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Correlations between the urban built environmental factors and the spatial distribution at the community level in the reported COVID-19 samples: A case study of Wuhan

Jingwei Wang\textsuperscript{a,}\textsuperscript{*}, Fanbo Zeng\textsuperscript{b}, Haida Tang\textsuperscript{c,d}, Junjie Wang\textsuperscript{c,d}, Lihua Xing\textsuperscript{e}

\textsuperscript{a} School of Architecture, Southeast University, Nanjing 210096, China
\textsuperscript{b} Faculty of Innovation and Design, City University of Macau, Macau 999078, China
\textsuperscript{c} School of Architecture & Urban Planning/BenYuan Design and Research Center, Shenzhen University, Shenzhen 518000, China
\textsuperscript{d} Shenzhen Key Laboratory of Architecture for Health & Well-being (in preparation), Shenzhen, China
\textsuperscript{e} Shenzhen General Institute of Architectural Design and Research CO., LTD, Shenzhen 518000, China

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\textbf{ABSTRACT}

COVID-19 has dramatically changed the lifestyle of people, especially in urban environments. This paper investigated the variations of built environments that were measurably associated with the spread of COVID-19 in 150 Wuhan communities. The incidence rate in each community before and after the lockdown (January 23, 2020), as respective dependent variables, represented the situation under normal circumstances and non-pharmaceutical interventions (NPI). After controlling the population density, floor area ratio (FAR), property age and sociodemographic factors, the built environmental factors in two spatial dimensions, the 15-minute walking life circle and the 10-minute cycling life circle, were brought into the Hierarchical Linear Regression Model and the Ridge Regression Model. The results indicated that before lockdown, the number of markets and schools were positively associated with the incidence rate, while community population density and FAR were negatively associated with COVID-19 transmission. After lockdown, FAR, GDP, the number of hospitals (in the 15-minute walking life circle) and the bus stations (in the 10-minute cycling life circle) became negatively correlated with the incidence rate, while markets remained positive. This study effectively extends the discussions on the association between the urban built environment and the spread of COVID-19. Meanwhile, given the limitations of sociodemographic data sources, the conclusions of this study should be interpreted and applied with caution.

1. Introduction

Since December 2019, Corona Virus Disease 2019 (COVID-19) caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) had spread all over the world (Guan et al., 2020). Densely populated metropolitan areas were the most vulnerable and were believed to intensify the spread of COVID-19 (Hamidi et al., 2020a; Mollalo et al., 2020). In order to control the spread of COVID-19 and reduce the number of infections and deaths, governments had adopted several non-pharmaceutical interventions (NPI), including urban lockdown, home isolation, social distancing and travel restrictions (Lee et al., 2021; Sharifi & Khavarian-Garmsir, 2020).

The influence of the urban environment on COVID-19 has attracted worldwide attention. A variety of studies focused on factors related to social demographics and the urban built environment. In relation to social demographics, the elderly and children were at a higher risk of infection (Gao et al., 2022; Mollalo et al., 2020; Wang et al., 2020; Wang et al., 2021). Regarding ethnicity, in the United States, the incidence rate of COVID-19 was higher in communities with large populations of African-American, Latino and foreign immigrants (Abedi et al., 2021; Figueroa et al., 2020; Holtgrave et al., 2020). The level of economic development of the region was also demonstrated to influence the spread of COVID-19 (Aycock & Chen, 2021; Mo et al., 2021; Oshakbayev et al., 2022). People living in low-income areas and old communities were considered more vulnerable to COVID-19 (Ahmed et al., 2020; Das et al., 2021; Finch & Hernandez Finch, 2020). The availability of health insurance was highly correlated with COVID-19 transmission (Wang et al., 2021). A high literacy rate at the county level was proved to

\textsuperscript{*} Corresponding author.
\textsuperscript{E-mail address:} jingweiwang@seu.edu.cn (J. Wang).

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reduce the incidence rate of COVID-19 by Logistic Regression (DuPre et al., 2021). Meanwhile, other factors, including blood type, chronic diseases, personal habits and other respiratory diseases were also believed to be associated with the transmission of COVID-19 (Onder et al., 2020; Zhou et al., 2020). Strict enforcement of NPI was proved to effectively mitigate the spread of the virus (Anderson et al., 2020; Ficetola & Rubolini, 2021; Prem et al., 2020). During the pandemic, human behavior patterns changed due to NPI measures and concerns about the pandemic (Pakoz & Isik, 2022). The living range of urban residents was greatly minimized, which made residents more dependent on the built and natural environment around their residence (Allam & Jones, 2020). The surrounding environment had a direct impact on the physical and mental health of residents (Mouratidis & Yiannakou, 2022). Low-density communities, larger dwellings, developed surrounding infrastructure and more green spaces could substantially increase the life satisfaction and happiness of residents during the pandemic (Mouratidis, 2022). Especially for the elderly, the accessibility of primary health services needs to be improved to reduce the potential impact of the COVID-19 pandemic on the quality of life (Guida & Carpenteri, 2021).

In addition to sociodemographic factors, urban built environmental factors, which had been addressed by numerous studies, were an important aspect influencing the spread of COVID-19. The relationship between population density and COVID-19 transmission was controversial in previous studies. Cordes and Castro (2020) pointed out that in areas with dense populations, where person-to-person contact was frequent, COVID-19 transmission was rapid and the incidence rate was high. At the national level, the population density was shown to exhibit a positive association with COVID-19 cases by comparing data from 182 countries by the Linear Regression Model (Nguimkeu & Tadadjou, 2021). But at the city level, population density in Tehran was shown to be negatively associated with the spread of COVID-19 by applying Structural Equation Model (Khavarian-Garmsir et al., 2021). Some studies also showed that population density had no significant relationship with the transmission of COVID-19 (AbouKorin et al., 2021). Studies in the United States (Hamidi et al., 2020b), Netherlands (Boterman, 2020) and China (Lin et al., 2020) showed that the relationship between population density and the incidence rate was complex and the reactions from different governments and residents to the outbreak could lead to contrasting results. Similar to the population density mentioned above, the relationship between building density and COVID-19 transmission remained controversial (Khavarian-Garmsir et al., 2021; Liu, 2020). Several studies did not find an association between building density and COVID-19 transmission after removing some confounding factors (Boterman, 2020; Lin et al., 2020). During the pandemic, residents living in high-density areas felt lower life satisfaction and well-being, but the compact urban form makes healthcare resources more accessible and can improve the health of residents (Mouratidis, 2021; Pakoz & Isik, 2022).

