Assessing work resumption in hospitals during the COVID-19 epidemic in China using multiscale geographically weighted regression

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Abstract
The resumption of work and production is one of the key issues during the novel coronavirus (COVID-19) post-epidemic phase. We used location-based service data of mobile devices to assess the work resumption of 22,098 hospitals in mainland China. The multiscale influences of the determinants on work resumption in hospitals, including medical-service capacity, human movement, and epidemic severity, were examined using the multiscale geographically weighted regression technique. This study provides a novel insight into the assessment of work resumption in hospitals and its determinants, and is flexible to be extended to evaluate the work resumption of other industries. The findings can introduce helpful information for other countries to implement the strategies of work recovery during the post-epidemic phase.
In January 2020, the atypical pneumonia caused by novel coronavirus (COVID-19) was reported in Wuhan, Hubei Province, China (Zhu et al., 2020), and a large-scale outbreak started and spread to the entire country within 1 week. Concurrently, confirmed cases were identified in other countries (Holshue et al., 2020; Rothe et al., 2020) and the COVID-19 epidemic became a global public health concern (Wang, Horby, Hayden, & Gao, 2020; WHO, 2020). China made great efforts to control the epidemic spread in the next 2–3 months (Kraemer et al., 2020; Xu, Ao, et al., 2020), then to prevent international importations. At the same time, the COVID-19 pandemic has produced enormous shocks to the world in terms of health, socioeconomics, and natural environment (Sarkodie & Owusu, 2020). It is still a global ongoing threat, and the cumulative number of global confirmed cases is approaching 140 million (as at April 15, 2021; China CDC, 2021).

During the early phase of the COVID-19 epidemic, infections were mainly linked to Wuhan, China (Li, Guan, et al., 2020; Zhu et al., 2020), and human movement from the epidemic source explained the majority of the spatio-temporal spread of the virus nationwide and worldwide (Hu, Qiu, et al., 2020; Jia et al., 2020; Kraemer et al., 2020; Wu, Leung, & Leung, 2020). Strict control measures, such as transportation screening and self-isolation restrictions, were evidently effective to control massive human movement and large-scale epidemic spread (Chinazzi et al., 2020; Tian et al., 2020; Xu, Ao, et al., 2020). The epidemic spread was associated with regional population structure (O'Sullivan, Gahegan, Exeter, & Adams, 2020), meteorological factors, and air quality (Liu, Zhou, et al., 2020; Xu, Yan, et al., 2020). The regional disparities of healthcare resource availability introduced various levels of epidemic severity across regions (Ji, Ma, Peppelenbosch, & Pan, 2020). How people were exposed, such as through households, public transportation, or healthcare contacts between individuals, influenced the risk of infection (Luo et al., 2020). The transmission risk among train passengers showed significant differences with co-travel time and seat location (Hu, Lin, et al., 2020). Individual mobility restrictions were positively effective in controlling city-level outbreaks (Zhou et al., 2020).

During the COVID-19 post-epidemic phase, the resumption of work and production became the main focus in China. The timing for the resumption of work and its impact on the risk of a secondary outbreak can be estimated (Wang, Tang, et al., 2020). The work resumption strategies were evaluated and the corresponding risk assessments can be provided for decision-making (Bai et al., 2020; Zhang, Ge, et al., 2021; Zhang, Wu, Li, & Li, 2021). There is evidence that various resumption strategies might have different potential to control the outbreaks amid society reopening (Ge et al., 2021). Researchers are also focusing on the assessments of the regional resumptions of work, production, and social life (Shao, Tang, Huang, & Li, 2021; Tao, Fan, Gu, & Chen, 2020; Xu, Wang, Dong, Shen, & Xu, 2020).

