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Article

Exploring the Spatiotemporal Characteristics of COVID-19 Infections among Healthcare Workers: A Multi-Scale Perspective

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Abstract: The outbreak of COVID-19 has constantly exposed health care workers (HCWs) around the world to a high risk of infection. To more accurately discover the infection differences among high-risk occupations and institutions, Hubei Province was taken as an example to explore the spatiotemporal characteristics of HCWs at different scales by employing the chi-square test and fitting distribution. The results indicate (1) the units around the epicenter of the epidemic present lognormal distribution, and the periphery is Poisson distribution. There is a clear dividing line between lognormal and Poisson distribution in terms of the number of HCWs infections. (2) The infection rates of different types of HCWs at multiple geospatial scales are significantly different, caused by the spatial heterogeneity of the number of HCWs. (3) With the increase of HCWs infection rate, the infection difference among various HCWs also gradually increases and the infection difference becomes more evident on a larger scale. The analysis of the multi-scale infection rate and statistical distribution characteristics of HCWs can help government departments rationally allocate the number of HCWs and personal protective equipment to achieve distribution on demand, thereby reducing the mental and physical pressure and infection rate of HCWs.

Keywords: COVID-19; spatiotemporal distribution; healthcare worker infection; multi-scale perspective

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1. Introduction

By May 2021, there have been more than 160.81 million COVID-19 (Corona Virus Disease 2019) confirmed cases and over 3.33 million deaths all over the world (https://covid19.who.int/) accessed on 20 August 2021. The outbreak and spread of COVID-19 have posed an enormous challenge to the healthcare systems of each country. In the process of epidemic control, Healthcare Workers (HCWs) face a high risk of infection. While helping patients fight against the virus, HCWs also expose themselves to a high concentration of the virus at close range [1]. Therefore, how to better protect HCWs from virus infection is one of the most concerned issues in the world.

Studies have shown that nearly 14% of COVID-19 infections come from HCWs, with some countries reporting up to 35%, although HCWs do not make up a significant proportion of the population in most countries and regions (https://www.who.int/news/item/17-09-2020-keep-health-workers-safe-to-keep-patients-safe-who) accessed on 20 August 2021. In addition to the risk of long-term exposure to the virus, HCWs worldwide also have serious psychological problems, such as anxiety, depression, or suicidal tendencies [2]. To deal with the phenomenon of health care infection and alleviate the work pressure, researchers worldwide have carried out related studies from multiple fields. For example, from the perspective of epidemiology, relevant researchers explored the law of the spread of the virus in the outbreak process by examining whether the serological test was positive to determine the individuals with the highest risk in the medical institutions with the highest exposure, and further analyze the statistical characteristics of the infection and transmission of HCWs [3–5]. Some studies analyzed effective protective measures and resource allocation for COVID-19 from the perspective of medical resources, such as personal protective equipment (PPE) [6–8]. From a sociological perspective, other studies have shown significant differences in the degree of COVID-19 infection and mortality among people of different age structures. The hospitalization rate, intensive care rate, and mortality rate all increase with the age of patients, with the highest number of deaths among HCWs around 60 years old [9–11]. In addition, studying the spatial and temporal pattern of infection among HCWs from the perspective of geography, it is significant for relevant departments to formulate epidemic prevention and control policies, so some researchers studied the distribution and pattern of HCWs infection during COVID-19. Peixiao Wang et al. assessed the temporal and spatial characteristics and differences of HCWs infection. They pointed out that the spatial distribution of early epidemics can be inferred through the spatial distribution of infection among HCWs, which can provide relevant references for epidemic prevention and control [12]. Lichun Zheng et al. made the first in-depth analysis of the infection status of HCWs in Wuhan during the COVID-19 outbreak in Wuhan. They showed the infection rate of HCWs was higher than that of non-medical care workers, but the fatality rate was lower than that of non-medical care workers [13]. Paolo Bofetta used multiple logistic regression to analyze of 10,654 HCWs in Italy and map visualization of different cumulative infection rates. The results showed that the infection rate of HCWs ranged from 3.0% to 22.0% at 95% confidence intervals and was closely related to the region [14]. Although the above studies have analyzed the phenomenon of HCW infection from multiple fields, there are still some shortcomings. First, geographical phenomena are changeable, and the information presented at different scales is not consistent [15]. However, most of the above studies were carried out on a single scale without considering the influence of multi-scale effects on the conclusions [16]. Second, due to the lack of HCWs distribution data set at fine scale, most existing studies are based on the number of HCWs infections rather than the infection rate [17,18], which ignores the differences in the spatial distribution of HCWs.

To more accurately focus on the spread of the virus from the perspective of space-time, this paper takes HCW infection in Hubei as an example to study the spatiotemporal characteristics from a multi-scale perspective that includes three professions (doctor, nurse, and other staff) and three institutions (general, special, and grassroots hospital) by distribution fitting and chi-square test methods. Hubei has contributed to supporting the global fight against the epidemic as the first province in China to detect and contain the outbreak. This work takes Hubei Province as an example to reveal the fitted distribution of infections among HCWs. The results will help the relevant departments of other countries in the outbreak stage to learn from relevant experience and control the development of the epidemic in the same way. It is of practical significance to use the infection status of local HCWs of different occupations to estimate the spread of the epidemic and rationally allocate protective measures to HCWs of diverse occupations and various types of hospitals. We explore the infection differences among high-risk HCWs and the statistical fitting distribution, then provide some references for grid resource management and epidemic control.

The main contributions of this paper are as follows.

(1) Taking into account the spatial heterogeneity of the HCWs number, the infection rate rather than the number of infections was used to explore the impact of multi-scale effects on the infection of HCWs in different occupations and diverse types of hospitals.

(2) From a multi-scale perspective, we explored the effect of scale validity on the conclusion that the evolution distribution of HCWs infections in the worst-hit and surrounding areas over time.

(3) A detailed data list about the infection rate of HCWs is provided, which ensures the reproducibility of this study and provides a macro to micro reference on the HCWs infection for decision analysis departments.

2. Study Areas and Data Sources

2.1. Study Areas

Hubei Province is the first province in China to find novel coronavirus and the province with the most severe infection among HCWs in China. Since the epidemic outbreak, 3634 HCWs have been infected in the area, accounting for 98.163% of the total number in China. Therefore, it is of great significance to take Hubei Province as the research area. As shown in Figure 1, this paper mainly analyzes HCWs' infections in Hubei from four scales: provincial, municipal, county, and grid scales. In terms of grid-scale, Hubei is divided into 85 × 156 units.