It should be noted that during a pandemic, residents have to purchase necessities around their communities. Various factors in the built environment around them may influence the transmission and infection of COVID-19. Public transportation (Figueroa et al., 2021), point of interest (POI) (Liu et al., 2021), and leisure activity spaces (Wang et al., 2021) were considered to be positively related to COVID-19 transmission. Public transportation and transportation hubs were identified as dangerous hotspots for the spread of COVID-19. In the early stages of the outbreak, many governments recommended avoiding public transportation and encouraged residents to reduce the range of activities and use more transportation modes such as walking, cycling or driving private cars (Guida & Carpenteri, 2021). By using Geographically Weighted Regression (GWR) and Multi-scale GWR, high accessibility of health care resources around the communities was proven to suppress the spread of COVID-19 (Mollalo et al., 2020). Through the Structural Equation Model and the Hierarchical Regression Model, high-quality dwellings (Wang et al., 2021) and green space (Lu et al., 2021) were shown to be negatively correlated with the spread of the virus. In addition, large dwelling areas and surrounding green spaces could also combat the deterioration of urban health and well-being caused by the COVID-19 pandemic (Mouratidis, 2021). Meanwhile, Zhang et al. (2021) indicated that in Wuhan, at the community level, neighborhoods with higher community convenience, i.e., communities with more parks, stores, schools, and hospitals, had a higher risk of infection. Furthermore, restaurants and markets were consistently identified as risk places for COVID-19 transmission through a comparison of different NPI circumstances in Hong Kong (Yip et al., 2021).

During the COVID-19 pandemic, it was unrealistic to include all patients in high-grade urban hospitals, as it could cause a shortage of urban medical resources. Therefore, it was necessary to establish a comprehensive system to identify and isolate the infected patients at the community level (Wang, 2021). The exploration of the built environmental factors associated with COVID-19 transmission was the basis for the establishment of the prevention system at the community level. However, most of the studies at the community level merely applied the administrative boundary to delineate the scope of variable selection and failed to reflect the real activities of residents. Li et al. (2021a) innovatively extracted the built environmental factors around confirmed cases within a 1000 m buffer and used the Structural Equation Model to reveal the contribution of commercial vitality and transportation infrastructure to the increase in the number of confirmed cases. To measure the range of activity of residents more accurately, we introduced the 15-minute walking life circle (approximately 1 km range), which could effectively meet the daily consumption of residents under normal circumstances and was strongly advocated by the Chinese government (Weng et al., 2019). And the 10-minute cycling life circle (approximately 2.5 km range) was also added, considering the residents might walk or ride further to purchase necessities after the lockdown. By extracting the built environmental factors in the two spatial dimensions and examining the relationship between these factors and the COVID-19 incidence rate, the mechanisms of COVID-19 transmission before and after the lockdown at the community level can be analyzed more accurately.

This study investigated the relationship between the incidence rate of COVID-19 and the built environment at the community level through the survey of urban spaces in 150 Wuhan communities. The paper used data from two phases for modeling analysis: Phase 1, before the lockdown of Wuhan on 23 January 2020; Phase 2, after the lockdown from January 23 to February 12, 2020. Two phases covered the first wave of the COVID-19 pandemic in Wuhan. We identified the influencing factors that produced different effects on the spread of COVID-19 under normal conditions and during the lockdown period, based on comparing the differences between the two phases. To confirm the influence of the spatial dimensional variations in the built environment on the spread of COVID-19, we extracted elemental data in two spatial dimensions and confirmed the connection between built environmental factors and the incidence rate of COVID-19 through the Hierarchical Linear Regression Model and the Ridge Regression Model.

The rest of the paper was organized as follows: Part II described the research region, data, variables and methods. Part III summarized the results of the data analysis. Part IV discussed the main findings and limitations. Part V gave the conclusions.

2. Methodology

2.1. Research region and data

Wuhan was the first and most severely affected city in China by the COVID-19 outbreak. The paper used the main urban area within Wuhan City as the research region and selected 150 communities as the samples. In this study, correlation analysis was used to verify the relationship between each variable. The hierarchical Linear Regression Model was applied to identify the effect of built environmental factors on the
incidence rate of COVID-19 after controlling for population density, floor area ratio (FAR), property age and sociodemographic factors. The Ridge Regression Model was introduced to attenuate the effects of multicollinearity among the independent variables. The dependent variables were the incidence rates of COVID-19 in two time periods. The independent variables were extracted in three spatial dimensions. Firstly, population density, FAR and property age were confounding factors and extracted within the administrative scope of the community. Secondly, the 2019 GDP, the percentage of the population ≤14 years old and ≥60 years old of the district in which the community is located were also extracted as confounding factors. Thirdly, built environmental factors were extracted in two spatial dimensions around the corresponding community: the 15-minute walking life circle and the 10-minute cycling life circle.