Satellite remote sensing data, such as daily night-time light (NTL) images, help evaluate the COVID-19 impact on human activities (Liu, Sha, et al., 2020) and monitor the spatiotemporal variation of regional work resumption (Shao et al., 2021). Satellite observations are of obvious advantage in assessing work resumption in large-scale areas (Tao et al., 2020). Nevertheless, these assessments were still limited in resolution and accuracy. The location-based service (LBS) data of mobile devices with high-resolution spatiotemporal information can indicate explicit trajectories of human movement and help explore the spatiotemporal COVID-19 epidemic spread associated with population flow (Hu, Qiu, et al., 2020; Hu et al., 2021). The LBS data from specific locations (e.g., hospitals) provide a possible way to assess work resumption for a specific industry in a high-resolution space-time domain. In view of the above considerations, using the LBS requesting data of mobile devices, this study analyzed work resumption in the hospitals of mainland China from February 21 to March 18, 2020. We further evaluated the influences of fundamental medical-service capacity, human movement, and epidemic severity on work resumption in the hospitals using geographically weighted regression models. A better understanding of how these determinants influence work resumption in hospitals is important, and can introduce helpful information for other countries to implement strategies of work recovery during the post-epidemic phase. This study provides a novel insight into the assessment of work resumption in hospitals and its determinants during the COVID-19 epidemic.
2 | MATERIALS AND METHODS

2.1 | Definition of the hospital resumption rate

We concentrated on assessing the resumption of work in 22,098 general or specialized hospitals during the COVID-19 epidemic in mainland China. The number of medical visits can indicate the capacity of medical service provided by hospitals to a great extent. The comparative analysis of medical visits before and during the epidemic can help examine work resumption in hospitals. We compared the medical-service situations of hospitals during the COVID-19 epidemic with their fundamental capacities before the epidemic and subsequently assessed the work resumption of hospitals and its corresponding determinants. Here, a resumption rate was defined in a space-time domain to indicate the spatiotemporal resumption situations of hospitals, calculated as follows:

\[
y_{st} = \frac{v_{s,t}}{v_{s,0}}
\]

where \(y_{st}\) is the resumption rate of a specific hospital \(s\) at a given date \(t\), \(v_{s,t}\) denotes the corresponding daily medical visits, and \(v_{s,0}\) is the average of daily visits of hospital \(s\) during December 2019. Note that \(v_{s,0}\) is a geographical variable which indicates the spatial distribution of the fundamental capacity of medical service provided by hospitals nationwide and \(v_{s,t}\) indicates the spatiotemporal distribution of the visits of hospitals during the COVID-19 epidemic. Thus, the resumption rates of hospitals varied over space and time, and reflected the stronger and weaker situations of medical service with the estimates of \(y_{s,t} > 1\) and \(y_{s,t} < 1\), respectively.

2.2 | Data sources and variable selection

We used the data of LBS requests of mobile devices to indicate the visits of hospitals in a space-time domain. The LBS data used in this study cover over 80% of mobile devices supported by the three telecommunications operators in China. They were provided by Wayz Inc., Shanghai, China and had been used to identify the generation of early-phase COVID-19 epidemic spread in China (Hu, Qiu, et al., 2020). Private individual information was deleted from the raw data of the mobile devices and the LBS data are implemented every 2 h with high-resolution locations. The raw LBS requesting data indicate the individual trajectories of numerous mobile devices with high-resolution spatiotemporal information. The trajectory data used in this study were aggregated into individual hospitals by Wayz Inc. with a timestep of 1 day (i.e., medical visits were generated according to hospital and date).

The daily visits of mobile devices to hospitals were collected within two periods. The devices which activated their LBS requests in hospitals during December 2019 indicated the average number of daily visits in hospitals before the COVID-19 epidemic and the fundamental capacity of medical service provided by hospitals. On the other hand, we generated the daily visits in hospitals from February 21 to March 18, 2020, which were considered to indicate the medical-service situations of hospitals during the COVID-19 epidemic.

The observations of hospital resumption rate (i.e., the explained variable) were expected to be representative of work resumption in hospitals nationwide. Hospitals with resumption rates larger than one at a certain date during the epidemic had more daily visits than those prior to the epidemic, and were considered to have resumed their normal activities. Hospital resumption rates in mainland China were calculated from February 21 to March 18, 2020, and their daily geographical distributions dynamically show the corresponding work resumption in hospitals during the epidemic (Figure 1).