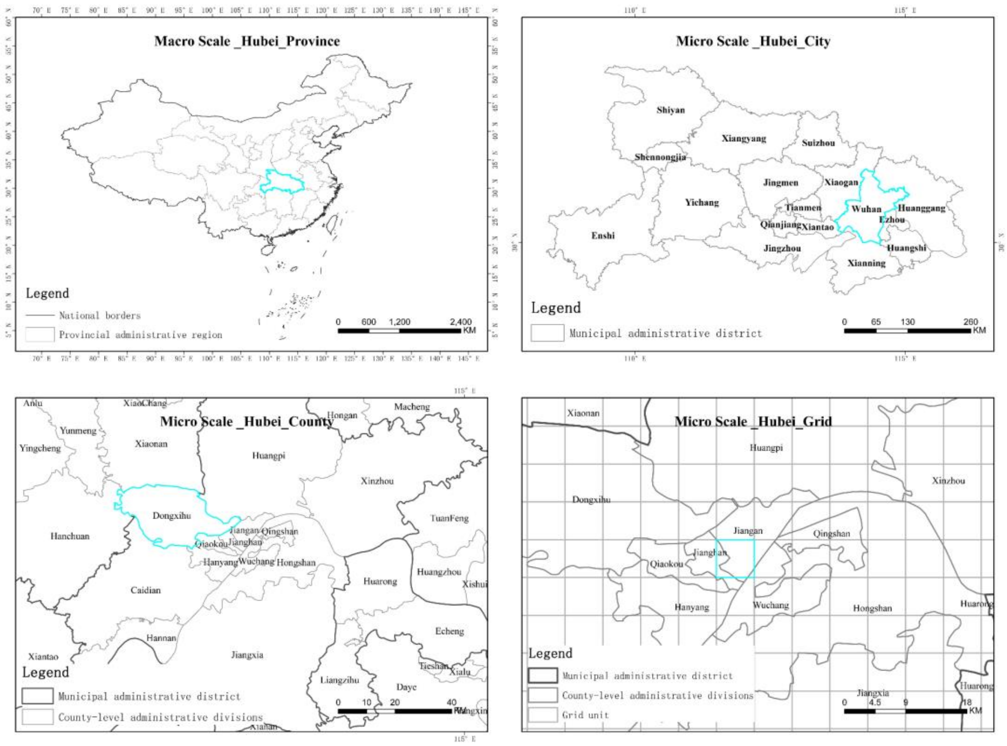

Figure 1. Survey map of the study area.

2.2. Data Acquisition and Data Preprocessing

2.2.1. Data Sources

The data used in this paper mainly consist of two parts: One part is the data of medical institutions information in Hubei Province, and the other part is the confirmed infection case data of HCWs in Hubei Province.

The data of medical institutions in Hubei Province are mainly from Hubei Provincial Health Commission (http://wjw.hubei.gov.cn/) accessed on 20 August 2021. This paper searches the medical institutions in Hubei using web crawler and analyzes the returned data to obtain the relevant information of medical institutions. Then, a total of 1939 pieces of medical institution information are received, whose format is shown in Table 1. Each record contains the unique identification of the medical facility, name, address, number of doctors, nurses, and other staff. The types of hospitals mainly include grassroots hospitals, specialized hospitals, and general hospitals.

Table 1. Dataset about hospital information.

Hospital Id	Hospital Name	Address	No. of Doctor	No. of Nurse	No. of Other Staff
1	***	***	154	165	220
2	***	***	16	3	24
3	***	***	75	52	66
……	……	……	……	……	……
1939	***	***	25	20	27

*** means the content is omitted.

The data of confirmed medical care in Hubei Province come from the Red Cross Foundation website of China (https://www.crcf.org.cn/) accessed on 20 August 2021, which has provided humanitarian assistance funds for 3735 health care workers infected or sacrificed by COVID-19 by the end of May 2021. This paper uses web crawler technology to obtain the data of all 3702 infection cases in the early epidemic. As shown in Table 2, each record contains the diagnosis time, province, city, hospital name, type of care, and other information of the confirmed HCWs.

Table 2. Dataset about confirmed healthcare workers.

User Id	Date	Province	City	Hospital Name	Type
1	20 January 2020	Hubei	Wuhan	***	Doctor
2	15 January 2020	Hubei	Jingmen	***	Nurse
3	4 February 2020	Shandong	Qingdao	***	Other staff
……	……	……	……	……	
3702	11 February 2020	Beijing	Beijing	***	Nurse

*** means the content is omitted.

2.2.2. Data Preprocessing

The names of institutions and descriptive addresses in the original confirmed data of medical institutions and HCWs obtained in this paper lack clear geographic information and are difficult to directly match with geographic maps. Therefore, data preprocessing is required. The preprocessing process is divided into three steps:

(1) Collected medical institutions and HCWs data are cleaned, then the medical institutions and confirmed medical information in Hubei Province are screened out.

(2) Name and address of the hospital are used to match the province, city, district, and specific latitude and longitude information of the medical institution by calling the AutoNavi Map API; similarly, the coordinate matching of the medical diagnosis data is performed.

(3) Match the coordinates of the obtained medical institutions and medical diagnosis cases according to the relationship of geographic coordinates. The intersection was acquired with the geographic base map at the scale of city, county, and grid, respectively, so as to obtain the information of medical institutions and the number of medical infections in different scale units. We then realize the spatial association of medical institutions, medical personnel, and geographical map.

3. Methods

The main research objective of this paper is to analyze whether scale effectiveness has an impact on the conclusion of medical care infection from the perspective of multi-scale and to analyze the differences and spatial distribution of HCWs infection among doctors, nurses and other staff, general hospitals, specialized hospitals, and grassroots hospitals. The overall framework, as shown in Figure 2, first collects and performs data preprocessing to build a tabulation of medical infections. Then, conducted multiple-scale analysis macroscopically analyzed the infection rate and spatiotemporal characteristics of the overall HCWs in Hubei Province. Finally, the statistics and chi-square test of medical infection rate within the same unit were conducted on three scales: municipal level, county level, and grid net, and the spatial distribution of infection rate (quantity) was explored.