In early December 2019, the first cases of COVID-19 were identified in Wuhan, which then spread rapidly in the city and led to a worldwide pandemic. Wuhan started the lockdown on January 23, 2020, that residents were not allowed to leave Wuhan and public transport was suspended. On February 12, 2020, a strict community quarantine policy was imposed, that residents were not allowed to leave their homes. Only community workers and volunteers could come to provide household necessities. The transmission data prior to 23 January 2020 (Phase 1) represented the pattern of virus transmission under normal circumstances. The epidemiological data from January 23 to February 12, 2020 (Phase 2) effectively reflected the impact of resident activity within the walking and cycling circle on virus transmission. To avoid the problem that the incidence rate may be underestimated due to insufficient detection tools in the early stages of the outbreak, and since the incubation period of the virus is 2 to 7 days, the data of incidence rate with a lag of 7 days were selected as the dependent variable, i.e., the data from January 30, 2020, were selected for Phase 1 and the data from February 19, 2020, were selected for Phase 2 (Guan et al., 2020). We selected 150 communities with early outbreaks of COVID-19 and early publication of case statistics. On January 30, 2020 (Phase 1), the cumulative number of confirmed cases reported in Wuhan was 2639, and the 150 communities sampled had 1270 confirmed cases, accounting for 48.1% of the total number of cases in Wuhan. Of the cumulative 45,027 confirmed cases, accounting for 7.4% of the total number of cases. The incidence rate in each community might be underestimated simultaneously, so the analysis of the association between the built environment and COVID-19 transmission in the regression analysis could only result in a small deviation.

The spatial distribution of 150 communities and their incidence rates on February 12, 2020, i.e., at the end of Phase 2 were shown in Fig. 1. As can be seen from Fig. 1, the sample of 150 communities is basically evenly distributed within Wuhan, which can accurately represent the overall pandemic situation in Wuhan. At the same time, the communities distributed in the northwest region of Wuhan are more severely affected, which is also the location of Hankou Railway Station and the origin of this outbreak, the South China Seafood Market. Incidence data were obtained from community field surveys and the Wuhan Municipal Health Commission website (http://wjw.wuhan.gov.cn/).

Population density, FAR and property age, were extracted within the administrative scope of the community. Population density is the ratio of a community’s population to its land area (Data source: China Community Network http://www.cnen.org.cn/). Floor area ratio (FAR) refers to the ratio of the total built-up area to the land area in the administrative boundaries of the communities and can represent the intensity of construction and building density of a community. (Data source: Wuhan Natural Resources and Planning Bureau http://zrzyhgh.wuhan.gov.cn/). Property age means the average age from the building was built to the present time in the community and can represent the quality of a community to some extent (Data source: Chain Home, one of the largest housing transaction platforms in China https://www.lianjia.com/). Due to limitations in data sources, data for GDP (2019), percentage of population ≤14 years old and ≥60 years old were extracted from the district in which the community is located (Data source: Wuhan Municipal Bureau of Statistics http://tjj.wuhan.gov.cn/).

The built environmental factors around the community contained two spatial dimensions. One was the 15-minute walking life circle and the other was the 10-minute cycling life circle. The 15-minute walking life circle is a basic community-based life circle, strongly advocated in many Chinese cities, which provides citizens with basic public services within the 15-minute walking distance (approximately 1 km range) (Guzman et al., 2021; Kissfazekas, 2022; Liu & Chai, 2015; Ma et al.,

Fig. 1. Incidence rates (‰) of 150 communities in Wuhan on 12 February 2020 (Incidence 2).
2.2. The Regression Model

We performed a three-step statistical analysis. Firstly, Pearson correlation analysis was conducted for all variables in the two dimensions of the 15-minute walking life circle and the 10-minute cycling life circle.

Secondly, the Hierarchical Linear Regression Model was used to examine the correlation between the COVID-19 incidence rate and the built environmental factors in two spatial dimensions, while controlling for population density, FAR, property age and sociodemographic factors. After taking the natural logarithm of Incidence 1 and Incidence 2, Ln_Incidence 1 (D = 0.064, p = 0.142) and Ln_Incidence 2 (D = 0.061, p = 0.190) passed the Kolmogorov-Smirnov test and obeyed normal distribution, so natural logarithm of the incidence rate was chosen as the dependent variable. In Phase 1, the model first included population density, FAR, property age and sociodemographic factors, and then built environmental factors were added. In phase 2, Ln_Incidence 1 was added for analysis, after which the steps were the same as Phase 1.

Thirdly, the variance inflation factor (VIF) was used to test for potential multicollinearity among the independent variables. The VIF of most independent variables were <5, but N_Hospital2 (VIF = 5.916), N_SC2 (VIF = 9.800), N_Hotel2 (VIF = 7.260), N_School2 (VIF = 5.683), N_Market2 (VIF = 6.839) and N_Bus2 (VIF = 9.286) were between 5 and 10. This indicated potential multicollinearity of the independent variables within the 10-minute cycling. But all the factors could still be brought into the Hierarchical Linear Regression Model. In order to avoid the effect of multicollinearity, the Ridge Regression Model was introduced to validate the results of the Hierarchical linear regression model (O’Brien, 2007). Meanwhile, as a robustness check, the incidence rate rather than its natural logarithm was selected as the dependent variable in the Ridge Regression Model.

Ridge regression is a modified form of Ordinary Least Squares (OLS) which works by abandoning the unbiasedness of OLS and at the expense of losing some information to find model equations that are slightly less effective but whose regression coefficients are more realistic. The mathematical presentation was shown as follows:

$$\tilde{y}_i = \alpha + \hat{\beta}x_i$$  \hspace{1cm} (1)

where $\hat{\beta}$ is the estimator of Ridge regression coefficients, $x_i$ is the set of all possible regressors. Ridge regression addresses the problem by estimating regression coefficients using:

$$\hat{\beta} = (X'X + kI)^{-1}X'Y; k \geq 0$$  \hspace{1cm} (2)

where X represents design matrix, Y represents the vector of dependent variable, I is the identity matrix, k is the Ridge parameter. The paper applied the algorithm of Hoerl et al. (1975) to determine the value of the Ridge parameter k (Hoerl & Kennard, 2000).

