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Investigating factors influencing takeout shopping demand under COVID-19: Generalized additive mixed models

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**ABSTRACT**

The COVID-19 pandemic severely hampered the freedom of shopping travel while increasing individuals’ interest in takeout. Although many studies have examined takeout shopping, the available literature provides insufficient evidence on the factors influencing takeout shopping demand under the COVID-19. In this study, generalized additive mixed models were developed based on sampling data of takeout orders in Nanjing before, during, and post the pandemic to measure the associations between takeout shopping demand and neighborhood characteristics at the business circle scale. The results show that population density, house prices, road density, and catering all have a significant impact on takeout shopping demand, while the roles of land use (residential and company indexes) before and post the pandemic are opposite. Besides, the factors influencing the recovery of the demand before and after the pandemic were analyzed. These findings provide important insights into the development of the takeout industry in the post-pandemic era.

**1. Introduction**

The COVID-19 pandemic is currently one of the greatest challenges to human life and health, economic development, and social stability (Kummitha, 2020). Beginning in December 2019 in Wuhan City, Hubei Province, China, the coronavirus rapidly spread around the world due to the interaction of globalization (De Vos, 2020). Authorities in various countries and regions have imposed strict control measures to limit the movement of people and goods to suppress the spread, including transport suspension (Li et al., 2021; Zhu and Guo, 2021), home isolation (Zhu and Tan, 2021), and 14 days of quarantine when traveling (Kapser et al., 2021). However, all these measures have profoundly altered how people live, travel, raise their families, and seek entertainment (Figliozi and Unnikrishnan, 2021a). Many offline retailers and catering companies were shut down as a result. Traditional business patterns were forced to make changes. Some survived and become profitable by transforming into online operations (Alaimo et al., 2021; Gao et al., 2020; Li et al., 2020; Yang et al., 2021). According to the statistics (iiMedia, 2020), the catering industry in China saw a 43.3% year-on-year drop in revenue from January to February 2020, but the number of restaurants opening online sales increased by 63.1% compared to the pre-pandemic period. On the consumer side, the demand for home delivery of daily necessities, such as food, beverages, and groceries, leaped dramatically as it provided a solution to some of the lockdown challenges, resulting in a significant

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increase in online shopping sales during the pandemic (Chen et al., 2021a, 2021b; Figliozzi and Unnikrishnan, 2021b). Until April 2020 when all the lockdown restrictions started to lift in Wuhan and other cities gradually, a return to normality began. However, the regular epidemic prevention and control measures remained unchanged in China, referring to the post-pandemic era.

In recent years, China’s food delivery market has expanded rapidly due to the advances in information and communication technology (ICT), the popularity of smart mobile terminals, and the expansion of logistics and distribution infrastructure (Li et al., 2020). In 2019, the scale of takeout catering reached 650 billion RMB, and nearly 4 million delivery riders earned money through the Meituan takeout platform (Institute, 2020). Takeout shopping has emerged as a new engine for driving consumer economic growth. Meanwhile, the current literature on online shopping (including takeout shopping) is rapidly evolving, e.g., the relationship between online shopping and shopping travel (Kim and Wang, 2021; Shi et al., 2020; Xi et al., 2020; Lee et al., 2017), the impact of the built environment on on-demand food delivery (Wang and He, 2021; Deng et al., 2020; Zhang and Zhen, 2019; Shi et al., 2019). Some studies have also explored the impact of the COVID-19 pandemic on home delivery accessibility and policy (Figliozzi and Unnikrishnan, 2021b), as well as the factors influencing home delivery during the pandemic (Andruetto et al., 2021; Figliozzi and Unnikrishnan, 2021a; Unnikrishnan and Figliozzi, 2021; Ali et al., 2021). However, the majority of the preceding studies rely on household survey data and thus cannot accurately obtain the characteristics of online shopping demand. To the best of the authors’ knowledge, no published study has examined the relationship between the external built environment and takeout shopping demand in the context of the COVID-19 pandemic using the actual takeout order data.

More specifically, there is an urgent need to examine the factors influencing takeout shopping demand before, during, and after the pandemic from the following aspects. First, takeout shopping differs from regular online shopping as the former requires instant or same-day delivery (by appointment). Most studies have focused on regular online shopping, fewer on takeout shopping. Second, understanding the spatiotemporal patterns of takeout shopping services, particularly the impact of the pandemic and other factors (e.g., land use, socio-economic features) on such an economic activity, is conducive to better inferring the recovery of the delivery industry in the post-pandemic era. Finally, non-linear effects of the built environment on takeout shopping demand have been explored in previous studies (Wang and He, 2021). False linear assumptions frequently lead to biased estimates of the impact of the built environment, resulting in erroneous policy implications (Ding et al., 2019). Detecting the impact threshold of the built environment elements can contribute to a rational layout of the takeout catering industry. Therefore, the purpose of this study was to investigate the spatiotemporal changes of takeout shopping demand, before, during, and post the pandemic by leveraging the order data of well-known local takeout platforms in Nanjing, China. Three questions were raised in this study: (i) How have the spatiotemporal characteristics of takeout shopping demands changed at different stages of the pandemic? (ii) Are the impacts of the pandemic on takeout shopping demand in areas with varying socioeconomic characteristics, land use, and traffic facilities different? and (iii) What factors would influence the recovery of the takeout shopping demand in the post-pandemic era?

To address these questions, the takeout shopping demand and relative change related to the pandemic in Nanjing were analyzed. The detailed descriptive statistics were performed to examine the spatiotemporal characteristics of takeout shopping demand. Then, the cross-section analysis of takeout shopping demand before, during, and after the COVID-19 was carried out using three generalized additive mixed models (GAMMs), which have proved to be suitable for complex nonlinear situations and provide good prediction accuracy (Hastie, 2015). Finally, a GAMM was fitted to investigate the factors influencing the recovery of takeout shopping demand, with the relative change in takeout shopping demand before and after the pandemic as the dependent variable, weather and seasonality being the controlling factors. The fixed effects are composed of socio-demographics, the characteristics of takeout business circles, the built environment of the business circle radiation areas, and time-varying variables. Notably, the analysis of takeout shopping demand characteristics was conducted at the business district scale to examine the association between takeout shopping demand and the built environment.