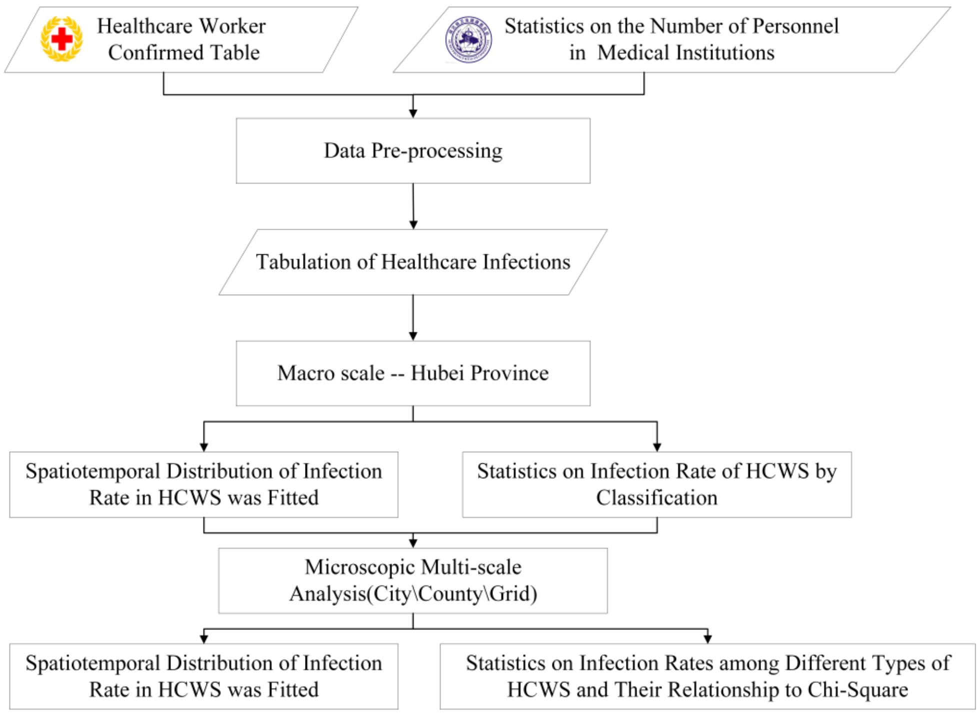

Figure 2. Research flow chart.

3.1. Generation of HCWs Infection Rate Tabulation

In order to analyze the situation of HCWs infections more accurately and finely, we referred to the method of Wang et al. of using HCWs confirmed data to estimate infections to obtain the number of HCWs infections [18]. Then, considering the spatial heterogeneity of the number of medical care, this article proposes the Daily Health Care Infection Rate (dCIR), which is defined as the ratio of the number of daily infected care within the study scale unit to the total number of HCWs within the area during the COVID-19 period:

$$dCIR_{(i,j)} = \frac{dM_{(i,j)}}{N_j}(i = 1,2,3\cdots, \ j = 1,2,3\cdots)(\%) \tag{1}$$

where N_j is the total number of HCWs in unit j of the research scale, $dM_{(i,j)}$ is the total number of infected HCWs in unit j on the i day of the outbreak, and $dM_{(i,j)}$ is calculated from the known confirmed medical cases.

The Cumulative Health Care Infection Rate (cCIR) is defined as the ratio of the cumulative number of infected HCWs to the total number of HCWs in the research scale unit during the COVID-19 period:

$$cCIR_{(i,j)} = \sum_{i=0}^{n} dCIR_{(i,j)} = \sum_{i=0}^{n} \frac{dM_{(i,j)}}{N_j}(i = 1,2,3,\cdots,n, j = 1,2,3,\cdots)(\%) \tag{2}$$

where N_j is the total number of HCWs in the research scale unit j, $dM_{(i,j)}$ is the total number of medical care infections in cell j on the i day of the outbreak, and n is the number of outbreak days until the cumulative date.

3.2. Statistical Distribution Function

Related research points out that when there are fewer HCWs infections, it can be considered Poisson distribution. When the frequency of infection is high, it can be regarded as an approximately normal distribution [19,20]. Therefore, this paper uses normal, lognormal, and Poisson distribution to describe the distribution characteristics of infected HCWs. The probability density functions of normal, lognormal, and Poisson distribution are shown in Equations (3)–(5), respectively.

$$\text{Normal}(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{(-\frac{(x-u)^2}{2\sigma^2})} \tag{3}$$

$$\text{Lognormal}(x) = \frac{1}{\sqrt{2\pi}\sigma_l} e^{(-\frac{(\ln x - u_l)^2}{2\sigma_l^2})} \tag{4}$$

$$\text{Passion}(X = k) = \frac{\lambda^k}{k!} e^{-\lambda}, k = 0, 1, \cdots \tag{5}$$

where u and σ are parameters in the normal distribution, u_l and σ_l are lognormal parameters, x is the HCWs infection rate, λ is the parameter in the Poisson distribution, and x is the number of health care infections. In the regression setting, the most commonly used measure is the mean squared error (MSE). In the process of function fitting, the mean square error (MSE) is used among different functions to select the best fitting curve [21]:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{f}(x_i) \right)^2 \tag{6}$$

where $\hat{f}(x_i)$ is the prediction that $\hat{f}$ gives for the ith observation. Here, $\hat{f}(x_i)$ we refer to the infection rate (number of infections) fitted by different models. The MSE will be small if the predicted responses are very close to the true responses.

3.3. Chi-Square Test

The Chi-square test is a widely used method of hypothesis testing for counting data. It mainly compares the rate of two or more samples (this paper specifically refers to the rate of HCWs infections) and the correlation analysis of two or more categorical variables [22].

$$\chi^2 = \sum \frac{(A - E)^2}{E} \tag{7}$$

Taking the infection of HCWs in different occupations as an example, A is the actual number of infections in three occupations, and E is the expected number of infections corresponding to different occupations. We use chi-square to test and analyze whether there is a difference among multiple infection rate variables, such as different types of HCWs and different hospital types. The more significant the chi-square result, the more significant the difference in infection rate of HCWs will be.

4. Result and Discussion

This section analyzes the HCWs' infection rate and distribution fitting from the multi-scale perspective of geographic space. The macro-scale takes Hubei Province as the basic research unit, and the micro-scale conducts comprehensive comparative analysis from three scales: city, county, and grid.

