Exploring the Spatiotemporal Patterns of SARS-CoV-2 Infection among Healthcare Workers and Patients in China

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Abstract

Studying the spatiotemporal distributions and differences of coronavirus disease (COVID-19) between social groups such as healthcare workers and patients can aid in formulating epidemic containment policies. Most previous studies of the spatiotemporal characteristics of COVID-19 were conducted in a single group and did not explore the differences between groups. To fill this research gap, this study assessed the spatiotemporal characteristics and differences in COVID-19 among patients and healthcare workers in Wuhan, Hubei (excluding Wuhan), and China (excluding Hubei) by combining data from healthcare workers and patients with confirmed COVID-19. The results show that: (1) the temporal difference in the early-onset region was greater than that in the late-onset region. That is, the temporal difference was greater in Wuhan than in Hubei (except Wuhan), and greater in Hubei (excluding Wuhan) than in China (except Hubei). (2) The spatial difference in the early stage and early-onset region were less than the temporal differences in the later stage and late-onset region. That is, the spatial difference was less in Wuhan than in Hubei (except Wuhan), and less in Hubei (excluding Wuhan) than in China (except Hubei).

Index Terms

Healthcare worker infection; patient infection; spatiotemporal distribution; spatiotemporal differences; COVID-19

I. INTRODUCTION

By the end of March 2020, the spread of coronavirus disease (COVID-19) in China, with Wuhan being the most affected area, had stopped, and there were no confirmed cases in most provinces. The growth rate of the epidemic was stabilizing, and the containment of the epidemic had achieved significant phased results [1]. At the same time, China paid a hefty economic price [2]. However, COVID-19 is still a pandemic in most countries and regions, and the number of cases continue to rise [3]–[5]. Overall, the world has been heavily hit by the COVID-19 pandemic caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [6], [7].

COVID-19 is a novel infectious disease caused by SARS-CoV-2. Since the outbreak of COVID-19, many researchers have performed classical, epidemiological, mathematical, and statistical analyses to carry out emergency research from the perspectives of pathology [8], [9], epidemiology [10], genomics [11], clinical medicine [12]–[14], and molecular biology [15]. They aimed to identify the genetic viral sequence, virus source, intermediate host, and related risk factors of SARS-CoV-2. They also sought to clearly understand the hazard potential, mechanism underlying the spread of the disease, and risk factors of SARS-CoV-2 infection to provide a scientific reference basis for the customization of diagnostic kits and the development of antiviral drugs. However, when a novel infectious disease is prevalent, the creation of specific vaccines and radical treatments generally takes a long time [16]–[18]. In the early stage of the epidemic, relevant preventative measures such as self-isolation, restriction of crowd movement and gathering, and wearing of masks have become important emergency containment measures [19]–[21]. To achieve targeted and accurate containment, it is necessary to understand the spatiotemporal spread of COVID-19 as time progresses and determine its development trend at the earliest [22].

In the early stages of the epidemic, patient confirmed data are a very important data source. The patient confirmed data contain a wealth of information that can be explored by spatio-temporal analysis [22]–[24]. Therefore, many researchers have used patient confirmed data to explore the spatiotemporal characteristics of COVID-19. However, studies using other data sources to assess the characteristics of the epidemic in social groups are scarce. For example, healthcare workers are one such special group [25]. Studying the spatiotemporal distributions and differences of healthcare worker infections can aid in better formulating epidemic containment policies, but the spatiotemporal characteristics of COVID-19 between healthcare workers are rarely studied. To fill the research gap, the spatiotemporal characteristics and differences between healthcare worker infections...
and patient infections were analyzed from the perspectives of Wuhan, Hubei (outside Wuhan), and China (outside Hubei) by combining data of healthcare workers with confirmed COVID-19 and data of patients. First, web crawler technology was used to obtain data of confirmed healthcare workers. Then, statistical indicators, Pearson correlation coefficients, thematic maps, and other methods were used for analyzing the spatiotemporal characteristics and differences. The main contributions of this article are as follows:

1) The spatiotemporal distributions of healthcare worker infections were analyzed from the perspectives of Wuhan, Hubei (outside Wuhan), and China (outside Hubei).

2) The spatiotemporal differences among healthcare worker infections and patient infections were also analyzed from the perspectives of Wuhan, Hubei (outside Wuhan), and China (outside Hubei).