ArcGIS software was used to analyze and present case spatial distribution, as well as to collect and organize spatial information of independent variables. IBM SPSS Statistics 24 software and Stata Version 13.1 software were used to analyze the data.

3. Results

3.1. Pearson correlation analysis

In this section, as shown in Fig. 3 and Fig. 4, the paper examined the association between Ln_Incidence 1, Ln_Incidence 2 and the other 14 factors by Pearson correlation analysis.

As shown in Fig. 3, in the 15-minute walking life circle, FAR (Pearson correlation coefficient is –0.25, p < 0.01) and GDP (Pearson correlation coefficient is –0.19, p < 0.05) were negatively correlated with Ln_Incidence 2. Percentage of population ≥ 60 years old was positively
Table 1
Descriptive statistics of the variables (full sample, n = 150).

| Variables                        | Unit  | Min  | Max  | Mean  | Std. dev |
|----------------------------------|-------|------|------|-------|----------|
| **Dependent variables**          |       |      |      |       |          |
| Incidence 1                      | %     | 1.27 | 29.41| 11.06 | 6.03     |
| Incidence 2                      | %     | 2.55 | 119.79| 31.28 | 20.18    |
| Ln_Incidence1                    |       | 0.24 | 4.54 | 2.71  | 0.82     |
| Ln_Incidence2                    |       | 0.94 | 4.79 | 3.25  | 0.64     |
| **Independent variables**        |       |      |      |       |          |
| **Built environment in administrative scope** |       |      |      |       |          |
| Pop. density                     | %     | 0.17 | 10.99| 3.29  | 2.72     |
| FAR                             | %     | 0.40 | 3.98 | 2.03  | 0.73     |
| Age                             | Year  | 5    | 41   | 20.87| 7.87     |
| GDP                             | 10^8 Yuan | 673 | 1522 | 1159.68| 308.09  |
| <14                             | %     | 10.76| 13.44| 11.84| 0.86     |
| ≥60                             | %     | 12.14| 25.22| 19.97| 3.80     |
| **Sociodemographic variables**   |       |      |      |       |          |
| GDP                             | 10^8 Yuan | 673 | 1522 | 1159.68| 308.09  |
| ≤14                             | %     | 10.76| 13.44| 11.84| 0.86     |
| ≥60                             | %     | 12.14| 25.22| 19.97| 3.80     |
| **Built environment in the 15-minute walking life circle** |       |      |      |       |          |
| N_Hospital_1                    | Number| 2    | 113  | 20.71| 17.13    |
| N_SC_1                          | Number| 1    | 22   | 6.43 | 3.80     |
| N_Hotel_1                       | Number| 1    | 113  | 20.71| 17.13    |
| N_Express_1                     | Number| 2    | 24   | 8.33 | 3.37     |
| N_School_1                      | Number| 0    | 34   | 6.59 | 4.63     |
| N_Market_1                      | Number| 2    | 80   | 20.11| 11.90    |
| N_BUS                          | Number| 4    | 36   | 16.93| 6.94     |
| N.Metro_1                       | Number| 0    | 3    | 1.01 | 0.80     |
| **Built environment in the 10-minutes cycling life circle** |       |      |      |       |          |
| N_Hospital_2                    | Number| 12   | 106  | 52.85| 21.40    |
| N_SC_2                          | Number| 7    | 58   | 22.96| 9.02     |
| N_Hotel_2                       | Number| 9    | 232  | 70.97| 39.40    |
| N_Express_2                     | Number| 12   | 60   | 23.07| 11.44 |
| N_School_2                      | Number| 4    | 78   | 23.07| 11.44 |
| N_Market_2                      | Number| 16   | 173  | 70.03| 35.79 |
| N_BUS                          | Number| 20   | 123  | 60.34| 22.66    |
| N.Metro_2                       | Number| 0    | 11   | 4.71 | 2.58     |

Fig. 3. Pearson correlations of factors in 15-minute walking life circle (* p < 0.05, ** p < 0.01).
correlated with Ln_Incidence 2 (Pearson correlation coefficient is 0.24, \( p < 0.01 \)). Among all the built environmental factors, only markets were positively associated with Ln_Incidence 2 at the confidence level \( p < 0.05 \) and the Pearson correlation coefficient is 0.20. Age, percentage of population \( \geq 60 \) years old, hotels, schools, markets and bus stations were positively correlated with Ln_Incidence 1.

As shown in Fig. 4, in 10-minute cycling life circle, markets were positively correlated with Ln_Incidence 2 (Pearson correlation coefficient is 0.22, \( p < 0.05 \)). Ln_Incidence 1, in particular, had the most significant positive relationship with Ln_Incidence 2, with a Pearson correlation coefficient of 0.77 that far exceeded the other variables. Hospitals, community service centers, hotels, schools, markets and bus stations were positively correlated with Ln_Incidence 1.

In particular, the markets and the percentage of population \( \geq 60 \) years old were the only two variables that were positively correlated with Ln_Incidence 1 and 2, whether in the 15-minute walking life circle or in the 10-minute cycling life circle. The built environmental factors were highly autocorrelated in two spatial dimensions, which was the reason why we planned to use Ridge Regression Model.