The spatiotemporal distributions of resumption rates in hospitals were considered to be affected by various potential factors. We selected three categories of explanatory variables to evaluate their influences on hospital resumption rate, including fundamental medical-service capacity, human movement, and epidemic
FIGURE 1  Geographical distributions of the hospital resumption rate in China during the COVID-19 epidemic: (a) February 21, 2020; and (b) March 18, 2020
| Category                | Variable                          | Proxy                              | Symbol   | Type        | Dataset                                                                 |
|-------------------------|-----------------------------------|------------------------------------|----------|-------------|-------------------------------------------------------------------------|
| Explained variable      | Work resumption in hospitals      | Hospital resumption rate           | $y_{s,t}$ | Space-time  | The ratio of the number of daily visits in hospital $s$ at date $t$ during the epidemic to that prior to the epidemic |
| Explanatory variables   | Fundamental medical-service capacity | Average daily visits before the epidemic | $v_{s,0}$ | Spatial     | The average of daily visits in hospital $s$ during December 2019        |
| Human movement          | Imported visits from Wuhan        |                                    | $d^{(a)}_{s,t}$ | Space-time | Daily imported visits from Wuhan in hospital $s$ at date $t$            |
|                         | Imported visits from elsewhere    |                                    | $d^{(e)}_{s,t}$ | Space-time | Daily imported visits from elsewhere excluding Wuhan in hospital $s$ at date $t$ |
| Epidemic severity       | New confirmed cases around hospitals |                                    | $c^{(c)}_{s,t}$ | Space-time | Daily new confirmed cases within * km of hospital $s$ at date $t$       |
severity. As shown in Table 1, the average of daily visits in hospitals before the epidemic, $v_{s,t}$, was considered the proxy variable of fundamental medical-service capacity, and two proxy variables were selected to indicate inter-city human movement, including daily imported visits from Wuhan, $d_{s,t}^{(w)}$, and from elsewhere excluding Wuhan, $d_{s,t}^{(e)}$, respectively. Based on the datasets of LBS requests, we collected the data of daily imported visits from Wuhan and elsewhere, which were associated with the dataset of daily hospital visits according to date and location (Table 1).

Epidemic severity was also considered to have a potential impact on the work resumption of hospitals. Based on various official and publicly available sources (e.g., the daily bulletins of the National Health Commission of the People’s Republic of China [NHC] and Provincial/Municipal Health Commissions), we collected the spatiotemporal data of daily new COVID-19 confirmed cases. The epidemic dataset was verified comparatively through the public platform of the 2019-nCoV-infected pneumonia epidemic from the Chinese Center for Disease Control and Prevention (China CDC, 2021). In addition, the data of daily new confirmed cases were associated with hospitals through individual location information and we consequently collected the data of daily new confirmed cases within multiple buffers around hospitals (Table 1), which also had a consistent date period with other datasets (from February 21 to March 18, 2020). The daily new confirmed cases within 1, 2, and 3 km of hospitals were considered the proxy variables of epidemic severity, respectively. However, these three variables represented redundant information and exhibited high collinearity based on the variance inflation factors (VIFs) reported in relation to them. Thus, we finally selected the daily new confirmed cases within 3 km of hospitals, $c_{s,t}^{(3)}$, as the proxy variable of epidemic severity.

These explained and explanatory variables have a certain degree of disparity in magnitude and were therefore log-transformed. The logged forms of the variables were standardized to have mean 0 and variance 1. This standardization also makes the parameter estimates of subsequent regressive modeling easy to compare with each other.

2.3 | Multiscale geographically weighted regression

2.3.1 | Ordinary least squares

In order to examine the associations between hospital resumption rate and its determinants, based on the selected explanatory variables and their datasets, a global ordinary least squares (OLS) linear regression model can first be applied. Note that the data of the resumption rate of hospitals were geographically generated at each given date. Thus, the daily OLS model can be implemented and formulated as:

$$\log y_{s,t} = \beta_0 + \sum_i \beta_i x_{i,s,t} + \epsilon_{s,t}$$

(2)

where $s$ and $t$ denote a hospital and a date, respectively, $y_{s,t}$ is the resumption rate of hospital $s$ at date $t$, $\beta_0$ is the intercept constant, $x_{i,s,t}$ denotes the $i$th explanatory variable, $\beta_i$ is the corresponding regression coefficient to be estimated, and $\epsilon_{s,t}$ indicates the estimation error.