The following section presents a review of the existing literature on takeout shopping. Section 3 provides the research design, including the study area, data sources, and modeling approach. Section 4 discusses the model results. Finally, section 5 concludes the study and offers suggestions for further research.

2. Literature review

2.1. Studies on takeout shopping (during regular periods)

Takeout shopping, as a special form of online shopping, has received attention from transportation scholars, and some of them focused on logistics and traffic behavior (Liu et al., 2020; Wang et al., 2021a, 2021b; Zhang et al., 2021). Besides, several scholars have investigated the factors that influence consumers’ takeout shopping services, primarily focusing on household and individual factors (Kim and Wang, 2021; Wang et al., 2021a, 2021b; Figliozzi and Unnikrishnan, 2021a). In general, there has been a general consensus on the important determinants of using takeout shopping services, i.e., younger people, as well as higher incomes, higher education, and household with more members are more likely to use the services (Lee et al., 2017; Dias et al., 2020; Wang et al., 2021a, 2021b; Kim and Wang, 2021). However, most studies were based on small sample survey data, which means that the demand characteristics of takeout shopping services cannot be accurately reflected. Furthermore, the influencing factors examined seldom address the spatial dimension (e.g., built environment, land use), which is of interest to stakeholders - where takeout demand is high and how spatial factors influence takeout shopping.

Existing studies involving the spatial factors that influence takeout shopping demand are limited. Notably, despite there are differences between takeout shopping and online shopping, this does not preclude the research findings from being an important reference for the study of takeout shopping. There is still no unified conclusion on the impact of built environmental factors on online...
shopping. Currently, three competing hypotheses are the mainstream: influential, non-influenced, and spatial differences in impacts. Factors such as urbanization (Wang and He, 2021; Cao et al., 2013), the socioeconomic background (Shi et al., 2021c), shopping convenience (Zhang and Zhen, 2019), and the accessibility to the nearest subway stations and commercial centers (Loo and Wang, 2017) influence whether and how long consumers shop online. Variables such as the distance from the commercial center (Deng et al., 2020) and the location of the shopping origin (Shi et al., 2019) affect the frequency of online shopping. However, some research has shown the opposing or contradictory views and suggested that residential location, distance from the CBD and congestion level (Krizek et al., 2005), location of the business circle (Shi et al., 2021c), and shopping accessibility (Deng et al., 2020; Krizek et al., 2005; Xi et al., 2021) have no impact on online shopping. Meanwhile, several studies found that the above mentioned built environmental factors have varying effects on online shopping (e.g., online shopping demand, frequency, and pattern) depending on countries, regions, shopping stages, and commodity types (Dai et al., 2021; Shi et al., 2020; Zhang and Zhen, 2019; Zhen et al., 2018; Maat and Konings, 2018; Xi et al., 2014). Furthermore, the more popular conceptual models related to such issues are the efficiency hypothesis and the technology diffusion hypothesis (Anderson et al., 2003; Farag et al., 2006). Existing research on these two hypotheses has been conducted and verified through variables such as the urbanization level of online shoppers’ residence, shopping accessibility, and built environment (Wang and He, 2021; Deng et al., 2020; Zhen et al., 2018; Cao et al., 2013).

Various methods have been developed to explore the use of online/takeout shopping services. Structural equation model (SEM) (Shi et al., 2021a, 2021b; Shi et al., 2020a), and regression models (e.g., ordered probit, ordinal logistic) (Kim and Wang, 2021; Deng et al., 2020) are primarily used to investigate household and individual factors using cross-sectional survey data. Spatial econometric models (Shi et al., 2021d), and counting models (Wang and He, 2021) are more commonly used in studies that consider the spatial factors of online/takeout shopping. However, the nonlinearity and heterogeneity of the built environment have not been fully considered in this type of research. Although the importance of nonlinearity has been realized by previous studies, the majority of them used machine learning models (e.g., random forest, GBDT) with poor interpretability, while generalized additive mixed models were gradually being adopted with good interpretability in capturing nonlinearity (Ding et al., 2019; Hu et al., 2021a, 2021b).

### 2.2. The impact of the pandemic on takeout shopping services

Takeout shopping and delivery riders provided a vital lifeline to tens of millions of people who were quarantined during the pandemic in 2020 (Li et al., 2020). Global consumer surveys (Boston Consulting Group, 2020; Deloitte, 2020) have revealed a shift in shopping preferences from offline to online in response to the pandemic. For example, 22.5% of the respondents reported an increased frequency of takeout shopping during the pandemic compared to regular periods due to convenience and the desire to avoid infection risk (Deloitte, 2020). Notably, ordering takeout food online is very popular among college students and office workers (Qiu and Kim, 2021; Shi et al., 2021c). During the pandemic, the number of orders from campuses decreased because students were unable to return to colleges, while more people who were forced to work from home increased their takeout shopping frequency to devote more time to jobs (Li et al., 2020). Furthermore, the catering and retail industries have been hit hard, and shifting from offline to online operations became an important way to stay afloat (iMedia, 2020). As a result, takeout delivery not only met consumers’ needs but also employed those who deliver orders (Noor and Renwick, 2020).