### 3.2. The hierarchical linear regression model

The combination of two temporal dimensions distinguished by the lockdown date (January 23, 2020), and the two spatial dimensions of the 15-minute walking life circle and the 10-minute bicycle circle, finally obtained four models. Adding built environmental variables sequentially to the Hierarchical Linear Regression Model, the paper determined the relationship between the incidence rate of COVID-19 and the independent variables in different phases and different spatial

![Fig. 4. Pearson correlations of factors in 10-minute cycling life circle (\( p < 0.05 \). ** \( p < 0.01 \)).](image)

| Variables | Phase 1 | Phase 2 |
|-----------|---------|---------|
|           | Model 1 | Model 2 |
|           | \( \beta \) | \( \beta \) | \( \beta \) | \( \beta \) |
| Ln_Incidence 1 | DV | DV | 0.770*** | 0.743*** |
| Population density | \(-0.188^*\) | \(-0.214^{**}\) | | \(-0.026\) | 0.001 |
| FAR | -0.088 | -0.194* | \(-0.110^{**}\) | \(-0.136^{**}\) |
| Age | 0.216* | 0.154 | 0.005 | 0.040 |
| GDP | 0.013 | 0.058 | \(-0.149^{**}\) | \(-0.178^{**}\) |
| \( \leq 14 \) | -0.004 | 0.056 | 0.020 | 0.042 |
| \( \geq 60 \) | 0.175* | 0.041 | 0.013 | 0.076 |
| N_Hospital | -0.103 | | | |
| N_SC | -0.121 | | | |
| N_Hotel | 0.075 | | | |
| N_School | -0.102 | | | |
| N_Market | 0.247 | | | |
| N_Bus | -0.030 | | | |
| N_Metro | -0.157 | | | |
| R^2 | 0.118/0.071 | 0.245/0.097 | 0.593/0.619 | 0.637/0.630 |
| R^2 Change | 0.127 | 0.044 | 0.030 |

* \( p < 0.05 \).
** \( p < 0.01 \).
*** \( p < 0.001 \).
dimensions.

Table 2 showed the association of built environmental variables with the incidence rate of COVID-19 in the 15-minute walking life circle for both Phase 1 and Phase 2. In Model 1, Ln_Incidence 1 was the dependent variable. Adding population density, FAR, property age and sociodemographic factors as independent variables, population density ($\hat{\beta} = -0.188$, $p = 0.025$) was found to be negatively associated with Ln_Incidence 1, while Age ($\hat{\beta} = 0.216$, $p = 0.010$) and percentage of population $\geq 60$ years old ($\hat{\beta} = 0.175$, $p = 0.049$) were positively associated with Ln_Incidence 1. The explanatory power of Model 1 was improved with the addition of the built environmental factors ($R^2$ Change = 0.127). Population density was still negatively correlated with Ln_Incidence 1, while its standardized coefficient ($\hat{\beta}$) changed from $-0.188$ to $-0.214$ and p-value changed from 0.025 to 0.010. The correlation between Age and Ln_Incidence 1 was not significant. FAR ($\hat{\beta} = -0.194$, $p = 0.033$) showed a negative correlation with Ln_Incidence 1. Among all the built environmental factors, N_School1 ($\hat{\beta} = 0.394$, $p = 0.013$) was positively correlated with Ln_Incidence 1, indicating that schools were risk areas for the pandemic in the 15-minute walking life circle before the lockdown.

Model 2 represented the association between the independent variables and Ln_Incidence 2 in the 15-minute walking life circle from lockdown (January 23, 2020) to February 12, 2020. Ln_Incidence 2 was the dependent variable and Ln_Incidence 1 was added as an independent variable. Firstly, adding only Ln_Incidence1 ($\hat{\beta} = 0.770$, $p = 0.000$) as independent variable, it was positively correlated with Ln_Incidence 2 and the $R^2$ was 0.593. This indicated that the pre-lockdown incidence rate had a dramatic effect on the post-lockdown incidence rate. After the addition of population density, FAR and property age and sociodemographic factors, FAR ($\hat{\beta} = -0.110$, $p = 0.046$) and GDP ($\hat{\beta} = -0.149$, $p = 0.007$) had significant negative correlation with Ln_Incidence 2. After adding built environmental factors in Model 2, N_Hospital1 ($\hat{\beta} = -0.189$, $p = 0.021$) showed a negative correlation with Ln_Incidence 2.

Comparing Model 1 and Model 2, this paper found that population density was negatively associated with Ln_Incidence 1 before the lockdown, but after the lockdown and adding Ln_Incidence 1 in Model 2 as an independent variable, population density was not significantly associated with Ln_Incidence 2. Furthermore, FAR, GDP and hospitals in the 15-minute walking life circle played a suppressive role in the community outbreak after the lockdown.

The association between built environmental variables and the incidence rate of COVID-19 in the 10-minute cycling life circle, both in Phase 1 and Phase 2, were shown in Table 3. Model 3 indicated the association between Ln_Incidence 1 and the other variables in the 10-minute cycling life circle before the lockdown. The results of adding only population density, FAR, property age and sociodemographic factors were consistent with Model 1. After adding built environmental variables, Population density ($\hat{\beta} = -0.264$, $p = 0.002$) were negatively correlated with Ln_Incidence 1. Meanwhile, N_Market2 ($\hat{\beta} = 0.470$, $p = 0.015$) was significantly and positively correlated with Ln_Incidence 1.

Model 4 indicated the association between the independent variables and Ln_Incidence 2 in the 10-minute cycling life circle from the lockdown to February 12, 2020. The results with the addition of Ln_Incidence 1, population density, FAR, property age and sociodemographic factors were consistent with Model 2. After adding built environmental factors, the $R^2$ of Model 4 was 0.684. Ln_Incidence 1 was positively correlated with Ln_Incidence 2 and had the highest standardized coefficient ($\hat{\beta} = 0.702$, $p = 0.000$). N_Bus1 ($\hat{\beta} = -0.550$, $p = 0.000$) were negatively correlated with Ln_Incidence 2. N_Market2 ($\hat{\beta} = 0.528$, $p = 0.000$) was positively correlated with Ln_Incidence 2. Comparing Model 3 and Model 4, population density was not significantly associated with Ln_Incidence 2. After the lockdown, N_Bus1 suppressed the growth of the incidence rate of COVID-19. Specifically, markets were consistently a possible reason for the spread of the pandemic, both before and after the lockdown.