2.3.2 | Geographically weighted regression

There could be some degree of positive spatial autocorrelation (SAC) appearing in the observations of the explained variable, which can be measured by the global Moran’s I statistic (Moran, 1950). Moreover, potential local variations always appear in the spatial relationships between explained and explanatory variables, and global
regression models (e.g., OLS) normally ignore the spatial non-stationarity. As a typical local multivariate regression model, the geographically weighted regression (GWR) extends global regression modeling by allowing both local and global parameters to be estimated, and can be applied to measure the spatially varying relationships between variables (Brunsdon, Fotheringham, & Charlton, 1996; Fotheringham, Charlton, & Brunsdon, 1998). Similarly, the daily GWR model used in this study is given by:

$$\log y_{s,t} = \beta_{0,t}^{(s)} + \sum_{i} \beta_{i,t}^{(s)} \log x_{i,s,t} + \epsilon_{s,t}$$

where $x_{i,s,t}$ is the $i$th local explanatory variable describing local variation, and the local intercept, $\beta_{0,t}^{(s)}$ and the local regression coefficients, $\beta_{i,t}^{(s)}$, both vary with location of hospitals. The location-specific parameter estimates allow the relationships between the explained variable and explanatory variables to vary between hospitals.

### 2.3.3 Multiscale geographically weighted regression

The GWR model can describe the spatial local heterogeneity in relationships between the explained variable and the explanatory variables. Nevertheless, the bandwidth parameter in the GWR model is identical for all explanatory variables. That is to say, all explanatory variables exhibit the spatial local heterogeneity at a consistent spatial scale. In fact, the explanatory variables, such as human movement and epidemic severity, might have different determinant powers for the work resumption of hospitals at various spatial scales. Multiscale geographically weighted regression (MGWR) removes the assumption of consistent spatial scale in GWR and allows that the explanatory variables have various specific bandwidths to represent spatial local heterogeneity at various spatial scales (Fotheringham, Yang, & Kang, 2017). The MGWR technique has been applied extensively to examine the multiscale influences of the determinants on health, socioeconomics, and natural environment (Cupido, Fotheringham, & Jevtic, 2020; Fotheringham, Yue, & Li, 2019; Hong & Yoo, 2020; Iyanda et al., 2020; Mollalo, Vahedi, & Rivera, 2020; Oshan, Smith, & Fotheringham, 2020; Yang, Zhan, Lv, & Liu, 2019). In this study, we further examined the determinants of the hospital resumption rate at various spatial scales using the MGWR model described as follows:

$$\log y_{s,t} = \beta_{bw0,t}^{(s)} + \sum_{i} \beta_{bw,i,t}^{(s)} \log x_{i,s,t} + \epsilon_{s,t}$$

where $\beta_{bw0,t}^{(s)}$, $\beta_{bw,i,t}^{(s)}$ are the local intercepts and regression coefficients of explanatory variables with various optimal bandwidths, respectively, and $bw$ in $\beta_{bw,i,t}^{(s)}$ denotes the specific bandwidth used for calibration of the $i$th conditional relationship. Note that the coefficients in MGWR also vary with the location of hospitals.

The experimental period was set from February 21 to March 18, 2020. We applied a consistent parameter setting to solve the above GWR and MGWR models at each date during the study period. A commonly used adaptive bi-square kernel function, which removes the influence of observations outside the neighborhood specified by the number of individuals, was used as the distance-weighting function to represent the relative importance between locations. The bandwidth (optimal number of nearest neighbors, i.e., individual hospitals) was determined through an iterative optimization process in GWR by minimizing the corrected Akaike information criterion (AICc). The significance of the estimated coefficients was checked with pseudo $t$ tests and the model significance was tested by variance analysis ($F$ tests). More specifically, the calibration in MGWR was implemented using a back-fitting algorithm and the iterative process is initialized with the GWR parameter estimates (Fotheringham et al., 2017). The local parameter estimates and optimized bandwidths are evaluated during each iteration. When the difference of the parameter estimates between sequential iterations reaches a given convergence threshold.
(1e−5 in this study), the iteration terminates. The MGWR2.2 software (https://sgsup.asu.edu/sparc/mgwr) was applied to implement the GWR and MGWR computations (Oshan, Li, Kang, Wolf, & Fotheringham, 2019).