II. RELATED WORKS

Many researchers have conducted extensive research on COVID-19 from different perspectives. In this section, we mainly present a review of relevant studies that explored the spatiotemporal distributions of COVID-19.

To explore the spatiotemporal distribution of COVID-19 is mainly to summarize the spread law of COVID-19, to provide the basis for the prevention and control of COVID-19. In the early stage of the epidemic, a large number of studies have been conducted based on patient confirmed data. For example, Zhang et al. [26] analyzed the epidemiological characteristics of COVID-19 in February 2020 based on patient confirmed data and reported the spatial distribution of COVID-19 at the early stage in China. Hu et al. [27] collected global patient confirmed data from different scales and established a data repository to provide data support for research related to the spatiotemporal distribution of COVID-19. Wang et al. [28] used spatiotemporal scanning statistics to detect the hotspots of new cases every week, based on the confirmed cases of COVID-19 at the county level in the United States, thereby characterizing the incidence trend of COVID-19. Zhang et al. [29] compared the spatiotemporal characteristics between COVID-19 and SARS at the provincial level, thereby revealing the spread of the COVID-19. Sun et al. [30] analyzed regional spatiotemporal changes of the epidemic, based on the daily new cases in 250 regions of South Korea, thereby evaluating South Korea’s containment strategy.

In addition, researchers have also combined patient confirmed data with other data sources to explore the spatiotemporal spread of COVID-19. For example, Zhang et al. [31] examined the factors influencing the number of imported cases from Wuhan and the spread speed and pattern of the pandemic by combining national flight and high-speed rail data. Based on mobile phone and confirmed patient data, Jia et al. [32] developed a spatiotemporal “risk source” model to determine the geographic distribution and growth pattern of COVID-19 and quickly as well as accurately assess the related risk. Zhang et al. [33] used the GeoDetector and the decision tree model to identify the main factors in low-risk and high-risk areas by combining multi-source data. Loske [34] explored the relationship between COVID-19 spread and transportation volume in food retail logistics by combining transport volume data and confirmed patient data. Zhang et al. [35] measured imported case risk of COVID-19 from inbound international flights by combining both daily dynamic international air connectivity data and the updated global COVID-19 data.

However, the above studies are mostly based on patient confirmed data. The spatiotemporal distributions of COVID-19 in other groups are rarely explored. To fill the research gap, spatiotemporal characteristics and differences between healthcare worker infections and patient infections were analyzed from the perspectives of Wuhan, Hubei (outside Wuhan), and China (outside Hubei).

III. STUDY AREA AND DATA SOURCES

A. Study Area

As of July 2020, the total number of locally confirmed COVID-19 cases in China had exceeded 80,000. Of these cases, 68,135 were confirmed in Hubei Province, among which 50,340 were confirmed in Wuhan, accounting for 81.5% and 60.80% of the country’s infected cases, respectively. To study the temporal and spatial spread of COVID-19 in China, the study area was divided into three parts: Wuhan City, Hubei Province (except Wuhan), and the rest of China. As shown in Figure 1, Hubei Province is located in the central region of China, and Wuhan City is located in the central region of Hubei Province.

B. Data Sources and Data Preprocessing

1) Data Sources: The data used in this study were divided into two categories: Confirmed Patient Inventory and healthcare workers confirmed information. Confirmed Patient Inventory was mainly obtained from the National Health Commission of the People’s Republic of China (http://www.nhc.gov.cn/) and spanned the period from January 15, 2020, to June 28, 2020. The confirmed information on healthcare workers was obtained mainly from the Chinese Red Cross Foundation (https://www.crcf.org.cn/). The Chinese Red Cross Foundation distributes relief funds to every confirmed healthcare worker. As of July 31, 2020, 81 batches of confirmed healthcare workers had received foundation assistance. We first used Python language and web crawler technology to obtain 3,741 reports on confirmed healthcare workers from Chinese Red Cross Foundation and then the Baidu API for address matching. After matching their address, details of the province, city, and
county of each confirmed healthcare worker were obtained. The data format is shown in Table 1. Each record shows the confirmed time, province, city, and county of each confirmed healthcare worker.