Recently, a significant number of studies have focused on the pandemic and takeout shopping using household surveys. Prasetyo et al. (2021) determined the factors that influence the satisfaction and loyalty of online food delivery during the new normal of the COVID-19 pandemic in Indonesia. Ali et al. (2021) investigated the moderating role of the situational effect of the pandemic on people’s online ordering behavior in Pakistan. The transition from physical to virtual in two European countries, Sweden and Italy, during the pandemic, was investigated by Andruetto et al. (2021), who found that the social demographic and family structure of the respondents played a key role in the shopping behavioral changes. Similarly, some studies conducted an online survey on socioeconomic characteristics and online shopping preferences, as well as takeout orders before, during, and after the pandemic (Unnikrishnan and Figliozzi 2021; Wang et al., 2021a, 2021b). In addition, some scholars have also focused on the relationship between home delivery and environmental justice and equity during the pandemic and proposed a new way to improve the inequality of home delivery (Figliozzi and Unnikrishnan, 2021b). Meanwhile, a few studies on the online food purchase behavior of urban residents in China during the pandemic have been conducted (Chen et al., 2021a, 2021b; Gao et al., 2020), and provided insights to understand the effect of the pandemic on takeout shopping usage. Unfortunately, no research has focused on the impact of spatial factors on takeout shopping under the COVID-19 using takeout order data.

It is also of concern that misconceptions about the current popularity of takeout shopping demand may mislead planning for the post-epidemic era (Wang et al., 2021a, 2021b). For example, Shamshiripour et al. (2020) suggested that current takeout delivery would continue to grow for a long time. However, Wang et al. (2021a, 2021b) found that approximately half of new takeout shopping consumers would discontinue using it after the pandemic ended, which indicates that the additional demand was not the result of market competition, but the disruption to offline shopping caused by the pandemic. Nevertheless, there is still a lack of studies that analyze the takeout shopping demand under the impact of the pandemic, particularly on which regions were most affected and which regions have recovered best from the impact of the pandemic.

### 2.3. Research gaps

In summary, although previous studies have examined the relationship between the built environment and online shopping (partially for takeout shopping), most of them used cross-sectional data or questionnaire data, which resulted in issues including insufficient sample size, limited research universality, and inability to explore the dynamic spatiotemporal changes of takeout demand.
Additionally, the impact of the pandemic on takeout shopping remains to be validated by data analysis of actual space-time dimensions. Finally, a better understanding of the recovery of takeout shopping demand after the pandemic and its influencing factors for subsequent planning was needed.

3. Research design

3.1. Study area

Nanjing is the capital city of Jiangsu Province, China, with an area of 6,587 km$^2$ and a permanent resident population of 9.31 million. In 2019, Nanjing ranked first in Jiangsu Province in terms of takeout order counts. As a non-downtown area, Jiangning District has a high demand for ordering takeout food online throughout the city, followed by Gulou and Qinhuai Districts in the urban area (Zhang, 2020). Delivery of goods has also expanded beyond traditional foods to include desserts, beverages, flowers, fruits, vegetables, and other daily necessities. It is worth noting that the operation mode of Chinese takeout enterprises differs from that of the western countries, where catering enterprises have their delivery team and the third-party platforms only provide ordering services, not delivery (Shi et al., 2021c). However, because delivery teams in China are mostly affiliated with third-party platforms, takeout services include all pick-up and delivery services provided by the platform’s delivery riders. In this study, takeout order data from a local takeout platform with a large market share in Nanjing was applied. Due to privacy protection, commercial confidentiality, and the lack of a unified data open policy, we only sampled the order data of 18 takeout business circles distributed in five urban districts (Xuanwu, Qixia, Gulou, Jiangning, and Yuhua) of Nanjing (Fig. 1).

In addition, it is worth mentioning that Nanjing made significant efforts in the prevention and control of the pandemic. Since the initial outbreak in Wuhan in early 2020, a total of 93 local cases were confirmed in Nanjing, and all were cured by the end of March 2020. In May 2020, Nanjing resumed normal production and life order. Until May 2021 (as of this writing), no confirmed cases have been found in Nanjing, which is also known as the post-pandemic era. Therefore, to better explain the impact of the pandemic on takeout shopping demand, we chose takeout order data for three representative periods, namely November 1 to 7, 2019 (before the pandemic), March 1 to 7, 2020 (during the pandemic) and November 1 to 7, 2020 (the post-pandemic period). It should be noted that the three chosen periods do not include holidays, major events, severe weather, and other interfering factors.

3.2. Data sources

Multi-source data were used in this study to examine how the socioeconomic and built environmental factors influence takeout shopping demand. The datasets include delivery order data, land use data, POI data, and weather data.

![Fig. 1. Distribution of takeout business circle of Nanjing.](image-url)
3.2.1. Dependent variable

Delivery order profile includes: Order date, geographic information for merchant and consumer, start delivery and arrival time, and the business district where the merchant is located. All sensitive personal data were removed to make sure that no individual can be identified. Orders with successful transactions and delivery duration (from the start to the arrival of delivery) between 5 min and 2 h (outside this range was treated as abnormal or not instant delivery) were kept. Finally, 92.3% of the delivery travel data was retained. Delivery orders were processed from 2338 different takeout merchants.

Based on the delivery distance, the business circle is divided into three levels: central (500 m), main (501–1000 m), and peripheral (1001–1500 m) (Alliance, 2015). This study found that a unified area with a radius of 500 m can cover 99.8% of takeout providers after matching their longitude and latitude coordinates. The research areas were divided into 18 takeout shopping circles with a radius of 500 m based on the consistency and availability of the data. All indicators were captured based on these areas. A similar method of taking a takeout business circle as a space measurement unit was employed in previous studies (He, 2019; Jiao et al., 2020; Shi et al., 2021c). Delivery Merchants with fewer than 10 orders per week were excluded. Finally, delivery orders of 1294 merchants were obtained, covering consumers in an area of about 500 km² in Nanjing.