4.1. Analysis of Infection Status in HCWs at Provincial (Macro) Scale

4.1.1. Distribution Fitting Analysis

This subsection uses 1 January 2020 to 19 March 2020 as the research interval to explore the statistical distribution characteristics of HCWs infections from a macro perspective. Figure 3 shows the change of the infection rate of HCWs and the fitting results of normal, lognormal, and Poisson distribution. The change of medical infection rate in Hubei province can be divided into two stages. Before Wuhan City, Hubei Province adopted the lockdown measures on 23 January, the rate of HCWs infection increased. After Wuhan, Hubei officially implemented the lockdown measures on 23 January, an inflection point appeared in the fitted distribution curve. The city has been completely closed, and public transportation such as buses, subways, and airplanes have ceased operations. Relevant departments have improved the prevention and control strategies to deal with imported risks so that the spread of the epidemic can be effectively controlled. Factors such as medical assistance from other provinces have led to a decline in the infection rate. This work uses MSE as the criterion for judging whether the curve fits optimally. The results show that the lognormal fitting MSE is the smallest, which means that the HCWs infection rate obeys the lognormal distribution in time. This result is consistent with the conclusion of Wang et al. [12]. In addition, the result of Poisson distribution is highest, which indicates that the Poisson distribution model cannot fit the distribution of the overall infection rate in Hubei Province.

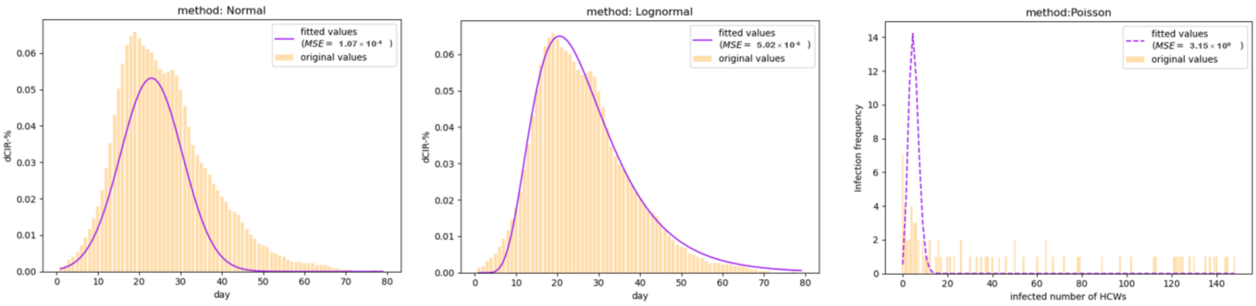

Figure 3. The time-fitting distribution of the infection rate/num of HCWs in Hubei Province.

4.1.2. Infection Rate and Chi-Square Analysis

Inspired by the ideas of Lichun Zheng et al., this section analyzes the differences of HCW infection among different professions and hospitals in Hubei Province. Table 3 summarizes the overall infection situation of different occupational health care and different types of hospitals on a macro scale. Table 4 shows the infection rate and death rate of HCWs and non- HCWs. The number of HCWs studied in this paper is 224,461. As of 19 March, a total of 3639 HCWs were infected, with an infection rate of 1.621%. The number of non-infected HCWs is calculated from the total population data of the Hubei Province Statistical Yearbook in 2020. We can see the infection rate of HCWs was higher than that of non-HCWs, but the death rate was lower than that of non-HCWs. In order to test the regularity of different types of HCWs infection rates and whether they are statistically significant, we use Chi-square to test the significance of bilateral values less than 0.05. The results show that the infection rate of nurses is higher than that of doctors. Although the number of infections in grassroots hospitals is more significant than that in specialized hospitals, the overall infection rate still follows the rule that general hospitals are higher than specialized than grassroots hospitals. Table 5 lists the results of the chi-square test for infection rate variables in this paper. The conclusions of Lichun Zheng et al. 's infection analysis on 2457 cases of confirmed medical data in Wuhan are consistent with the results of this analysis on a macro level [13]. Due to insufficient personal protective equipment and relatively long working hours of HCWs, reduced immunity has increased the risk of infection. Studies have shown that patients over the age of 65 have a higher mortality rate, their COVID-19 symptoms are more pronounced, and the proportion of intensive care during treatment is more elevated. Still, before the age of 60, the number of severe illnesses and deaths is minimal. However, in China, most in-service HCWs are under the age of 60, so the death rate of HCWs is lower than that of non-HCWs.

Table 3. Statistics of health care infection in Hubei province.

Type	Total	Infected	cCIR%	Type	Total	Infected	cCIR%
Nurse	62,989	1810	2.873	General	128,748	3140	2.439
Doctor	73,714	1203	1.632	Special	19,393	199	1.026
Other	87,758	626	0.713	Grassroots	76,320	300	0.393

Table 4. Comparison of Case Infection Rate and Case Death Rate Between HCWs and Non–HCWs in Hubei.

Parameters	HCWs	Non–HCWs
number of infected persons	3639	64,512
total people	224,461	592,475,539
Case Infection Rate (%)	1.621	0.109
number of deaths	34	4478
Case Death Rate (%)	0.934	6.941

Table 5. Chi-square test of infection rate variables in different types of medical care.

Type_Occupation	Chi-Square	*p*-Value	Type_Hospital	Chi-Square	*p*-Value
ALL	1035.369	0.000	ALL	1267.493	0.000
DN	232.203	0.000	GR	1181.95	0.000
DO	294.92	0.000	GS	147.458	0.000
NO	1038.557	0.000	SR	117.814	0.000

All is a chi-square test of infection rates between three occupations or three types of medical institutions. DN is a chi-square test of infection rates between doctor and nurse. DO is a chi-square test of infection rates between doctor and other staff. NO is a chi-square test of infection rates between nurse and other staff. GR is a chi-square test of infection rates between general hospital and grassroots hospital. GS is a chi-square test of infection rates between general hospital and special hospital. SR is a chi-square test of infection rates between special hospital and grassroots hospital.

4.2. Analysis of Infection Status in HCWs at Multi-Scale (Microcosmic)

The infection rates of different types of HCWs in the Hubei province have significant differences and regularities at the macro-scale. This subsection explores the regularities and spatial distribution characteristics of HCWs' infection rates at different scales (city, county, and grid levels).

4.2.1. Multi-Scale Distribution Fitting Analysis

In this subsection, the three scales of cities, counties, and grids are used as microscales to explore the spatial statistical distribution characteristics of HCWs infections from a multi-scale perspective. Figure 4 shows the distribution fitting of HCWs infections in each unit at the micro-scale. At the city scale, cities with Wuhan and Xiaogan as the center show a log-normal distribution, while in the more marginal cities of Hubei Province, the HCWs' infections show a Poisson distribution. At the county scale, central areas such as Qiaokou District, Hanyang District, and Qingshan District in the center of Hubei Province show a concentrated log-normal distribution, while the Poisson-distributed districts and counties are attached to the two sides of the log-normal distribution unit in an enveloping trend; In the same way, the grids in the center of Wuhan are mostly log-normal distributions, the surrounding extended grids are Poisson distributions, and most of the grid areas in the city center are log-normal distributions.