2) Data Preprocessing: The Confirmed Patient Inventory is collected and processed by a team at China Data Center and shared on the dataverse platform of Harvard University [27], [36]. Therefore, the Confirmed Patient Inventory does not require additional data preprocessing. In this study, we mainly conducted data preprocessing for confirmed case information of healthcare workers.

The confirmed information of healthcare workers is mainly reported to the China Red Cross Foundation in two ways [37]: (1) the confirmed information on healthcare workers is directly reported by individuals to the Red Cross Foundation of China, and (2) the confirmed information on healthcare workers is collected by their respective hospitals that then report to the Red Cross Foundation of China. First, after examination and approval by the Red Cross Foundation of China, the rescue information is published on the website, after which the hospital may review it. Those who fail to pass the review do not qualify to be rescued. Therefore, data records of unqualified persons should be deleted from the original data. Second, the Chinese Red Cross Foundation not only rescued the infected healthcare worker but also the infected or diseased staff during the epidemic, and such data records need be deleted. As shown in Figure 2, after data preprocessing, the data of a total of 3,701 confirmed healthcare workers remained, including 3,667 from Hubei Province and 3,060 from Wuhan City.
IV. METHODS

The overall framework of the study is shown in Figure 3. First, the confirmed healthcare worker inventories in China, Hubei, and Wuhan, which recorded a high number of confirmed healthcare workers each day, were constructed. Second, based on the confirmed healthcare worker inventory, relevant statistical indicators such as mean, variance, change speed (rise period and decline period), and inflection point were used to analyze the time spread characteristics of healthcare worker infection and patient infection; we used the Pearson correlation coefficient to calculate the time correlation between healthcare worker infection and patient infection. Finally, the thematic map method was used to analyze the spatial spread characteristics of infections among healthcare workers and patients. We also calculated the spatial correlation between healthcare worker infection and patient infection.

A. Construction of Confirmed Healthcare Worker Inventory

The confirmed healthcare worker data collected using the crawler record the basic information of the confirmed healthcare workers but cannot visually display the temporal and spatial distribution and spread of the confirmed healthcare worker’s infection. Therefore, based on the modeling idea of “province - city - county,” this study constructed Confirmed Healthcare Worker Inventories.
based on Partition Statistics from three perspectives: China, Hubei, and Wuhan. The Confirmed Healthcare Worker Inventory of China records the number of confirmed healthcare worker infections every day in each province of China, the Confirmed Healthcare Worker Inventory of Hubei records the number of confirmed healthcare worker infections every day in each city of Hubei Province, and the Confirmed Healthcare Worker Inventory of Wuhan records the number of confirmed healthcare worker infections every day in each county of Wuhan City. For example, the calculation method for the number of confirmed healthcare worker infections on day \( t_0 \) in Hongshan, Wuhan City, is shown in Equation (1).

\[
\text{Inventory}_{Wuhan,Hongshan}^{Wuhan,Hongshan} = \sum_{i=1}^{N} \{\text{cms}_i \in \text{Hongshan} \land \text{cms}_i,\text{Date} = t_0\}
\]

where \( N \) is the total number of confirmed healthcare worker infections in China; \( \text{cms}_i \) represents the information of a specifically confirmed healthcare worker; Hongshan is a county of Wuhan City; \( \text{Inventory}_{Wuhan}^{Wuhan} \) represents the Confirmed Healthcare Worker Inventory from the perspective of Wuhan, which describes in detail the changes in confirmed healthcare worker infections in every county of Wuhan over time. The corresponding Confirmed Healthcare Worker Inventory in China and Hubei can be expressed as \( \text{Inventory}_{China}^{China} \) and \( \text{Inventory}_{Hubei}^{Hubei} \), respectively. Table 2 shows the specific contents of the Confirmed Healthcare Worker Inventory in Wuhan.

B. Temporal and Spatial Characteristics Index

The Confirmed Healthcare Worker Inventory and the Confirmed Patient Inventory are essentially a collection of time series that contain spatial location information. Therefore, we further analyzed the temporal and spatial distribution characteristics of healthcare worker infections and patient infections.