3 | RESULTS

3.1 | Spatiotemporal characteristics of the hospital resumption rate

The daily work resumption rates of 22,098 hospitals during the COVID-19 epidemic in mainland China were evaluated explicitly from February 21 to March 18, 2020. Their geographical distributions show that provinces surrounding Hubei in central China had a relatively normal resumption of work in hospitals until the experiment end date (Figure 1). The temporal boxplots of the resumption rates in hospitals are shown in Figure 2. Although the average resumption rate was still lower than 1 until that date, it exhibited an obvious ascending trend throughout the entire period. The "boxes" are narrower during the first 2 weeks, whereas those during the later period arise in part over the rate value of 1 (Figure 2), which can be explained by more hospitals achieving better resumption of work in the post-epidemic phase. Approximately 23.3% of hospitals had resumption rates higher than 1 before March 2020. Nevertheless, this number became 30.8% after the first week in March, and increased to 41.8% on March 18. China made a success of the work resumption of hospitals, and nearly half of the 22,098 hospitals had resumed their medical-service situations after fighting the epidemic for 2–3 months.

We calculated the daily global Moran’s I statistics for the geographical distributions of the resumption rates in hospitals with an inverse Euclidean distance conceptualization of spatial relationships between hospitals. This achieved an average value of 0.1479 (p < .001), with a standard deviation (SD) of 0.1115. Figure 3a reveals that the resumption rate distributions exhibited weak spatial autocorrelation during the early phase (excluding the first two abnormally high values), whereas the spatial autocorrelation indicated a gradual increase in the later period. Especially after March 8, the spatial autocorrelation was strong to some extent and the resumption of work in hospitals indicated a low-value clustering characteristic. Most hospitals with low resumption rate values were geographically clustered, whereas those with high values exhibited no significant clustering characteristic.
3.2 Performance comparison of the GWR and MGWR models

The OLS, GWR, and MGWR models were implemented to examine the associations between hospital resumption rate and its determinants, respectively. The daily OLS results achieved an average adjusted $R^2$ value of 0.3320 ($SD = 0.1382$) and global OLS had poor performance in assessing the determinant power of explanatory variables on hospital resumption rate. As shown in Figure 3b, the spatial autocorrelation was weak before March 8 and OLS exhibited a relatively acceptable performance ($R^2 > 0.4$). However, the performance declined sharply when the
spatial autocorrelation became stronger after that date. The adjusted $R^2$ value of the OLS result decreased to less than 0.1 until the experiment end date.

The spatially varying relationships between explained and explanatory variables are considered in the GWR/MGWR technique, and thus it usually outperforms the OLS model, which assumes the relationships are globally identical. Table 2 indicates that the average AICc values of the GWR/MGWR results were 35,939.72 and 35,384.62, and the average root mean square error (RMSE) values were 0.5780 and 0.5727, respectively, which were both lower than those values of the OLS result. Meanwhile, the GWR/MGWR results showed the average adjusted $R^2$ values of 0.6198 and 0.6276, respectively, which were much higher than that of the OLS result (Table 2). During the early phase (before March 8), the population imports contributed to the medical visits in hospitals to some extent and the corresponding influence on resumption rate exhibited strong spatial heterogeneity. Therefore, GWR/MGWR obviously improved the performance compared to OLS, with the $R^2$ values increasing from 0.3–0.5 to 0.7–0.9 (Figure 3b). Although the determinant powers of the explanatory variables decreased after that date and the performance of the models declined, GWR/MGWR still had a certain degree of performance improvement, with approximately 20% higher $R^2$ values than those of the OLS model (Figure 3b). Furthermore, as shown in Table 2, MGWR exhibited a slight performance improvement compared to GWR, with an increase of the average adjusted $R^2$ values from 0.6198 ($SD = 0.2439$) to 0.6276 ($SD = 0.2372$). This performance improvement was almost steady within the entire experimental period (Figure 3b).

The temporally average residuals generated by the OLS, GWR, and MGWR models in 22,098 hospitals were applied to calculate their corresponding spatial autocorrelation, respectively. The Moran’s $I$ value of the OLS residuals was 0.0089 ($p = .4600$), and those of the GWR/MGWR residuals were 0.0197 ($p = .1214$) and 0.0198 ($p = .1213$), respectively. The residuals from all three models exhibited a consistent random pattern, which means that the residuals had no significant spatial dependency and were randomly distributed in space. However, the GWR/MGWR models both produced fewer residuals than the OLS model and reduced the error variance, in which MGWR introduced a slightly better improvement. Figure 4 further presents the geographical distributions of the residuals and the local $R^2$ values generated by the MGWR model. The residuals showed a random spatial pattern and no obvious clusters were found in both positive and negative residuals. The local $R^2$ distribution presented the random spatial pattern as well, and there were no obvious clusters of high or low $R^2$ values. Besides, the MGWR technique can explain the scale effects of the influence of the determinants on hospital resumption rate. Consequently, we conclude that MGWR can effectively help improve goodness-of-fit performance, eliminate residual dependency, reduce error variance, and eventually was selected to assess work resumption in hospitals during the COVID-19 epidemic in China.