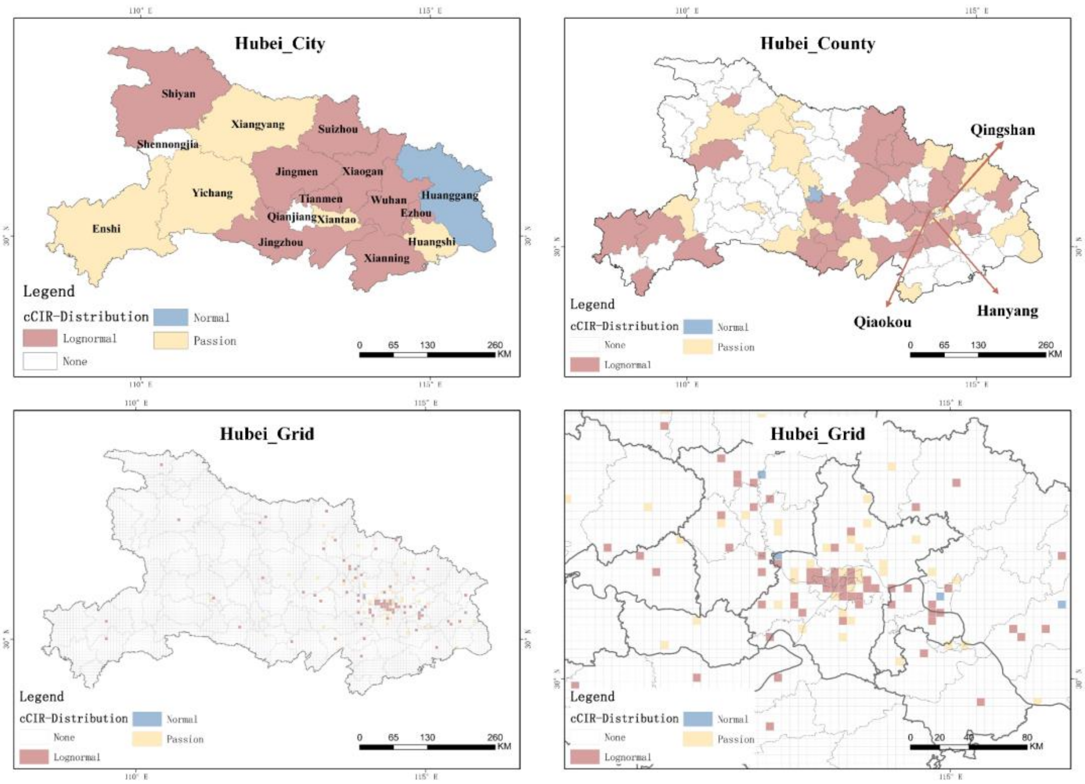

Figure 4. Fitting statistics of the spatial distribution of HCWs CIR at multiple scales.

It can be found from the curve fitted by the variation of the infection rate of HCWs over time that most of the research units at multiple scales are in line with the lognormal distribution, and the units in line with the lognormal distribution in space are clustered in the epicenter of the epidemic and radiate in the form of stars. However, Poisson distribution elements surround the lognormal elements, forming the overall situation that Poisson distribution elements surround lognormal distribution elements. The results show that the change of the HCWs infection rate over time is a skewed distribution, but this skewed distribution is not continuous in the entire space. In the process of spreading from the epicenter to the periphery, the law of this skewed distribution gradually evolved into Poisson distribution. That is, HCWs infection has steadily become a random and independent event. In addition to the lockdown of Wuhan, on 24 January, Hubei Ezhou, Huanggang, Xiantao, Qianjiang, Xianning, Huangshi, Enshi, and other places adopted traffic control measures to control the development of the epidemic, forming a pattern with Wuhan and surrounding areas as the epicenter of the epidemic.

At the micro-scale, the distribution of HCWs infections over time presents a log-normal distribution in the region with a severe outbreak. The log-normal region surrounds the Poisson distribution units. This paper further adopts quantitative analysis to explore the rationality of the distribution law. To better display the results, the semi-logarithmic coordinate system is used for display, and the number of HCWs infections on the y-axis is logarithmic. Figure 5 shows the scatter plot of the number of HCWs infections corresponding to the three distribution types of log-normal, Poisson, and normal distributions in different scale units. It can be seen that at different scales, the units that obey the lognormal distribution and the Poisson distribution have a significant dividing line in the number of infections. Among them, in the log-normal distribution label, the scattered points below the dividing line are Xianning City and Shiyan City. Their number of infections are 1 and 2, respectively, and the model fitting error term causes the result to be a log-normal distribution. Similarly, this model fitting error exists in both the county and grid scale, which is ignored in this paper.

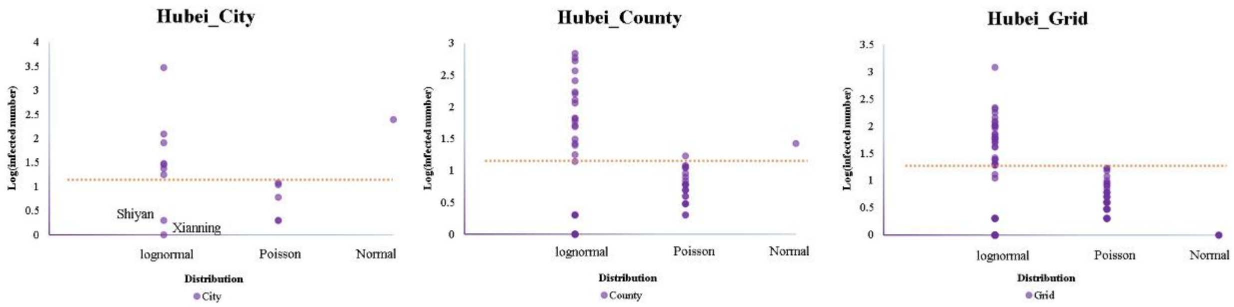

Figure 5. Scatter diagram of the number and distribution of medical infections.

Results show that the distribution of medical infection is associated with the severity of infection. When the number of infected HCWs is small, HCWs infections are often seen occasionally. That is to say, the medical infection is completely controllable in the early period of the epidemic, and when the number of HCWs infections is more significant than a certain threshold (the dividing line), the turning point from quantitative change to qualitative change will appear, and the whole scenario presents a lognormal distribution.