Comparing the results of the two spatial dimensions, as shown in Table 3. Population density was negatively correlated with Ln_Incidence 1 before the lockdown. In Phase 2, FAR and GDP were negatively correlated with Ln_Incidence 2 in both spatial dimensions. In the 15-minute walking life circle, hospitals were negatively correlated with Ln_Incidence 1. In the 10-minute cycling life circle, bus stations were negatively correlated with the Ln_Incidence 2 and markets were positively correlated with the Ln_Incidence 1 & 2.

### 3.3. Excluding multicollinearity with the Ridge Regression Model

Table 4 expressed the results of the four Ridge Regression Models in 15-minute walking life circle and the 10-minute cycling life circle. Ridge regression intervened mainly because the multicollinearity of independent variables was present in the 10-minute cycling life circle. Although these independent variables could still be brought into the Hierarchical Linear Regression Model, the findings of the ridge regression analysis could be used as a validation and supplement (O’Brien, 2007). The Ridge traces for the Ridge Regression Models were shown in Figs. A.1 to A.4, in Appendix A.

It can be seen in Table 4 that in the 15-minute walking life circle, in Phase 1 (before the lockdown) (Model 5), Population density ($\hat{\beta} = -0.164$, $p = 0.009$) and FAR ($\hat{\beta} = -0.149$, $p = 0.019$) were negatively correlated with Incidence 1, while N_School1 ($\hat{\beta} = -0.162$, $p = 0.014$) were positively associated with Incidence 1. But in Phase 2 (Model 6), after adding Incidence 1 as an independent variable, Population density and N_School1 did not have significant correlation with Incidence 2. Meanwhile, FAR ($\hat{\beta} = -0.107$, $p = 0.029$), GDP ($\hat{\beta} = -0.121$, $p = 0.011$) and N_Hospital1 ($\hat{\beta} = -0.149$, $p = 0.007$) had negative association with Incidence 2. Among all built environmental factors, N_Market1 ($\hat{\beta} = 0.128$, $p = 0.017$) was the only variable that positively correlated with Incidence 2. Most importantly, Incidence 1 was found to have a huge influence on Incidence 2 with Ridge regression standardized coefficient ($\hat{\beta} = 0.573$, $p = 0.000$) far exceeding the other variables.

In the 10-minute cycling life circle dimension, Population density ($\hat{\beta} = -0.177$, $p = 0.004$) and FAR ($\hat{\beta} = -0.122$, $p = 0.048$) were negatively associated with Incidence 1. Meanwhile, N_School2 ($\hat{\beta} = 0.135$, $p =
0.030) and N_Market2 ($\hat{\beta} = 0.138, p = 0.022$) was positively correlated with Incidence 1 in Phase 1 (Model 7). In Phase 2, Incidence 1 as the independent variable was brought into Model 8 with the highest Ridge regression standardized coefficient ($\hat{\beta} = 0.521, p = 0.000$). Similar with the results in the 15-minute walking life circle, N_Market2 ($\hat{\beta} = 0.162, p = 0.000$) was positively correlated with Incidence 2.

In Phase 1, Population density and FAR were negatively correlated with Incidence 1 and schools facilitated the spread of COVID-19 in Phase 2. Population density and FAR were positively correlated with Incidence 1 in models 6, 7, and 8. What differs in the two spatial dimensions was that, among all the built environmental factors, hospitals in the 15-minute walking life circle were negatively correlated with the incidence rate of COVID-19 in Phase 2.

In contrast to the Hierarchical Linear Regression Model, in model 2 and 4, GDP was negatively correlated with Ln_Incidence 2. In model 1 and 3, without the addition of built environmental factors, percentage of population $\geq$ 60 years old were positively associated with Ln_Incidence 1 and property age was negatively correlated with Ln_Incidence 1.

4. Discussion

This study investigated the association between the incidence rate of COVID-19 and urban built environmental factors by the Hierarchical Linear Regression Model and the Ridge Regression Model at the community level. The study was divided into two spatial dimensions (15-minute walking life circle and 10-minute cycling life circle) and two temporal dimensions (before and after the lockdown).

4.1. Sociodemographic and built environmental factors

In the study, before the lockdown (January 23, 2020) of Wuhan, residents were living normally and were not seriously affected by the pandemic. Contrary to the studies of Li et al. (2021a) and Zhang et al. (2021), we found a significant negative correlation between population density and the incidence rate of COVID-19 in phase 1. However, in phase 2, there was no significant correlation between population density and incidence. It was probably due to developed commercial activity in areas with high population density. Residents could obtain necessities in a small range after a potential outbreak was known. However, residents of low population density areas had to travel further to purchase necessities, which led to more contact with strangers and a higher risk of infection. Another study in Wuhan indicated that population density was not significantly associated with the spread of COVID-19 after controlling for the proportion of the external population in Wuhan (Li et al., 2020). Different from the relationship between population density and the incidence rate, this paper showed a negative correlation between floor area ratio (FAR) and the incidence rate both before and after the lockdown with the Ridge Regression Model, which was different from the studies of Lee et al. (2021); Liu et al. (2021). On the one hand, high density increases the possibility of human contact, which facilitates the spread of the virus. However, after the implementation of lockdown measures, residents could only move around in a small area and the virus could not spread across regions. On the other hand, areas with higher density usually have relatively well-developed infrastructure, which provides accessible and timely treatment to the residents, thus suppressing the spread of COVID-19 (Hamidi et al., 2020b; Liu, 2020). In particular, Under the strict NPI, the outdoor activities of the residents were restricted, which effectively inhibited the spread of the virus in high density areas (Khavarian-Garmsir et al., 2021; Sun et al., 2020). Overall, in communities with high population density and FAR, the transmission of COVID-19 can be restrained through the reasonable management of the government or community.