According to the takeout industry report (Club, 2018), takeout consumption scenarios can be divided into morning (6:00–10:00), noon (10:00–14:00), afternoon (14:00–18:00), and evening (18:00–22:00), which correspond to breakfast, lunch, afternoon tea and dinner (including night snack), respectively. Fig. 2 shows that the highest volume of the order is at noon and the lowest in the morning. The first dependent variable in this study is the total takeout order demand of different business circles in different periods to compare its changes before, during, and after the pandemic. The comparison between variance and mean is found to be large, and there is obvious over-dispersion. The other dependent variable is the relative change of takeout shopping demand at the corresponding time before and after the pandemic, which is used to characterize the recovery of takeout order demand in the post-pandemic era. Similar approaches were used in previous studies (Hu et al., 2021a, 2021b).

$$\Delta \phi_{x(t)} = \frac{Y_{x(t)} - Y_{x(t)'}}{Y_{x(t)'}}$$  \hspace{1cm} (1)

where \(\Delta \phi\) is the relative change of takeout shopping demand in time period \(t\) of business circle \(i\) on day \(x\) of a week; \(Y_{x(t)'}\) is the takeout shopping demand in time period \(t\) of business circle \(i\) on day \(x\) of a week after the pandemic; \(Y_{x(t)}\) is the takeout shopping demand in time period \(t\) of business circle \(i\) on day \(x\) of a week before the pandemic. It is important to note that we match the same weekday before and after the pandemic, rather than the same month day, because order demand is more closely related to the weekend and workday.

3.2.2. Independent variables

The data of the independent variables include socioeconomic characteristics, weather conditions, and built environment factors within the business circle and the corresponding radiation area.

First, we extracted 10 categories of POI data of the 18 takeout business circles (within 500 m) from Baidu Map API, including supermarkets, restaurants, places of employment, hospitals, and transportation facilities (i.e., bus stops and subway stations). We also obtained the rental data in the takeout business circles from Soufang.com.

Second, takeout providers are only permitted to deliver within the business circle radiation range, which is generally set at 3 or 4 km (Liu et al., 2020; Wang, 2020) so the food freshness and the distribution cost can be guaranteed. We matched the Euclidean distance

![Fig. 2. Frequency distribution for takeout order counts at various times of the day.](image-url)
between merchants and consumers and confirmed that 99.95% of the deliveries were within 3 km. Therefore, the radiation range of the business circle was set to be 3 km. In addition, 10 categories of POI data from the 3 km business circle radiation area (data within the business circle is not included) were crawled on Baidu Map API. The different types of land use index of the business circle radiation areas, e.g., commerce, residential, and company, were also obtained. The house price within the area was extracted from https://nj.lianjia.com/.

Third, Shi et al. (2021c) found that the takeout order demand in Shanghai’s business circles was gradually decreasing from the inner ring to the outer ring, and argued that the socioeconomic background was the most important factor influencing the spatial differences of takeout orders. However, the online catering space in Nanjing (Qing et al., 2020) presents a “horizontal, multi-center” network structure. To better understand the impact of spatial location and socioeconomic background, we set a regional commercialization level indicator as a dummy variable: The demographic, economic, and social characteristics of the district in which the business circle is located, as well as the indicators of the supermarket, restaurant, entertainment and transportation within the business circle, are normalized, and the business circle is divided into higher or lower commercialized by averaging (Shi et al., 2021c; Deng et al., 2020; Chen et al., 2011). In addition, a binary variable is set to distinguish the business circle as being in the urban or suburban district (Zhang and Zhen, 2019; Du et al., 2017).

Finally, we divided the independent variables into several categories, e.g., socio-demographic, economic level, traffic factors, land use, and weather (Shi et al., 2021c). Then, we use the variance inflation factor (VIF) to conduct a multicollinearity test, remove the variables with a VIF value greater than 10, and finally get the preliminary variable set. Table 1 shows all variables after screening. In addition, we investigate whether the impacts of independent variables differ between higher and lower commercialized, as well as urban and suburb business circles by adding their interactions with the commercialization level and location variable. After testing all the interaction items, excluding collinearity and insignificant interaction items, only the interaction between the commercialization level variable and the traffic facilities in the business circles and the house price in the radiation areas are retained.

### 3.3. Modelling approach

To investigate the impact of the built environment and other urban characteristics on takeout shopping demand during the pandemic, we employed the semi-parametric model GAMM applied to the count response variables. Simple linear regression cannot satisfy the assumptions of normality and independence, nor capture the potential non-linear and random effects. The GAMM can fit various nonlinear effects, such as random effects and nonlinear interactions, in a framework by changing spline functions (Hu et al., 2021b, 2021a; Ding et al., 2019). The dependent variable of the first type of GAMM in this study is takeout shopping demand, and the variance of the demand is larger than the mean, so the GAMM assumption follows the negative binomial (NB) distribution. The demand relative change, which is assumed to follow the Gaussian distribution, is the dependent variable in the second type of GAMM. In addition, GLM (2) and generalized additive model (3) as benchmark models, were applied for comparison with GAMM. The Goodness-of-fit of the models was compared using Akaike Information Criterion (AIC) and adjusted $R^2$.

| Factors | Description | Mean | St.d. | Min | Max |
|---------|-------------|------|------|-----|-----|
| **Dependent Variables** | Takeout shopping demand | 27.66 | 27.08 | 0 | 163 |
| | Relative change | 0.80 | 0.81 | −1 | 4.5 |
| **Independent Variable** | Socio-demographic | | | | |
| | Population density | 3.19 | 1.56 | 0.76 | 5.48 |
| | Employment density | 2.35 | 1.56 | 0.41 | 5.77 |
| **Economic level** | Business circle rent | 2.97 | 1.19 | 1.3 | 6 |
| | Average house prices | 34.98 | 16.11 | 4.4 | 70 |
| | Commercialization | 0.55 | 0.49 | 0 | 1 |
| **Traffic factors** | Traffic facilities in the business circle | 80 | 69 | 5 | 241 |
| | Road density | 34.67 | 12.09 | 20 | 60 |
| | Traffic facilities in the radiation area | 51 | 35 | 6 | 130 |
| **Land use** | Catering index | 91 | 124 | 7 | 559 |
| | Residential index | 54.10 | 9.24 | 32.39 | 65.42 |
| | Company index | 43.21 | 15.52 | 23.17 | 76.53 |
| | College area | 31.26 | 12.16 | 13.72 | 71.31 |
| | Hospital area | 9.93 | 6.02 | 0 | 16.59 |
| | Leisure service | 7.76 | 2.52 | 4.12 | 13.12 |
| **Temporal Periods** | Dummy variable: 0 = morning; 1 = noon; 2 = afternoon; 3 = evening | 1.50 | 1.11 | 0 | 3 |
\[ g(\mathbb{E}(Y|X_1, X_2, \ldots, X_p)) = \beta_0 + \sum_{j=1}^{p} \beta_j X_j + \theta \] (2)