### 3.3 Parameter estimates of the GWR and MGWR models

The parameter estimates generated by the MGWR model are summarized in Table 3, which covers the local coefficients of 22,098 hospitals at 27 dates. More specifically, the proportions of significant coefficients ($p < .05$),

| Parameter Estimates | OLS | GWR | MGWR |
|---------------------|-----|-----|------|
| Mean                | SD  | Mean| SD   | Mean | SD  |
| RMSE                | 0.6798 | 0.1782 | 0.5780 | 0.2098 | 0.5727 | 0.2072 |
| AIC                 | 53.33786 | 4,507.89 | 35,934.16 | 16,614.22 | 35,381.64 | 16,787.72 |
| AICc                | 53.33986 | 4,507.89 | 35,939.72 | 16,612.98 | 35,384.62 | 16,787.95 |
| $R^2$               | 0.3320 | 0.1381 | 0.6235 | 0.2423 | 0.6306 | 0.2353 |
| Adjusted $R^2$      | 0.3320 | 0.1382 | 0.6198 | 0.2439 | 0.6276 | 0.2372 |
FIGURE 4  Geographical distributions of the MGWR results: (a) residuals; and (b) local $R^2$ values
positive coefficients to significant ones (+), and negative coefficients to significant ones (−) are illustrated in the third column, respectively. A total of 69.96% of the space-time points had local intercepts significantly different from zero, of which 67.42% were positive and 32.58% negative. The intercept estimates had an average of 0.0362 and the hospital resumption rate had a slightly increasing or decreasing trend, varying in space given the conditions of the variables in the model. The local parameter estimates from average daily visits before the epidemic, \( v_{s,t} \), were significant for nearly all the space-time points, in which 99.65% of those were negative. The hospitals with stronger fundamental medical-service capacities found it harder to rapidly resume their work situations. Human movement had a strongly positive impact on the resumption of work in hospitals. The local parameter estimates from daily imported visits from Wuhan, \( d_{s,t}^{(w)} \), and from elsewhere, \( d_{s,t}^{(e)} \), were significant for 91.05 and 99.30% of space-time points, of which 98.57 and 100% were positive, respectively. The latter estimates had an average of 0.5694, which was higher than that of the former. Inter-city population flow considerably influenced work resumption in hospitals, and increasing human imports introduced higher resumption rates. The local parameter estimates from daily new confirmed cases within 3 km of hospitals, \( c_{s,t}^{(3)} \), were significant for 98.40% of space-time points, of which 100% were negative. The parameter estimates had an average of −0.0573, which was much lower than those from other exploratory variables. The surrounding epidemic severity had a weakly negative impact on the resumption of work in hospitals.

Due to the variable standardization before modeling, the local parameter estimates can relatively represent the influence of exploratory variables on hospital resumption rate across the entire area. Figure 5 provides geographical distributions of the temporal averages of the MGWR parameter estimates. Note that the parameter estimates in hospitals were aggregated into the corresponding administrative cities for an acceptable visualization of thematic mapping. Consequently, the positive/negative influence of the determinants might be exaggerated in several regions with rare hospitals, due to the aggregation process. In general, human importations were the positive determinants of hospital resumption rate and medical-service capacity was the negative one. The resumption of work in hospitals during the post-epidemic phase was closely related to virus testing, quarantine, and protective isolation. The local parameter estimates for the intercept were slightly positive across the entire area, ranging from −0.04 to 0.11 (Figure 5a), whereas the parameter estimates of \( v_{s,t} \) in Figure 5b were significantly negative, ranging from −0.48 to −0.21. The negative influence of the medical-service capacity on hospital resumption rate was concentrated on several economically developed areas, such as the Yangtze and Pearl river deltas. Figures 5c and d reveal the distributions of the local parameter estimates of \( d_{s,t}^{(w)} \) and \( d_{s,t}^{(e)} \), respectively. They were significantly positive across nearly the entire area, ranging from 0.23 to 1.26 and from 0.42 to 0.84, respectively. The population imports from Wuhan still played a more important role in hospital resumption rate than that from elsewhere during the post-epidemic phase. These positive influences presented a relatively low-value clustering characteristic, primarily in eastern coastal areas, whereas no obvious clusters were found in other areas. The local parameter estimates of \( c_{s,t}^{(3)} \) in Figure 5e were weakly negative, ranging from −0.08 to −0.03. The epidemic severity indicated no obvious regional variation of the negative influence on hospital resumption rate across the entire area.
3.4 Optimized bandwidths and scale effect