In terms of temporal characteristics, we first calculated the changes in the number of healthcare worker infections and patient infections in China (outside Hubei), Hubei (outside Wuhan), and Wuhan based on the Confirmed Healthcare Worker Inventory and the Confirmed Patient Inventory in China, Hubei, and Wuhan. The calculation results are shown in Tables 3 and 4, respectively. Then, based on the calculated results, we used eight indicators, namely, mean, standard variance, peak, rising period, rising rate, falling period, falling rate, and inflection point, to study the time spread characteristics of healthcare worker infection and patient infection.

In terms of spatial characteristics, we divided the Confirmed Healthcare Worker Inventory and the Confirmed Patient Inventory based on time and used thematic maps to show the spatial distribution characteristics of healthcare worker infection and patient infection at each time node from China, Hubei, and Wuhan.

We determined the spatiotemporal differences between infections in healthcare workers and patients by assessing the differences in indices. A relatively small difference in indices is indicative of a relatively small spatiotemporal difference between infections in healthcare workers and patients, and vice versa.

C. Pearson Correlation Coefficient

The Pearson correlation coefficient was calculated to quantitatively measure the spatiotemporal correlation between healthcare worker infections and patient infections, i.e., the difference in space and time between healthcare worker infections and patient infections.
infections. The Pearson correlation coefficient is a statistic that measures the degree of linear correlation between two random variables. It is defined as the quotient of covariance and standard deviation between two random variables. The calculation method is shown in equation (2).

\[
\begin{align*}
    r &= \frac{\text{Cov}(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}} \\
    \text{Cov}(X,Y) &= E((X - EX)(Y - EY))
\end{align*}
\]

where \( \text{Cov}(X,Y) \) is the covariance of random variables \( X \) and \( Y \), \( E(X) \) is the mean value of the random variable \( X \), \( D(X) \) is the variance of the random variable \( X \), and \( \sqrt{D(X)} \) is the standard deviation of the random variable \( X \). The value range of correlation coefficient \( r \) is \([-1, 1]\). When \( r > 0 \), the random variables \( X \) and \( Y \) are positively correlated; when \( r = 0 \), the random variables \( X \) and \( Y \) are not correlated; and when \( r < 0 \), the random variables \( X \) and \( Y \) are negatively correlated. To measure the time correlation between healthcare worker infections and patient infections, \( X \) and \( Y \), respectively, represent the time series of healthcare worker infections and patient infections in the same study object. Similarly, to measure the spatial correlation between healthcare workers and patients, \( X \) and \( Y \), respectively, represent the number of healthcare worker infections and patient infections in multiple regions at a specific time. A strong positive correlation between two random variables is indicative of a relatively small spatiotemporal difference between infections in healthcare workers and patients, and vice versa.

V. Experimental Results and Analysis

A. Temporal Differences between Healthcare Worker and Patient Infections

In this paper, the statistical graph was first used to qualitatively describe the changes in the number of daily healthcare worker infections and patient infections over time. To make the curve smoother, we used the moving average method to smooth the curve using a time window of seven days. The results are shown in Figure 4. Overall, the curves of daily confirmed healthcare worker and daily confirmed patient in China (except Hubei), Hubei Province (except Wuhan), and Wuhan City all initially show a rising trend followed by a falling one. At the same time, the peaks of infections in China (except Wuhan), Hubei (except Wuhan), and Wuhan have successively decreased. However, the curves of confirmed healthcare workers and confirmed patients were significantly different over time. For example, Figure 4(a) shows the onset of infection in healthcare workers, while it was absent in patients during the first week. There are two main reasons for this difference. First, the statistical approaches of the two data sources are different, which leads to the difference between the data. Second, more importantly, data of healthcare worker infections were retrospective, while patient confirmed data were reported in real time. In the early stage of the epidemic, due to the lack of a clear understanding of SARS-CoV-2, some people could only be regarded as suspected cases, rather than confirmed cases.