\[ g(\mathbb{E}(Y|X_1, X_2, \ldots, X_p)) = \beta_0 + \sum_{j=1}^{p} \beta_j X_j + \sum_{j=m+1}^{p} \beta_j f(X_j) + \theta \] (3)

where \( Y \) is the dependent variable, that is, the demand for takeout orders; \( X_p \) is the explanatory variable; \( p \) is the number of explanatory variables; \( \beta_0 \) is the intercept term; \( \beta_j \) is the explanatory variable parameter; \( \mathbb{E}(Y) \) is the average demand for takeout orders; \( g() \) is the connection function; \( f(X_j) \) is smooth function; \( \theta \) is the error term.

\( \text{GAMM is a non-parametric extension of GLM, that is, the linear term in Eq. (2) is replaced by non-parametric function terms of unknown form, and the basic framework of GLM model is still retained.} \)

\[ Y_{(1)} \sim NB\left(\mu_i, \mu_i + \frac{\mu_i^2}{k}\right) (i = 1, 2, 3) \] (4)

\[ Y_{(2)} \sim \text{Gaussian}(\mu, \sigma^2) (i = 1, 2, 3) \] (5)

\[ g(\mathbb{E}(Y|X_1, X_2, \ldots, X_p)) = s_{(0)} + \sum_{j=1}^{p} s_j X_j + \sum_{j=m+1}^{p} \beta_j f(X_j) + \tilde{R}_j + \theta \] (6)

where \( Y_{(1)} \) represents the demand for takeout orders at different times of the day in different business circles; \( Y_{(2)} \) represents the relative change of takeout shopping demand; \( i \) represents before, during and post the pandemic, respectively; \( s_{(0)} \) is the intercept term; \( s() \) is a smooth function to specify the nonlinear dependence of the dependent variable on the explanatory variable (i.e., thin plate regression splines, cubic regression splines, and p-splines); \( m \) is the number of smoothing items, namely the number of explanatory variables in the model that have nonlinear effects on dependent variables. \( \tilde{R}_j \) is the random effect at the business circle level (the spline function penalized by a ridge penalty). \( \theta \) is the error term. The R “mgcv” package is used to realize the estimation of GAMM (Wood, 2017).

4. Results and discussion

4.1. Descriptive analysis

This section reports the descriptive analysis of the delivery order trips. The total number of takeout orders decreased during the pandemic, but increased again in the post-pandemic period (Fig. 2). Although previous studies have shown that people’s interest in takeout shopping and shopping frequency increase during the pandemic (Andruetto et al., 2021; Unnikrishnan and Figliozzi, 2021; Chen et al., 2021a, 2021b; Gao et al., 2020), the number of takeout orders did decrease. We argue that this is due to the loss of some consumer groups, such as college students, and office workers, who stayed at home during the pandemic. Besides, the numbers of delivery merchants and riders also decreased, resulting in supply and transportation shortages.

The average delivery distance (Euclidean distance (Liu et al., 2020)) is 1,749 m with 38.8%, 82.2%, and 98.6% within 1 km, 2 km, and 3 km, respectively (Fig. 3). Orders with a delivery distance of 1,400 to 1,600 m account for the highest proportion. The average delivery time of orders is 28 min, among which, those took 24–27 min account for the highest proportion (Fig. 4). In addition, the
average distance and duration of delivery increased during the pandemic. We believe that such changes are due to fewer nearby takeout supplies being available.

Fig. 5 depicts the time patterns of takeout orders before, during, and after the pandemic. The darker the color, the higher the takeout order volume. It seems that the overall order volume before and after the pandemic is higher than that during the pandemic. The order volume at noon (10:00–12:00) and in the afternoon (17:00–18:00) are relatively concentrated, corresponding to lunch and dinner time respectively. Orders from 13:00 to 16:00 before and after the pandemic are also higher than those during the pandemic. In addition, order volume on Sunday is higher in the post-pandemic era than on other days.

4.2. Cross-sectional analysis and results

The results of the goodness-of-fit of the two benchmark models and the GAMM are shown in Table 2. GAMMs present the lowest AIC value and the highest adjusted $R^2$ in all three models, indicating that the goodness-of-fit of GAMM is the best. These three GAMMs respectively reveal the similarities and differences regarding the influencing factors of takeout shopping demand under regular, pandemic, and post-pandemic conditions (Table 3). A summary of the findings from this study and other studies is presented in Table 4.

In terms of socio-demographics, the population density in the three models all has a significant positive correlation, indicating that the higher the population density of the business circle radiation area, the higher the demand for takeout. Such finding is in line with previous research (Wang et al., 2019; Zhu, 2019). It is intuitive since the population density of the business circle radiation area implies the number of potential customers in the business circle, which has a positive effect on order generation. Additionally, regarding the economic level, house prices in the business circle radiation area can indicate the economic level of the residents to some extent, but the negative coefficient of house prices indicates that people are less likely to order takeout food online in the radiation area with a higher economic level. The commercialization level variable of the business circle is positively related to the takeout shopping demand, while the coefficient of its interaction term with house price shows a significant negative correlation. This indicates that the negative impact of house prices in the business circle radiation area on takeout shopping demand differs between higher and lower commercialized business circles. The discovery of this interaction is similar to Wang and He (2021). Specifically, the higher the house price in the more commercialized business circle radiation areas, the greater the reduction in takeout shopping demand compared to a less commercialized business circle. One possible explanation is the low price of takeout food, which is less appealing to consumers living in radiation areas with high house prices and high commercialization level; they may have higher requirements for food quality and are more likely to consume offline. The interaction between the commercialization level of the business circle and house price in the radiation area further clarified the heterogeneity mechanism of takeout shopping demand, while the previous study only analyzed the economic level and house price within the business circle separately (Shi et al., 2021c).