The optimized bandwidths generated by the GWR and MGWR models are listed in Table 4, respectively, including the daily averages and the corresponding standard deviations. The GWR model suggested a consistent optimized bandwidth for all exploratory variables, which had an average of 1157 nearest neighbors and a standard deviation of 315 nearest neighbors. The single bandwidth of GWR, which was much lower than the average of MGWR, being 4288 nearest neighbors, indicated that all exploratory variables affected hospital resumption rate at a uniformly
local scale. In fact, the influences of various variables on the resumption rate probably varied at different spatial scales. MGWR can further reveal the spatial scale effect with variable-specific optimized bandwidths and indicate the influences of various variables at different scales.

The intercept of the MGWR model had an optimized bandwidth with a temporal average of 2090 nearest neighbors \((SD = 2413)\). Compared to the single bandwidth of GWR, it had a higher value and a larger variation, indicating that the elevated or lower levels of hospital resumption rate given the conditions of exploratory variables were different at a larger scale and obviously varied over time. The optimized bandwidth of \(v_{s,0}\) had an average of 1888 nearest neighbors \((SD = 785)\). The fundamental medical-service capacity affected the resumption rate at a regional scale. Its negative influence was significant across nearly the entire area and demonstrated the variation from hospital to hospital. The optimized bandwidths of \(d_{(w)}(s,t)\) and \(d_{(e)}(s,t)\) had temporal averages of 3786 and 804 nearest neighbors, and standard deviations of 2684 and 288 nearest neighbors, respectively. Population imports had different local effects on the hospital resumption rate. The imports from elsewhere had a very small optimized bandwidth, indicating that it affected the resumption rate at a very local scale. Its influence exhibited a much stronger spatial heterogeneity than that of the imports from Wuhan, which was at a relatively global scale. The optimized bandwidth of \(c(3)(s,t)\) had a temporal average of 12,872 nearest neighbors \((SD = 4528)\), suggesting that the epidemic severity affected hospital resumption rate at a very global scale (i.e., it had a similar influence on the resumption rate in all hospitals, or the influence exhibited extremely weak spatial heterogeneity).

4 | DISCUSSION

The resumption of work and production is the main focus during the COVID-19 post-epidemic phase in China and other countries. High-resolution LBS requesting data of mobile devices contain substantial spatiotemporal information associated with population flow and specific locations, and therefore provide the potential to assess work resumption and the corresponding determinants in a high-resolution space-time domain. In this study, based on the LBS request data aggregated in hospitals, we explicitly analyzed work resumption in 22,098 Chinese hospitals from February 21 to March 18, 2020. The MGWR technique was further used to evaluate the determinants of hospital resumption rate, as well as their various spatial scale effects.

This study concentrated on the assessment of work resumption in hospitals, which is explicitly targeted at the work resumption of a specific industry instead of the overall resumption of work and production in a study area. The LBS request datasets used in this study cover the majority of mobile devices in mainland China, and are obviously advantageous, with high spatiotemporal resolution on a very large scale. The assessment of the resumption of work and production can be implemented in a specific industry with high-resolution spatiotemporal information. A novel insight has been provided into the assessment of work resumption during the post-epidemic phase. Another main contribution of the current study is the quantitative evaluation of the determinants of the

| Variable | GWR | MGWR |
|----------|-----|-------|
|          | Mean | SD    | Mean | SD    |
| Intercept| 1.157| 315   | 2090 | 2413  |
| \(v_{s,0}\) | 1888 | 785   |
| \(d_{(w)}(s,t)\) | 3786 | 2684  |
| \(d_{(e)}(s,t)\) | 804  | 288   |
| \(c(3)(s,t)\) | 12,872 | 4528 |

**TABLE 4** Optimized bandwidth(s) generated by the GWR and MGWR models
hospital resumption rate and their multiscale influences, including medical-service capacity, human movement, and epidemic severity.