In addition, there were also significant differences in the statistical characteristics of the curves for healthcare worker infection and patient infection. The differences are shown in Table 5. Mean time of onset of infection for healthcare workers in Wuhan, Hubei (except Wuhan), and China (except Hubei) was January 27, February 1, and February 2, 2020, while that for patients was February 8, February 2, and January 31, 2020, the differences being 12, 1, and 2 days, respectively. The standard deviation values of infection onset time for healthcare workers in Wuhan, Hubei (except Wuhan), and China (except Hubei) were 9, 10, and 6 days, while those for patients were 7, 7, and 6 days, the difference being 2, 3, and 0 days, respectively. The inflection points of the infection time for healthcare workers in Wuhan, Hubei (except Wuhan), and China (except Hubei) were January 22, January 29, and January 30, 2020, while the inflection points of the infection time for patients were February 12, February 1, and January 31, 2020, the differences between the above infection times being 21, 2, and 1 days, respectively. From the peak of peak, rising rate, and falling rate, the peak and rate for healthcare worker infection and patient infection in Wuhan, Hubei (except Wuhan), and China (except Hubei) gradually decreased. The rising period for healthcare worker infection in Wuhan, Hubei (except Wuhan), and China (except Hubei) lasted for 15, 19, and 12 days, and the falling period lasted for 34, 27, and 19 days, respectively. However, the rising period for patient infection in Wuhan, Hubei (except Wuhan), and China (except Hubei) lasted for 23, 14, and 10 days, and the falling period lasted for 20, 22, and 19 days, respectively. The differences between the rising periods were 8, 5, and 2 days, and the differences between the falling periods were 14 days, 5 days, and 0 days, respectively. Finally, the Pearson correlation coefficient was used to measure the temporal correlation between healthcare worker infections and patient infections, the results are shown in Figure 5. The correlation coefficient \( r \) values for Wuhan, Hubei (except Wuhan), and China (except Hubei) were 0.26, 0.852, and 0.95, respectively, which confirms the temporal difference between healthcare worker infections and patient infections.

In general, the phenomenon of healthcare worker infection is contained earlier and faster. The temporal difference in Wuhan was greater than that in Hubei (except Wuhan), and the temporal difference in Hubei (excluding Wuhan) was greater than that in China (except Hubei). Combined with the time of epidemic occurrence in different regions, the temporal difference in the early phase was greater than that in the later phase, and the temporal difference in the early-onset region is greater than that in the later-onset region.
### Table 1: Comparison of Healthcare Worker and Patient Infection Characteristics

| Index          | Healthcare Worker | Patient |
|----------------|-------------------|---------|
| **Mean**       | Wuhan             | Jan 27  |
|                | Hubei (outside Wuhan) | Feb 1   |
|                | China (outside Wuhan) | Feb 2   |
|                | Wuhan             | Jan 31  |
| **Standard deviation** | Wuhan             | 9 days  |
|                | Hubei (outside Wuhan) | 10 days |
|                | China (outside Wuhan) | 6 days  |
| **Infection point** | Wuhan             | Jan 22  |
|                | Hubei (outside Wuhan) | Jan 29  |
|                | China (outside Wuhan) | Jan 30  |
|                | Wuhan             | 128     |
|                | Hubei (outside Wuhan) | 25      |
|                | China (outside Wuhan) | 3       |
| **Peak**       | Wuhan             | 3550    |
|                | China (outside Wuhan) | 1058   |
| **Rising period** | Wuhan             | 15 days |
|                | Hubei (outside Wuhan) | 19 days |
|                | China (outside Wuhan) | 12 days |
| **Rising rate** | Wuhan             | 64      |
|                | Hubei (outside Wuhan) | 12      |
|                | China (outside Wuhan) | 4      |
| **Falling rate** | Wuhan             | 34 days |
|                | Hubei (outside Wuhan) | 27 days |
|                | China (outside Wuhan) | 19 days |

### B. Spatial Differences between Healthcare Worker Infection and Patient Infection

The spread of COVID-19 in space is a dynamic process. To further compare the spatial distribution characteristics and differences between healthcare worker infection and patient infection, we first qualitatively analyzed medical care infection and patient infection at each time node at a time interval of 10 days. We first analyzed the spatial distribution characteristics of healthcare worker infection and patient infection at each time node with a time interval of 10 days and then quantitatively determined the spatial correlation between healthcare worker infection and patient infection at each time node.

1) **Spatial Characteristics of Healthcare Worker Infection:** As shown in Figure 4, the healthcare worker infection mainly occurred within the period from mid-January to mid-February 2020. Therefore, the period from January 7, 2020, to February 16, 2020, was selected as the research interval in this section. Figure 6 shows the spatial distribution of healthcare worker infection in China, Hubei, and Wuhan at 10-day intervals.

