people exposed to an infectious virus.

That said, this study adds a valuable contribution to the risk analysis and risk communication field. First, the study analyzed the complete information regarding the infected people and people exposed to the infectious virus, showing the empirical analysis as the most accurate calculation about the impacts of risk communication failure. In most of infectious disease outbreak—particularly with more than a hundred laboratory-confirmed coronavirus outbreak, to the best of our knowledge, no case study has been reported and used the data that a government tracked and kept all the records of infected people’s movements throughout the country’s regions. The quality of the data utilized in this study as well as modeling from this empirical data make a significant contribution to the existing knowledge.

Additionally, this study contributes to the risk analysis field by showing the case of risk communication failure and people’s reaction to this failure both with empirical data analysis and simulation. Indeed, previous studies have emphasized the importance of information sharing and public trust in CERC. They did not, however, have the opportunity to consider the consequences of failing to achieve the aforementioned emphases. This is particularly important, as a case of failure is rarely studied and measuring the impacts of risk communication are rarely tested empirically. In other words, the evidence-driven examination of numbers and the simulations with testable data are the most valuable contribution to the risk communication literature.

Lastly, the contribution of this study lies in the fact that the study has documented with supporting computations that the appropriate early action following the standard procedure for preventing the rapid outbreak of a contagious disease has similar positive effects to those of vaccination or social distancing. Many studies have emphasized the importance of CERC. However, to the best of our knowledge, it is rare to see a study that has actually calculated and measured the CERC failure impacts, and the effect of risk communication is almost the same level as that of vaccination or social distancing. We believe this is a unique and valuable contribution of this study.

While this study is interested in the behavioral consequences due to the failure of risk communication by the government, it does not cover the individual psychology affected by the disease or the effect of misdirected information such as fear or panic. The study also leaves out the response of central and regional government organizations and their collaboration with other first response units which have been studied elsewhere (cf. Kim et al., 2017). Instead, the model in this study used the number of people infected and the number of people exposed to the virus as the aggregated result based on the tremendous efforts of these organizations.

Other limitations of this study should be noted. First, this study did not incorporate assessments of social media effects. The circulation of information within and via social media can greatly influence the number of people getting infected. Fortunately, the omission of social media modeling is largely irrelevant in this case, as MERS affects the elderly the most. The elderly was most likely not to use social media at the time of the outbreak; thus, social media effects were minimized in this population at that time. Second, this simulation is based on the simplest assumptions. More complex modeling would help to explain the number of those exposed by including the behavioral aspect of preventive measures, mass media effects, and so on. Third, the external validity of this study needs to be cautiously assessed. It could be the characteristics of MERS disease, which mainly spread through healthcare facilities and spread only when symptoms are onset. While this study used the case that tracked all the infected and exposed people, not all cases of infectious disease spread can be tracked and traced without community-associated infection, which makes it difficult to validate the study result by comparing it with other cases.
APPENDIX

Summary of Model Configuration and Interaction Rules

A. Model Environment

| Table A1. Grid and Agents Setting |
|-----------------------------------|
| Total number of the spatial grid | 1,000,000 |
| Total number of people in the grid | 50,000 |
| Healthcare facility class | N | Max. N Exposed |
| Clinic | 820 | 25 |
| Hospital | 150 | 481 |
| General Hospital | 30 | 1861 |

B. Model Parameter: The rate of infection after exposure is 0.245%

Fig A1. Model Synopsys.
C. Model Assumption (Interaction Rules)

1. bullet-Four patterns of Diffusion (Visiting Patterns of Healthcare Facilities)
2. Infection—Clinic Visit—Clinic Visit—Clinic Visit—Quarantined
3. Infection—General Hospital Visit—Quarantined
4. Infection—Clinic Visit—Clinic Visit – General Hospital—Quarantined
5. Infection—Clinic—Hospital—General Hospital—Quarantined
6. bullet-Completion of each pattern is one day.

D. Stylized Modeling Strategy

Fig A2. Virus Diffusion Curve and Reduction Pattern with Preventive Measures. (Top Left) Vaccination: Number of Infections (Top Right) Social Distancing: Number of ICU Beds Required (Bottom) CERC Early Warning: Number of Virus Exposures.
Sensitivity of Information Disclosure

Table A2. Sensitivity Test of IBM Model

| Date of Information Disclosure and Healthcare Facility Closure | Date       | Real Event | May 27 | May 29 | May 31 | June 1 | June 2 | June 3 |
|---------------------------------------------------------------|------------|------------|--------|--------|--------|--------|--------|--------|
| 05-27-2015                                                    | 120        | 144.8      | 144.9  | 145.6  | 145.0  | 144.4  | 145.4  |
| 05-28-2015                                                    | 127        | 285.8      | 287.0  | 287.9  | 287.0  | 286.4  | 288.3  |
| 05-29-2015                                                    | 129        | 388.9      | 429.6  | 429.4  | 428.7  | 427.9  | 430.8  |
| 05-30-2015                                                    | 468        | 491.4      | 559.9  | 633.3  | 627.0  | 623.7  | 629.4  |
| 05-31-2015                                                    | 723        | 1,417      | 491.8  | 586.5  | 859.9  | 1,417.3| 1,547.4| 1,562.8|
| 06-01-2015                                                    | 1,732      | 491.9      | 586.8  | 919.8  | 1,624.6| 1,907.0| 2,108.5|
| 06-02-2015                                                    | 2,045      | 492.1      | 586.9  | 978.7  | 1,804.6| 2,236.3| 2,614.3|
| 06-03-2015                                                    | 2,257      | 492.1      | 587.0  | 1,037.1| 1,991.9| 2,567.7| 3,139.2|
| 06-04-2015                                                    | 2,926      | 492.2      | 587.2  | 1,095.8| 2,183.9| 2,912.6| 3,634.4|
| 06-05-2015                                                    | 3,096      | 492.4      | 587.3  | 1,153.9| 2,378.8| 3,266.7| 4,142.2|

Similarity in the Infection Reduction Trend Between Early Warning CERC, Vaccination and Social Distancing

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