This paper found a positive correlation between property age and Ln_Incidence1 without built environmental factors by the Hierarchical Linear Regression Model before the lockdown. It was consistent with many previous studies (Li et al., 2021a; Zhang et al., 2021). New communities are usually considered to have developed infrastructure, excellent community management systems, and well-trained community staff, which can effectively isolate infected individuals and protect vulnerable populations in a pandemic (Hamidi et al., 2020b; Khavarian-Garmsir et al., 2021). Hung (2003) revealed that old houses have more housing quality defects, which could exacerbate the spread of the virus between neighborhoods through elevators, stairs, sewerage, and other communal facilities. In the early stages of the outbreak, the government should focus on old communities and distinguish for pre-existing cases as soon as possible. At the same time, the existing old communities need to be transformed to increase the activity space and green space. More
importantly, update and maintain its ventilation, water supply and drainage system. Similar to property age, we found that the percentage of the population ≥ 60 years old was positively correlated with Ln_Incidence 1. However, this correlation disappeared after the lockdown, which shows that the lockdown had effectively protected the elderly from COVID-19 infection.

Economic activity has a strong influence on COVID-19 incidence rate (Oshakbayev et al., 2022). In this paper, we found that the transmission of COVID-19 could be effectively suppressed in areas with high GDP after the lockdown. Some studies proved that economic development contributed to the spread of COVID-19 (Aycock & Chen, 2021; Mo et al., 2021), but it was probably influenced by the response of the government to the pandemic. Since the Wuhan government took timely measures to lockdown and effectively mobilized social resources, regions with high economic levels could suppress the virus more rapidly.

In the study, markets were positively associated with the incidence rate of COVID-19 both in the 15-minute walking life circle and the 10-minute cycling life circle before and after the lockdown. In large Chinese cities, most supermarkets are usually underground with poor ventilation. The small shops around the community were very crowded during peak hours, which could greatly increase the probability of COVID-19 transmission (Li et al., 2021b; Li & Tang, 2022). Due to the panic and shortages of household goods, the spread was exacerbated by the massive flow of residents into the markets after the lockdown, which was one of the reasons why the Wuhan government had to impose stricter NPI on February 12, 2020, to forbid its residents to leave their home (Yip et al., 2021).

In Phase 1, schools promoted the spread of COVID-19 both in the 15-minute walking life circle and the 10-minute cycling life circle. Schools were crowded places where interaction between students and teachers could accelerate the spread of the virus. After students contracted the virus at school, COVID-19 could easily infect their family members through parent-child interactions. Since the lockdown resulted in the closure of schools, the correlation between schools and the incidence rate became insignificant in Phase 2, but many schools were requisitioned for isolation of patients and played a positive role in controlling the outbreak after the lockdown. Alfano et al. (2021) showed that the premature opening of schools significantly increased the number of COVID-19 cases in Italy. During an outbreak, the government should enforce strict NPI measures in schools while safeguarding educational equity. Online classes should be organized, especially in the case of a severe pandemic. At the same time, careful consideration should be given to the re-opening of schools after the pandemic.

After the lockdown, the number of hospitals in the 15-minute walking life circle was shown to be negatively associated with the incidence rate. It meant that the infectors in communities with high accessibility to medical resources could easily receive medical services and recovered quickly because of the reduced transportation time and distance that the infectors could contact fewer people during their journeys from home to the hospital. In order to deal with the next pandemic that may occur in the future, the government should reasonably plan the medical infrastructure around the community to make it more accessible, especially for the old community.

In model 4, the N_Bus was negatively related to Ln_Incidence 2 by Hierarchical Linear Regression Model. The studies of Li et al. (2021a) and Liu et al. (2021) suggested that public transportation systems facilitated the spread of the virus, which was contrary to our results. The negative association between N_Bus and Ln_Incidence 2 could be mainly due to the fact that the Wuhan government shut down all public transportation infrastructures and requisitioned a large number of buses for the transportation of medical staff and community workers during the lockdown. Generally, public transportation infrastructure that increases the contact of the population is considered a key factor contributing to the spread of infectious diseases (Abou-Korin et al., 2021). In the early stages of the pandemic, several governments recommended avoiding public transportation. After the pandemic, a number of effective initiatives should be made to limit the spread of disease within public transportation, including limiting passenger density, increasing the frequency of service, and reserving tickets. Other low-carbon and environmentally friendly active transport modes such as walking and cycling should also be encouraged.

In particular, there was a strong causality between the pre-lockdown incidence rate and the post-lockdown incidence rate. This could be mainly due to the fact that the infected people before the lockdown were the main source of COVID-19 transmission. The government should quickly identify and cure the existing infected people when enforcing strict NPI, otherwise, their families and neighbors would quickly become the sources of infection.

4.2. Research limitations

This study has limitations. Firstly, the number of cases published by the Wuhan Municipal Health Commission was at the district level. Therefore, most of the outbreak data in the study came from the transcriptions of community announcements, and only 150 community samples were included in the research, which could not represent all communities. Secondly, the paper was not able to obtain additional demographic data of community residents, such as demographic structure, gender, basic diseases, and profession, which were considered to be related to the transmission of COVID-19 in previous studies. Meanwhile, the living activities of residents were complex and disorganized during the pandemic. Only 14 variables were selected, but other potential variables, such as restaurants, road networks and green spaces, could also influence virus transmission. More variables need to be considered in future studies to explore the effects of the built environmental factors on COVID-19. Thirdly, although the spatial dimensions were divided into two dimensions of the 15-minute walking life circle and the 10-minute cycling life circle, the effect of spatial autocorrelation still could not be avoided. Our future study will apply Multiscale Geographically Weighted Regression Model for further analysis under the premise of obtaining more data at the community level.