In the early stage of the epidemic, healthcare worker infection first occurred in Hubei, and then the phenomenon of healthcare worker infection gradually spread outwards through Hubei Province. As of February 6, 2020, the number of healthcare worker infection in different provinces of China significantly differed. Generally, the provinces with severe healthcare worker infection in China are mainly located in the southeast coastal areas of China, and these provinces are close to Hubei Province and have better economic development. The provinces with relatively mild healthcare worker infection are mainly located in northwestern China, and these provinces are far from Hubei and economically underdeveloped.

In the early stage of the epidemic, the healthcare worker infection first occurred in Wuhan and Huanggang and then spread across, with mainly Wuhan and Huanggang as the center. As of January 27, 2020, most of the cities in Hubei Province have had different degrees of healthcare worker infection, among which Wuhan and Huanggang had more serious cases. Generally,
cities with more severe healthcare worker infections are mainly concentrated in the eastern part of Hubei province, while the cities with fewer healthcare worker infections are mainly concentrated in the western part of Hubei Province.

During the early stage of the epidemic in Wuhan, healthcare worker infection first occurred in Wuhan Jianghan District and Jiangan District and then spread to the adjacent two districts. As of February 06, 2020, all districts in Wuhan had different degrees of healthcare worker infection, among which the districts with more severe healthcare worker infections mainly occurred in the central district of Wuhan, such as Jianghan and Wuchang, where the number of healthcare worker infection exceeded 500. The districts with mild healthcare worker infections were mainly located in Jiangxia and Huangpo outside Wuhan, but there were still more than 10 cases of healthcare worker infections. In general, healthcare worker infections in Wuhan were severe.

2) Spatial Characteristics of Patient Infection: As a comparison with the spatial distribution characteristics of healthcare infection, we show the spatial distribution characteristics of patient infection during the same period. As it is difficult to obtain data on patient infections at the county level in Wuhan from mid-January to mid-February, we show the spatial distribution characteristics of patient infection only at the scale of China and Hubei province. The results are shown in Figure 7.

In China, the first case of infection in a patient was reported in Hubei Province and then spread outward through Hubei Province. As of February 06, 2020, the number of patient infections in different provinces of China was significantly different. Compared with healthcare worker infections, in addition to the difference in the number of infections, there are also certain differences in the spatial distribution of infection. For example, the patient infections in Guangdong and Zhejiang are relatively serious, but the healthcare infection in the two provinces are relatively mild. This may be attributable to the differences in the epidemic prevention strategies of different provinces. For example, Guangdong Province acquired relatively more valuable experience during the SARS outbreak and thus managed to swiftly protect healthcare workers.

In Hubei, the first case of infection in a patient was reported in Wuhan City and then spread outward throughout Wuhan City. As of February 06, 2020, the difference between infection distribution was relatively small except for the large difference in the number of infections. In other words, cities with relatively more severe patient infections have relatively more severe healthcare infections, and cities with less patient infections have less healthcare infections.

To further quantitatively measure the degree of correlation between healthcare worker infection and patient infections, we analyzed the spatial correlation between healthcare worker and patient infections, and the results are shown in Table 7. The correlation coefficients, r, for China (except Hubei) on January 27, February 06, and February 16 were 0.132, 0.135, and 0.252 respectively, indicating that the spatial distribution of healthcare worker and patient infection in China (except Hubei) is quite different. The correlation coefficients, r, for Hubei (except Wuhan) on January 27, February 06, and February 16 were 0.845, 0.816, and 0.859, respectively, which indicated that the spatial distribution difference between healthcare worker infection and patient infection in Hubei (except Wuhan) was small.

In general, healthcare worker infection and patient infection in China spread mainly throughout Hubei as the center. Healthcare worker infection and patient infection in Hubei spread mainly throughout Wuhan and Huanggang as the center. Healthcare worker infection and patient infections in Wuhan spread mainly throughout Jianghan and Jianan as the center. In addition, spatial distributions of healthcare worker infection and patient infection also differed from different perspectives. Furthermore, in addition to the differences in the number of healthcare worker and patient infection, spatial distribution was different to some extent. Among them, the spatial distribution difference in Hubei (except Wuhan) was greater than that in China (except Hubei), that is, the difference in the late stage was greater than that in the early stage; the difference in late-onset regions was greater than that in the early-onset regions.
VI. DISCUSSIONS AND CONCLUSION

At present, COVID-19 is still a pandemic. As specific vaccines and fundamental treatments take a long time, relevant measures such as self-isolation, restriction of crowd activities and gathering, and wearing of masks have become important emergency containment measures. To accurately formulate epidemic containment policies, it is important to study the temporal and spatial spread of COVID-19 in social groups.