In conclusion, when the number of HCWs infections exceeds the threshold value, it presents lognormal distribution in time and space. In contrast, when the number of infected HCWs in a unit is only a few random, it is considered an occasional phenomenon. Reliable protective or isolation measures are effective for controlling the spread of medical infections. This paper also considers the spatial dependence of different types of HCWs infection rates. Figures S1 and S2 in the appendices support the correctness of the fitted distribution results. They also confirm the importance of multi-scale HCWs infection rate analysis. On 12 February, all communities in Wuhan adopted closed management. After that, the province implemented the strictest 24-h closed control of all village groups, communities, and residential areas in urban and rural areas. This reduced the transmission route of the source of infection, so as to show a log-normal distribution in a small space with severe epidemics. In a well-controlled surrounding area, the condition becomes a random event with a small probability, presenting a Poisson distribution.

4.2.2. Multiscale Infection Rate and Chi-Square Analysis

In this section, the infection rates among doctors; nurses; other staff; and general, specialist, and grassroots hospitals are analyzed on the three scales of city, county, and grid, and the chi-square test is used to test the difference between the categories. Figures 6 and 7 show the occupations and hospital types with the highest infection rates in different kinds of HCWs, respectively. The p-value markers were divided into four grades, corresponding to the confidence of 99% ($\alpha \leq 0.01$), 95% ($\alpha \leq 0.05$), 90% ($\alpha \leq 0.1$), and no significance.

At the city scale, except for doctors in Huangshi, the infection rate of nurses was higher in other areas that passed the p-value test. At the county scale, the infection rate of doctors in Zengdu, Anlu, and Xiaonan District was the highest, and the infection rate of nurses in other areas that passed the p-value test was significant. However, in terms of the number of health care infections in Zengdu, the number of nurses infected was more than that of doctors. At the grid-scale, the infection rate of other occupations within the cell was also significant, especially in the internal grid of Wuhan, where the infection rate of doctors was significant at the 95% confidence level in many grids, which was different from the result at the overall city scale.

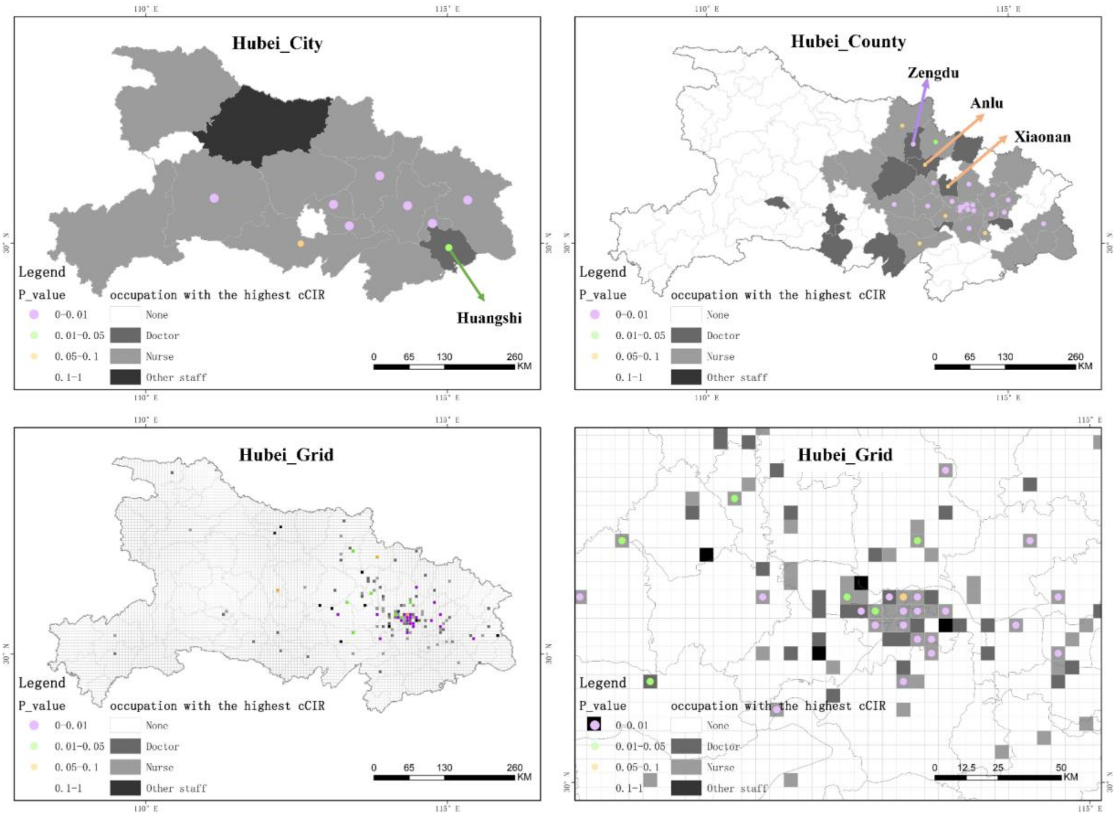

Figure 6. The occupation type with the highest infection rate and chi-square *p*-value classification.