5. Conclusion

The study drew preliminary conclusions on the association of the built environmental factors in Wuhan with the spread of COVID-19 at the community level. The paper focused on the built environmental factors in the 15-minute walking life circle and the 10-minute cycling life circle around the community. Through the Hierarchical Linear Regression Model and the Ridge Regression Model, the paper identified the correlation between urban built environmental factors and the spread of COVID-19. The main conclusions were summarized as follows:

1. Before the lockdown, the percentage of population ≥ 60 years old, schools and markets both in the 15-minute walking life circle and the 10-minute cycling life circle were positively associated with the incidence rate of COVID-19. Population density and FAR were negatively correlated with the incidence rate.

2. After the lockdown, FAR and GDP were negatively correlated with the incidence rate and the number of markets was positively associated with the incidence rate. In the 15-minute walking life circle, hospitals (p = 0.021) were negatively associated with the incidence rate. In the 10-minute cycling life circle, bus stations (p = 0.000) were shown to be negatively associated with the incidence rate.

3. Comparing the results of the model analysis before and after the lockdown, the market was found to be positively associated with the spread of the virus both in the 15-minute walking life circle and the 10-minute cycling life circle. The government needs to establish policies to provide residents with safe access to necessities during a pandemic. Before the lockdown, except for FAR and population density, no built environmental factor was...
negatively associated with the incidence rate in Phase 1. But after the lockdown, hospitals in the 15-minute walking life circle and bus stations in the 10-minute cycling life circle were negatively correlated with the incidence rate of COVID-19.

To deal with potential future outbreaks, this paper recommends changes in future community planning and construction. First of all, the concept of the circle of life should be enforced so that residents can obtain the necessities of life within convenient walking or cycling distance. This satisfies the daily needs of residents, saves travel costs, reduces human contact and controls the spread of viruses. Second, strict and effective management policies are needed for areas with high population and building densities. If a potential outbreak emerges, the advantageous resources should be fully mobilized and strict NPI should be implemented. Third, special policies and planning are needed to improve old and unsanitary communities in order to reduce the risk of disease infection. Meanwhile, elderly people are at high risk of contracting COVID-19, and the government needs to take effective NPI measures to protect the elderly when a new potential pandemic arrives, especially in nursing homes where the elderly are concentrated. Fourth, public transportation is still the first choice for urban residents to travel, which is also the trend of low-carbon urban development. Limiting the number of passengers, increasing service ratings, and safe social distances can be effective in limiting the spread of the virus within the public transportation space. Other modes of travel, such as walking, bike-sharing and car-sharing, should be encouraged. Fifth, medical infrastructure around the community plays an important role in suppressing the spread of disease, and the government should invest more in medical resources while planning rationally to ensure their equity. Last but not least, schools and markets were found in this study to be dangerous places for COVID-19 transmission. They should be closed or the number of people inside them should be limited during an outbreak. For areas where the pandemic is particularly severe, community workers and volunteers should be organized to provide non-contact home delivery services in order to ensure the supply of essential goods. As the COVID-19 pandemic continues to spread globally, the recommendations proposed in this study may provide reference solutions for other cities to control the spread of the virus at the community level. In addition, since the early outbreak data from Wuhan were selected as the research sample, and the characteristics of COVID-19 were not analyzed in depth at that time, the findings of this paper may provide valid suggestions for suppressing potential respiratory disease outbreaks. It has to be mentioned that the sociodemographic variables in this paper are only mentioned that the sociodemographic variables in this paper are only

Nomenclature

| Definition of the variables | Independent variables | Ln_Incidence 1 | Ln_Incidence 2 | Ratio of community's population (10,000) to its land area (km²) |
|-----------------------------|-----------------------|----------------|----------------|---------------------------------------------------------------|
| Dependent variables Incidence 1 | Population density FAR | Ratio of COVID-19 cases to community population (10,000) on 30 January 2020. | | |
| Incidence 2 | | Ratio of COVID-19 cases to community population (10,000) on 19 February 2020. | | |
| Ln_Incidence 1 | Natural logarithm of Incidence 1 | (continued on next column) | | |
| Built environment in administrative scope N_Hospital Number of government-run medical facilities | N_SC Number of community service centers | | | |
| N_Hotel Number of hotels | | | | |
| N_Express Number of express stations | | | | |
| N_School Number of schools (including primary, junior and senior high schools and universities) | | | | |
| N_Market Number of markets (including Supermarkets, convenience stores and food markets) | | | | |
| N_Bus Number of bus stations | | | | |
| N_Metro Number of metro stations | | | | |
| Subscript: 1. Built environmental factors in the 15-minute walking life circle. 2. Built environmental factors in the 10-minute cycling life circle.|

CRediT authorship contribution statement

Jingwei Wang: Conceptualization, Methodology, Data analysis, Writing—original draft. Fanbo Zeng: Supervision, review. Haida Tang: Methodology, Data analysis, Writing—review & editing. Junjie Wang: Visualization. Lihua Xing: Supervision, review.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, and there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled “Correlations between the urban built environmental factors and the spatial distribution at the community level in the reported COVID-19 samples: A case study of Wuhan”.

Data availability

Data will be made available on request.

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Appendix A

Fig. A.1. Ridge Trace for the 15-minute walking life circle in Phase 1 (Model 5) ($k = 0.3$).

Fig. A.2. Ridge Trace for the 15-minute walking life circle in Phase 2 (Model 6) ($k = 0.2$).
Fig. A.3. Ridge Trace for the 10-minute cycling life circle in Phase 1 (Model 7) (k = 0.3).

Fig. A.4. Ridge Trace for the 10-minute cycling life circle in Phase 2 (Model 8) (k = 0.3).

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