As for traffic factors, the number of traffic facilities in the takeout business circle has a positive effect on the takeout demand in all three periods, which is consistent with Shi et al. (2021c). However, its interaction with the higher commercialization level variable has a negative coefficient, indicating that the positive effect of traffic facilities on the takeout shopping demand is much weaker in higher commercialization level business circles, and the magnitude of the positive correlation is stronger in lower commercialization level business circles. The possible explanation is that a higher commercialized business circle with convenient transportation is more attractive for offline consumption by neighboring consumers. In addition, there is a weak negative correlation between traffic facilities and road density in the radiation area and demand for takeout food online. This suggests that consumers are more likely to go shopping for food or eat at restaurants due to the well-developed transportation infrastructure (Shi et al., 2018). In other words, convenient transportation systems can enhance shopping accessibility, and reduce takeout shopping to some extent, confirming the efficiency hypothesis proposed by Farag et al. (2006).

The number of catering merchants in the business circle has a weak positive correlation with the land use characteristics. Food merchants have a spatial agglomeration effect because they can benefit from obvious economies of scale (Wang et al., 2019). Besides, such findings explain why takeout practitioners tend to gravitate toward the existing catering agglomeration area when deciding on

![Fig. 4. The distribution of the delivery time.](image-url)
locations. The index of company land shows a weak positive correlation with the pandemic period, but no significant correlation before the pandemic, indicating that the pandemic has stimulated the interest of individual employees to order takeout food online. Another intriguing finding is that the residential index only demonstrated a significant positive correlation during the pandemic. The lockdown during the pandemic led to more telecommuting from home (Mouratidis et al., 2021) and more home isolation that limited outdoor activities, all of which contributed to an increase in demand for daily groceries and food deliveries in residential areas. In the post-pandemic period, normal life and commuting returned to the same level as in the pre-pandemic, and result in decreased demand from residential areas (Li et al., 2020). Besides, the number of universities has significantly positive effects on the demand before and after the pandemic, but there is no significant correlation during the pandemic. This is understandable given that college students were forced to stay at home during the pandemic, resulting in the loss of such consumer groups. Furthermore, the number of hospitals in the business circle radiation area presents a similar change. As expected, leisure services have a negative correlation with takeout shopping demand, which is consistent with the previous study (Wang and He, 2021). Individuals may be more inclined to get out for shopping trips in areas with a higher density of leisure services. Finally, the spatial location is not significant, indicating that the location of the business circle has no significant influence on takeout shopping demand.

Regarding the nonlinear effects, Figs. 6, 7, and 8 depict the nonlinear effects of several variables estimated with smooth splines. The business circle rent and road density (before and during the pandemic), as well as the business circle rent and company index (in the post-pandemic period), were used to fit the nonlinear effect through thin plate regression splines. The estimated degree of freedom (e.d.f) is greater than 1.0 (Table 3), indicating that the variable is nonlinear. It can be seen from these figures that the variance of e.d.f (the shaded areas) stays at a high level, indicating that the influence of these independent variables varies among business circles.

The business circle rent exhibits a nonlinear effect at various stages of the pandemic, with highly similar trends. Overall, takeout shopping demand shows an upward trend as the rent rises. The business circle rent reflects the economic and consumption levels of the

Table 2
Comparison of the goodness of fit between different models.

| Models | Before the pandemic | During the pandemic | Post-pandemic period |
|--------|---------------------|---------------------|----------------------|
|        | AIC | R² | AIC | R² | AIC | R² |
| GLM    | 4035.2 | 0.352 | 3823.8 | 0.421 | 4134.9 | 0.433 |
| GAM    | 3916.4 | 0.421 | 3613.4 | 0.472 | 4103.4 | 0.512 |
| Gamm   | 3847.6 | 0.493 | 3544.2 | 0.536 | 4017.6 | 0.564 |

Fig. 5. Temporal distribution of the order volume before, during, and post the pandemic.
business circles (Shi et al., 2021c). Individuals in business circles with high consumption levels and relatively strong economic vitality are more inclined to order takeout. However, in the model before and during the pandemic, the growth of takeout demand leveled off, even decreased when the rent increased to a certain value. Road density shows significant nonlinearity both before and during the pandemic, as well as a high degree of similarity in both models. In general, road density is negatively related to takeout order demand. The demand rises first and then falls as road density increases, with demand peaking at around 30 on the road density index. In the post-COVID-19 period, the company index also shows a high degree of nonlinearity. Takeout shopping demand tends to rise and then fall as the company index goes up, with demand essentially peaking when the company index rises to about 35. This nonlinear variation trend indicates that the influence of built environment elements does not grow inexorably with their numerical value, but tends to saturate after exceeding a certain threshold (Chen et al., 2021a, 2021b).

4.3. Analysis of relative change in takeout shopping demand

Table 5 shows the results of the relationship between the relative change in takeout shopping demand and independent variables. Fitting this model has the goal of examining which factors influence the relative change after the pandemic, i.e., order demand recovery. The goodness-of-fit of the model is lower than that of the previous three cross-sectional models because the relative changes are more volatile and difficult to capture. The model shows no nonlinearity in the independent variables, and the periods are heterogeneous, while the level of commercialization variable to be examined is not significant.