This study analyzed the temporal and spatial spread characteristics and differences of COVID-19 among patients and healthcare workers from three perspectives: China (outside Hubei), Hubei (outside Wuhan), and Wuhan.

In terms of temporal characteristics, healthcare worker and patient infections in Wuhan, Hubei (outside Wuhan), and China (outside Hubei) initially tended to increase and then decrease, and the peak value of infection gradually decreased. However,
there are great differences between the two curves. For example, the correlation coefficients, r, between healthcare worker and patient infections for Wuhan, Hubei (outside Wuhan), and China (outside Hubei) were 0.26, 0.852, and 0.95, respectively. In other words, the temporal difference between healthcare worker and patient infections is relatively large in Wuhan, whereas it decreases successively in Hubei (outside Wuhan) and China (outside Hubei). Combined with the time of the occurrence of the epidemic in different regions, the temporal difference in the early stage is greater than that in the later stage between healthcare

| Index       | China (outside Hubei) | Hubei (outside Wuhan) |
|-------------|-----------------------|-----------------------|
| 2020-01-27  | r = 0.132             | r = 0.845             |
| 2020-02-06  | r = 0.159             | r = 0.816             |
| 2020-02-16  | r = 0.252             | r = 0.859             |
worker and patient infections, and the temporal difference in the early-onset region is greater than that in the late-onset region. Through temporal difference, different policies can be formulated for different social groups through the following aspects. For example, it is very important to strengthen the protective measures for healthcare workers in the early stage of the epidemic. Because the healthcare workers work in a relatively closed space, the battle is on the frontline of the epidemic. Even if the number of patients infected is small, it can still result in a large number of infections among healthcare workers. In addition, we also can use the temporal difference to predict the peak time of infection in patients [38].

In terms of spatial characteristics, healthcare worker infection and patient infection in China spread mainly throughout Hubei as the center. Healthcare worker infection and patient infection in Hubei spread mainly throughout Wuhan and Huanggang as the center. Healthcare worker infection and patient infections in Wuhan spread mainly throughout Jianghan and Jiangan as the center. In addition, spatial distributions of healthcare worker infection and patient infection also differed from different perspectives. For example, on January 27, February 06, and February 16, 2020, the correlation coefficients, r, between healthcare worker infection and patient infection for China (outside Hubei) were 0.132, 0.135, and 0.252, respectively. The correlation coefficients, r, between healthcare worker infection and patient infection in Hubei (outside Wuhan) were 0.845, 0.816, and 0.859, respectively. Combined with the time of epidemic occurrence in different regions, the spatial difference between healthcare worker infection and patient infections in the early stage was less than that in the later stage, and the spatial difference in the early-onset region is less than that in the late-onset region between healthcare worker infection and patient infection. The results of this study offer significant guidelines for the epidemic containment departments to accurately formulate different epidemic containment policies for different social groups. Through spatial correlation, we can use the spatial distribution of healthcare worker infection to infer the spatial distribution of patient infection in the early stage of the epidemic.

The limitations of this study are as follows: (1) the coverage of healthcare worker infection data was narrow, and this study only examined the temporal and spatial distribution and differences between healthcare worker and patient infections in China. Due to the difficulty in obtaining data on healthcare worker infection in other countries, the temporal and spatial distributions and differences in other countries were not compared and analyzed. (2) The infection data of healthcare workers were not comprehensive. As the information on healthcare worker infections is published on the official website of the Red Cross Foundation in batches, the information may continue to be published in the future; thus, this study may have missing information. (3) In terms of spatial distribution, it is difficult to obtain patient infection data at the county level in Wuhan for the same period. This study examined the spatial distributions and differences only in China (outside Hubei) and Hubei (outside Wuhan).

In response to the above problems, future study will focus on further collecting domestic and foreign healthcare worker and patient infection data to more accurately and comprehensively analyze the temporal and spatial distributions and differences between healthcare worker and patient infections.

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