Previous studies have applied the MGWR technique to explore the determinants of health effects, such as obesity rate (Oshan et al., 2020), mortality rate (Cupido et al., 2020), incidence rate (Mollalo et al., 2020), and confirmed cases (Iyanda et al., 2020). To our knowledge, this study is the first application of the MGWR technique to examine the multiscale influences of the determinants on the resumption of work and production. Population imports were found to be the positive determinants of hospital resumption rate, whereas medical-service capacity and epidemic severity had negative influences. However, their positive/negative influences exhibited different spatial scale effects. The medical-service capacity negatively affected hospital resumption rate at a local scale, whereas the epidemic severity had the influence at a very global scale. Population imports from elsewhere affected the hospital resumption rate at a very local scale, whereas the imports from Wuhan affected it at a relatively global scale.

MGWR has been considered a significant improvement on GWR since it allows variable-specific bandwidths (Fotheringham et al., 2017). The MGWR software makes it easy to implement the computation and extensive applications (Oshan et al., 2019). Although several theoretical improvements have been implemented to optimize the MGWR framework, such as parallel computational improvements to the calibration (Li & Fotheringham, 2020), bandwidth uncertainty measurement (Li, Fotheringham, Oshan, & Wolf, 2020), and inference of local parameter estimates (Yu et al., 2020), there were still several issues appearing in MGWR computations. For instance, the datasets in this study included the observations in 22,098 hospitals and the MGWR computation was extremely time-consuming. MGWR is currently calibrated using a back-fitting algorithm and it is hard to achieve a tolerable run time with moderately large datasets (Li & Fotheringham, 2020). The bandwidth optimization is related to the calibrating algorithm and the chosen criterion, and is subject to uncertainty (Li, Guan, et al., 2020). That is to say, for the optimized bandwidths in the MGWR model, it is hard to indicate the strictly “best” ones. This also causes a probable limitation on the improvement of model performance, such as the less satisfactory goodness-of-fit indicators of MGWR compared to GWR (Oshan et al., 2020). In this study, the daily MGWR model provided a better goodness-of-fit performance than GWR model at most dates. Nevertheless, the GWR model still achieved slightly higher $R^2$ values than the MGWR model at several dates (Figure 3b). This may be caused by overfitting to the data in GWR, or calibrating algorithm and bandwidth uncertainty in MGWR.

This study has several limitations and has identified several further analyses in future work. First, the study date period was set from February 21 to March 18, 2020, which did not cover all of the various phases of the epidemic. Only four explanatory variables were selected to examine their influence on work resumption in hospitals. Long-term assessment of the resumption of work and production is required in future work, as well as introducing more potential explanatory variables. Moreover, the multiscale influences of the determinants on work resumption in hospitals were examined in this study, and more potential information could be introduced if the objective unit is changed (e.g., the assessment of medical-service resumption in prefecture-level cities). In addition, the assessment of work resumption of other industries can be implemented using similar techniques and datasets, which is one of our ongoing works. Finally, our study assessing work resumption in hospitals has considered just spatial non-stationarity and spatial autocorrelation during daily modeling; spatiotemporal modeling requires further consideration of temporal/spatiotemporal autocorrelations, which can be a theoretical optimization work in the future.

5 | CONCLUSIONS

In conclusion, this article provided a novel insight into the assessment of work resumption based on the LBS request data of mobile devices, and then presented an experimental application of the MGWR technique to characterize the multiscale influences of the determinants on the hospital resumption rate. The results show that: (1)
nearly half of the 22,098 hospitals had resumed their medical-service situations after fighting the epidemic for 2–3 months; (2) most hospitals with low resumption rates were spatially clustered, whereas those with high values exhibited no significant clustering characteristic; (3) population imports had a strongly positive impact on the resumption of work in hospitals, whereas the imports from Wuhan and elsewhere affected the resumption rate at a relatively global scale and at a very local scale, respectively; (4) the fundamental medical-service capacity was the primary negative determinant of hospital resumption rate, affecting at a local scale; (5) the epidemic severity had a weakly negative impact on hospital resumption rate at a very global scale.

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CONFLICT OF INTEREST
The authors declare no competing interests.

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