The results in this section should be interpreted in conjunction with the descriptive statistics and cross-sectional model above. Regarding the economic level, business circle rent is positively correlated with demand relative change, whereas average house price is negatively correlated, suggesting that higher rent is associated with better demand recovery in business circles, and higher house price is associated with less demand recovery. In terms of traffic factors, traffic facilities in the business circle radiation area have a positive correlation, while road density is negative, indicating that regions with more traffic facilities have a more significant relative change in takeout demand after the pandemic; whereas road density has the opposite effect. As for land use, the residential index, companies, universities, and hospitals in the radiation area show a positive correlation with the relative change, indicating that business circle radiation areas with more residential houses, companies, and universities have a greater relative recovery in takeout demand after the pandemic. One possible explanation is that consumers in these areas may still rely on takeout shopping in post-epidemic era (Li et al., 2020).

5. Conclusions and implications

Takeout shopping, as a popular sharing economy mode, has received increased attention during the pandemic, effectively replacing shopping activities, thereby facilitating residents’ daily lives, avoiding heavy traffic, maintaining social distance, and reducing the possibility of virus transmission (Li et al., 2020). Leveraging the takeout order data of the sampled business circles before, during, and
Table 4
Results comparison.

| Variables       | Literature                                      | This research                                      | Before the pandemic | During the pandemic | Post-pandemic period |
|-----------------|-------------------------------------------------|----------------------------------------------------|--------------------|---------------------|----------------------|
| **Socio-demographic** | Population density, household size               | Population density                                 | Population density  | Population density  | Population density   |
| **Economic level** | Capita consumption, urbanization                | Commercialization, rent (–), house prices (-)      | Commercialization  | Commercialization, rent (–), house prices (-) | Commercialization, rent (–), house prices (-) |
| **Traffic factors** | Bus stops, subway stations                      | road density (–)(–), traffic facilities in radiation area (–) | road density (–) (–), traffic facilities in business circle (–) | road density (–), traffic facilities in radiation area (–), traffic facilities in business circle (–) |
| **Land use**     | Catering, company, green (-), industrial (-), rural residential (-), leisure service (-) | Catering, college, hospital, leisure service (-) | Catering, residential, company, leisure service (-) | Catering, company (-), college, hospital |
| **Temporal**     | Weekends (-)                                    | Periods (-)                                        | Periods (-)         | Periods (-)         | Periods (-)          |

Note: (–) indicates a negative correlation, if not marked, the default is a positive correlation; (~) indicates that the nonlinearity is captured.
after the pandemic in Nanjing, this study examined the influencing factors of takeout shopping demand. Four sets of GAMMs were used to examine the spatiotemporal patterns and relative changes in takeout shopping demand, capturing the nonlinear and heterogeneous effects of various influencing factors. The main conclusions in response to the three questions raised in the introduction and policy recommendations on how the takeout industry can respond to the impact of the pandemic are as follows.

(1) The findings show that the overall order demand decreased during the pandemic, but recovered rapidly in the post-pandemic era. Besides, both delivery time and distance increased slightly during the pandemic, suggesting that some takeout shops near residential areas might have closed down during the pandemic, causing consumers to order from takeout shops farther away.

(2) Traffic facilities in takeout business circles and population density, and catering in radiation areas are positively related to takeout shopping demand before, during, and after the pandemic, while house prices, road density, and leisure facilities in radiation areas are all negatively related. However, the results of land use (residential and company index) in two periods before and post the pandemic are opposed. The two variables are significantly positively correlated during the pandemic, indicating that residents and office workers are more willing to order takeout food online during the effect of the pandemic. Besides, in the
post-pandemic period, the residential index returned to its previous insignificant status, while the company index remained significantly positive. Moreover, the magnitude of the effects of the traffic facilities in the business circles and the house prices in the radiation areas are different between higher and lower commercialized business circles. In terms of nonlinear influence, business circle rent has a similar nonlinear trend in all three models, and takeout shopping demand reaches a threshold as rent rises. Road density and company index also show strong nonlinearity during different periods, with an irregular inverted-V relationship with takeout shopping demand.

(3) Finally, it is worth noting that the above inference is supported by the model of relative change in takeout shopping demand. Specifically, the higher the business circle rent, the more traffic facilities, residential index, enterprises, universities, and hospitals in business circle radiation areas, the better the recovery of takeout demand, while the average house price and road density are the opposite.

The modeling results contribute to a better understanding of the impact of the pandemic on takeout shopping demand and its recovery in the post-pandemic period. Besides, several findings are worth noting for takeout platforms and merchants in reasonable layout of the takeout industry. First, to attract more consumers, takeout practitioners generally prefer to locate their restaurants in densely populated areas, e.g., transportation hubs and shopping centers. However, the potential heterogeneity effect of the interaction between the commercialization level of business circles and built environment variables such as house prices and traffic facilities should also be considered. Then, as illustrated by the preceding analysis, the potential nonlinearity and threshold effect on the built environment complicate such issues, necessitating further investigation of the optimal layout location of takeout catering. Additionally, the impact of the post-pandemic era on takeout shopping is not invariable. Although the takeout order data from November

Table 5
Results of relative changes in takeout shopping demand.

| Category     | Variable                                      | Relative change | Estimate | P-value |
|--------------|-----------------------------------------------|-----------------|----------|---------|
| Intercept    |                                               |                 | −46.987  | 0.045   |
| Economic level | Business circle rent                          |                 | 2.109    | 0.016   |
|              | Average house prices                          |                 | −0.106   | 0.069   |
| Traffic factors | Road density                                 |                 | −0.170   | 0.057   |
|              | Traffic facilities in the radiation area      |                 | 0.154    | 0.025   |
| Land use     | Residential index                             |                 | 0.330    | 0.037   |
|              | Company index                                 |                 | 0.179    | 0.021   |
|              | College area                                  |                 | 0.212    | 0.079   |
| Category     | s(Periods)                                    |                 | 2.865    | 0.000   |
|              | e.d.f                                         |                 | 0.295    |         |
|              | Deviance explained                            |                 | 32.8%    |         |