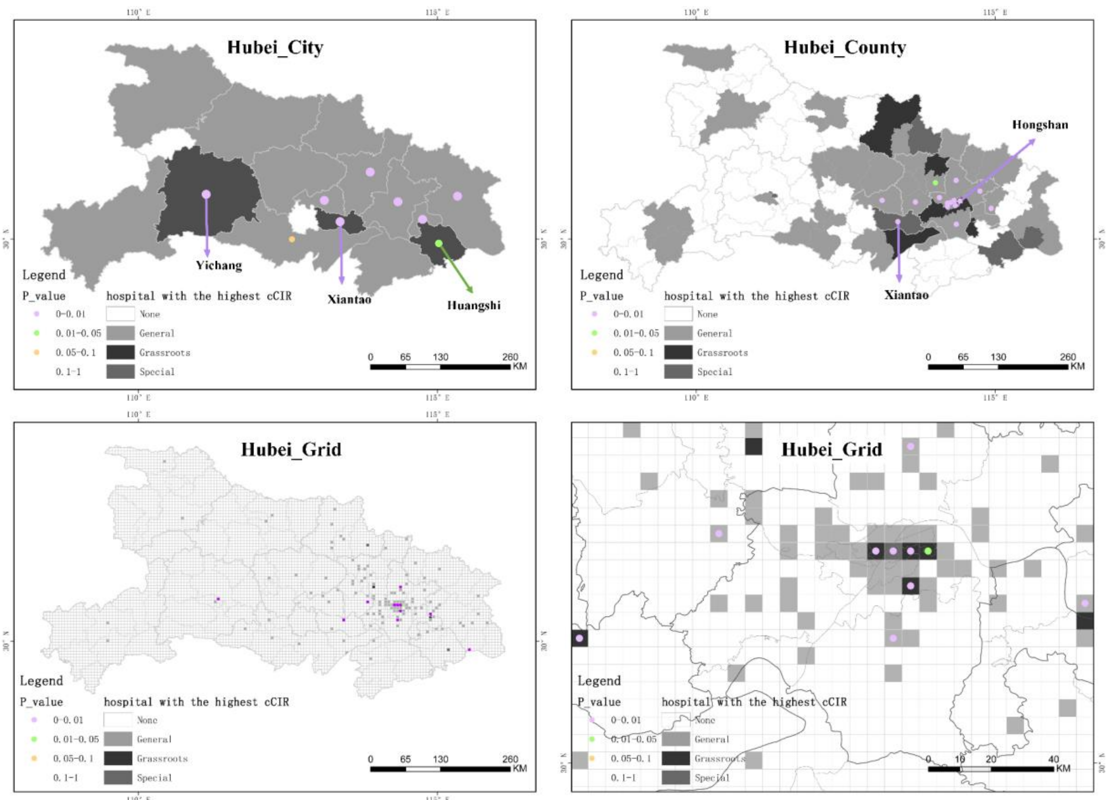

Figure 7. The hospital type with the highest infection rate and chi-square *p*-value classification.

At the city level, the cCIR of specialized hospitals in Yichang, Xiantao, and Huangshi was higher than that in general hospitals, and the cCIR in grassroots hospitals was not significant. At the county level, the cCIR of specialized hospitals in Xiantao is significant, and the cCIR of grassroots hospitals in Hongshan is significant. Similarly, under the grid scale, most of the grids that passed the inspection in Wuhan were specialized hospitals or grassroots hospitals with significant infection rates. This paper also conducts a multi-scale stratified analysis of the infection rates of different occupations and different hospitals. Figures S3–S8 (in the Supplementary Materials) focus on the Chi-square test results between any two categories.

The reasons for the difference in the types of cCIR under different scales are analyzed. One reason is that when the number of HCWs in a certain category is similar between the scale units, the disparity in the number of HCWs infections will cause a significant difference in the infection rate. The second reason is that this article considers the spatial heterogeneity of the number of HCWs; only considering the number of infections cannot entirely reflect the actual infection situation inside the unit. If the number of medical staff inside the unit is huge, the calculated infection rate may not be significant. On 29 January, Hubei set up designated hospitals for the treatment of new crown patients, including specialized hospitals and other categories, which may slightly impact the infection rate of HCWs in individual grid cells. By considering the heterogeneity of the number of HCWs can reflect the degree of local infection more accurately. The result also confirms the defect that the analysis of the infection rate in Wuhan using a single scale and the number of general medical care can only obtain a macro conclusion [13].

The previous part has analyzed the differences in the infection rates of different occupations and hospitals. This article uses SPSS to standardize the data and select the data within twice the standard deviation for scatter plots to avoid extreme values from biasing the subsequent experimental results. Figures 8 and 9 are the scatter plots between the Chi-square results and the infection rates of different types of HCWs. On the microscopic scale, as the infection rate of different types of medical care increases, the overall chi-square continues to increase, which means that the difference in infection between different types of HCWs is gradually expanding. The slopes at the city level are higher than those at the county and grid levels among different scales. On a large scale, as the cCIR of HCWs increases, the difference among different types of infection becomes more evident. Regarding different medical professions, the slope of the infection rate of other medical staff and the chi-square linear result is the largest at the city and county levels, and they are more sensitive to COVID-19. Nurses with the slightest slope indicate they are least susceptible to the epidemic; with a small grid, nurses are most sensitive to the epidemic, while other medical care providers are the least sensitive to COVID-19.

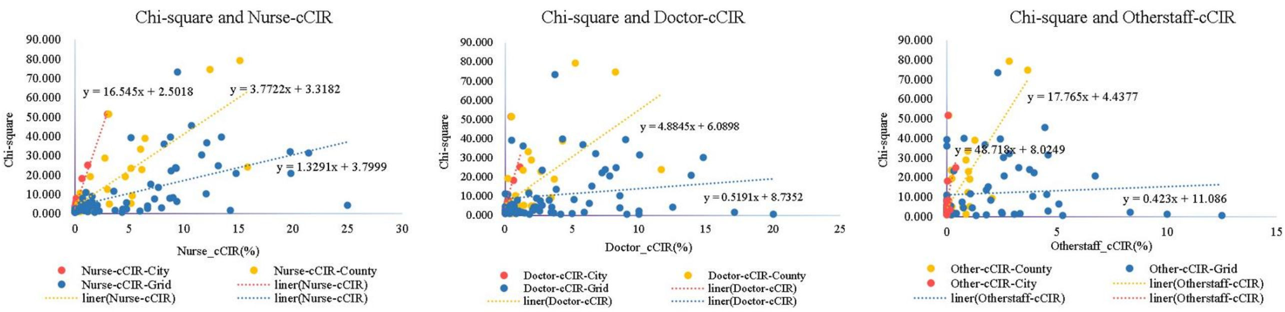

Figure 8. Infection rate and chi-square trend chart of different professions.

After analyzing the above reasons, we found that the number of HCWs in larger-scale units is relatively large. When the epidemic is severely short of medical resources, other HCWs will also fight against the epidemic. If the number of other staff continues to increase, it means that the epidemic is aggravating, so other HCWs will become the most sensitive occupational category. In the small-scale unit, the overall number of HCWs is small, and the nurses have a longer exposure time in the first line. In the early small units, the nurses are more sensitive to COVID-19 than other staff.

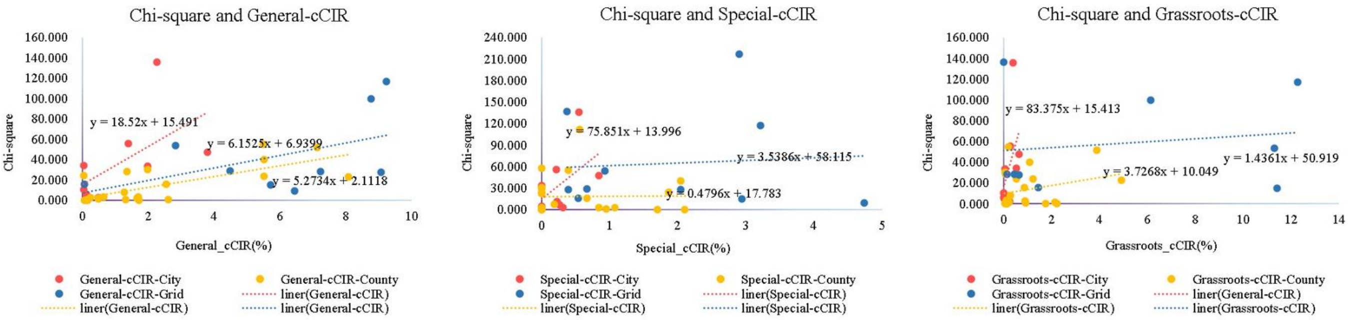

Figure 9. Infection rate and chi-square trend chart of different hospitals.

In terms of different types of hospitals, the slope of the trend line in the city-level grassroots hospitals is the largest, and the general hospital is the smallest; at the county-level, general hospitals are more sensitive to COVID-19, and specialty hospitals are the least sensitive. On the grid-scale, general hospitals are more susceptible to the epidemic, and grassroots hospitals are less sensitive. In summary, there are differences in the sensitivity of different types of HCWs to COVID-19 at multiple scales, and the reasons for this difference are different.

The analysis of the reasons can be combined with a comparison of the HCW infection rates of different types of hospitals at the municipal level. General hospitals with a significant infection rate are more spatially distributed. Overall, Hubei Provincial General Hospital is the main institution of receiving infected patients. The infection rate of HCWs is in a "steady state" and is less subject to external interference. However, due to the gap between diagnosis and treatment capabilities and other types of hospitals, grassroots hospitals have a certain degree of vulnerability, weak anti-interference ability, and more sensitivity to COVID-19. At the county level and grid-scale, when the epidemic worsens, the infection rate of HCWs in general hospitals is more sensitive, while the sensitivity of specialist hospitals is weaker. In smaller research units, most suspected or confirmed cases are admitted to large general hospitals for treatment, so the HCWs in general hospitals are more sensitive.

There are two reasons for the weaker sensitivity of specialty and grassroots hospitals: one is there are few specialized hospitals within a small unit, and even some units have no specialized hospitals. Second, when a confirmed or suspected case is found, the first choice is to treat it in a general hospital or a designated hospital, which weakens the sensitivity of specialty and grassroots hospitals, and the chi-square change tends to be flat as the infection rate rises.

5. Conclusions

The new coronavirus continues to sweep the world, and the outbreak of the epidemic in India will sound a wake-up call to humanity. Analyzing the infection spatiotemporal characteristics of HCWs on the front line through a multi-scale perspective can attract widespread public attention to medical staff. At the same time, the multi-scale analysis of infection rates of different types of HCWs can provide valuable references for the grid-based precision management of the government and relevant epidemic prevention departments. The results can also help government departments rationally allocate the number of HCWs and personal protective equipment to achieve distribution on demand, thereby reducing the mental and physical pressure of health care workers and the infection rate of HCWs.

This paper first collects the total amount of HCWs and infection data from the official websites of the Red Cross and the Hubei Provincial Health Commission. Then, post-processes them to refine a tabulation of HCWs infection rates, finally conducts a multi-scale statistical analysis of HCWs infection rates through macro and micro. In different scale units, we completed the study from two aspects: fitting the distribution of HCWs infection and chi-square statistics of infection rate, and then analyzed the HCWs of doctors, nurses, and other staff, and the HCWs of general hospital, specialized hospital, and grassroots hospital.

The results show that (1) at multi-scales, the epicentral unit of the epidemic presents a lognormal distribution and a peripheral Poisson distribution. There is a clear dividing line between the number of infections of HCWs corresponding to the log-normal distribution and the Poisson distribution, indicating that the distribution of HCWs infections is related to the severity of the epidemic. When the number of HCWs infections is small, the Poisson distribution is an accidental phenomenon, which means that the infection of HCWs has been controlled during the epidemic. Fitting the temporal and spatial distribution of the number of HCWs can provide a reference for relevant departments to supply protective equipment and formulate applicable policies and measures rationally. (2) The infection rates of different types of HCWs are not consistent at multiple scales. On the macro-scale, on the one hand, the cCIR of nurses is the highest among all kinds of HCWs. On the other hand, the cCIR of HCWs in general hospitals is higher than that of specialized and grassroots hospitals. However, the micro-scale results are not consistent compared with the macro-scale conclusions. The finding shows scale differences in the infection rates of different HCWs caused by the spatial heterogeneity of the number of HCWs. The result means that analyzing the infection rate of different occupations can provide a reference for the spread of the epidemic and take more effective control measures. (3) As the cCIR of HCWs continues to increase, the infections difference among different types of HCWs is also gradually increasing. The difference in infections becomes more and more evident in a large-scale range, and different types of HCWs have different susceptibility to COVID-19 under multi-scale units, which means that different occupations have different exposure risks in the epidemic.

Although this paper analyzes the health care infection rate and the fitting distribution results from macro and micro scales, there are still some shortcomings. After the epidemic outbreak, China issued a series of measures and policies to control the spread of the epidemic. In order to make rational use of existing medical resources, relevant departments have requisitioned medical institutions in batches as the designated hospitals for fever, which will have a specific impact on the difference in infection rates among different types of medical care. Second, the HCWs studied in this paper without including the medical staff comes from across the country to aid Hubei. As a result, when calculating the infection rate within each scale unit, the infection rate of some units may be higher. Finally, due to the lack of data on medical and protection resources in different periods and regions, this article does not consider the impact of personal protective equipment (PPE) on health workers.

In this paper, it is found that there is a significant threshold between a lognormal distribution and Poisson distribution when fitting the distribution law of HCWs infection in time and space. However, the definition of the threshold value still needs more regional HCWs infection data for horizontal comparative analysis, which is one of our tasks in the near future.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/ijgi10100691/s1, Figure S1: Gi* statistic results of HCWs infection rates in different occupations. Figure S2: Gi* statistic results of HCWs infection rates in different hospital. Figure S3: p values of Chi-square test for different types of HCWs at the city scale. Figure S4: Occupations with the highest rate of infection in HCWs at the city scale. Figure S5: P values of Chi-square test for different types of HCWs at the county scale. Figure S6: Occupations with the highest rate of infection in HCWs at the county scale. Figure S7: P values of Chi-square test for different types of HCWs at the grid scale. Figure S8: Occupations with the highest rate of infection in HCWs at the grid scale.

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contributed to the manuscript revision. All authors have read and agreed to the published version of the manuscript.

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