Fig. 8. Estimated degrees of freedom in the post-pandemic period.
2020 is leveraged to characterize takeout shopping in the post-pandemic era, there is still the possibility of an outbreak in the future due to the pandemic’s volatility and repeatability. Incidental pandemic control measures have become a “new normal”, imposing some external environmental uncertainty on the food delivery industry (Srivatsa Srinivas and Marathe, 2021; Thomas et al., 2021). For example, in the post-epidemic era, there may be a sizable proportion of takeout consumers who may discontinue online grocery shopping (Wang et al., 2021a, 2021b). Takeout merchants and platforms need to make dynamic adjustments to food purchases and delivery riders based on the real-time epidemic prevention and control situation. Finally, differences in the recovery of takeout shopping demand in business circles with various characteristics should also be taken seriously, rather than simply planning and laying out along the lines of the pandemic era.

The main contributions of this study can be summarized as follows: This study is the first to use takeout order data to explore the spatiotemporal patterns and relative changes of takeout shopping demand under the influence of the pandemic at the business circle scale. It enriches the literature on the relationship between socioeconomic attributes and built environment and takeout shopping demand. Second, this study employed the GAMM to model takeout shopping demand, capturing the nonlinearity in partial independent variables and heterogeneous effect by interactions. The benefit of this method is its high performance in dealing with data of nonlinear nature. Finally, this study provides new insights into the changing demand for takeout shopping in the post-pandemic era, as well as policy recommendations to help takeout merchants adjust their business layout.

The study is not without limitations. First, different types, prices, and discounts of takeout may affect consumers’ choices, however, the heterogeneous effects of type of products are not considered due to the limitation of data sources. Second, there is only one week’s order data in each period, which may not be the same as the seasonal fluctuations. In addition, although the takeout business circle as a basic spatial measurement unit can compensate for the deficiencies of the urban macro-level or larger region research, this study only included a general evaluation of the order amount of each radiation area, without considering the differences in different types of consumers. Therefore, given the possibility of ecological fallacies, these conclusions should not be extrapolated to individuals. Third, considering that the GAM model is a statistical technique designed to examine the association rather than causal impact and there may be other unmeasured factors that may still bias the estimates, further studies can consider other causal inference models, such as Two-Stage least squares (2SLS) regression and difference-in-difference to test the robustness of the results, as well as more detailed information about business circle to address endogeneity. Finally, since only the order data of partial business circles was obtained for this study, and consumers in the radiation areas are distributed in a wide range, even the adjacent radiation areas overlap with each other, which is consistent with the actual takeout shopping scenario, more data are needed to verify the generality of the research results.

CRediT authorship contribution statement

Fan Zhang: Conceptualization, Methodology, Software, Writing – original draft. Yanjie Ji: Supervision, Funding acquisition, Writing – review & editing. Huitao Lv: Methodology, Writing – review & editing. Xinwei Ma: Writing – review & editing. Chencheng Kuai: Data curation, Validation. Wenhao Li: Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Alaimo, L.S., Fiore, M., Galati, A., 2021. Measuring consumers’ level of satisfaction for online food shopping during COVID-19 in Italy using POSETs. Socioecon. Plann. Sci. 101064 https://doi.org/10.1016/j.sps.2021.101064.
Ali, S., Khalid, N., Javed, H.M.U., Islam, D.M.Z., 2021. Consumer adoption of online food delivery ordering (Ofdo) services in Pakistan: The impact of the covid-19 pandemic situation. J. Open Innov. Technol. Mark. Cult. 7, 1–23. https://doi.org/10.3390/joitmc7010010.
Ali, S., Khalid, N., Javed, H.M.U., Islam, D.M.Z., 2021. Consumer adoption of online food delivery ordering (Ofdo) services in Pakistan: The impact of the covid-19 pandemic situation. J. Open Innov. Technol. Mark. Cult. 7, 1–23. https://doi.org/10.3390/joitmc7010010.
Anderson, W.P., Chatterjee, L., Lakshmanan, T.R., 2003. E-commerce, transportation, and economic geography. Growth Change 34 (4), 415–432.
Andreetto, C., Bin, E., Sunio, Y., Pernestål, Å., 2021. Transition from physical to online shopping alternatives due to the COVID-19 pandemic 1–41.
Cao, X., Chen, Q., Choo, S., 2013. Geographic distribution of e-shopping: application of structural equation models in the Twin Cities of Minnesota. Transp. Res. Rec. 2383 (1), 18–26.
Chen, E., Ye, Z., Wu, H., 2021a. Nonlinear effects of built environment on intermodal transit trips considering spatial heterogeneity. Transp. Res. Part D Transp. Environ. 90, 102677 https://doi.org/10.1016/j.trd.2020.102677.
Chen, J., Zhang, Y., Zhu, S., Liu, L., 2021b. Does covid-19 affect the behavior of buying fresh food? Evidence from Wuhan, China. Int. J. Environ. Res. Public Health 18 (9), 4469.
Chen, W., Meng, D., He, Z., 2011. Comprehensive evaluation and spatial pattern of regional urbanization level in Henan. Prog. Geogr. 30, 978–985.
Club, T., 2018. What is the busiest time for takeout orders? [WWW Document]. URL https://www.sohu.com/a/282424252_100083738.
Thomas, F.M.F., Charlton, S.G., Lewis, I., Nandavar, S., 2021. Commuting before and after COVID-19. Transp. Res. Interdiscip. Perspect. 11, 100423 https://doi.org/10.1016/j.trip.2021.100423.

Unnikrishnan, A., Figliozzi, M., 2021. Exploratory analysis of factors affecting levels of home deliveries before, during, and post- COVID-19. Transp. Res. Interdisciplinary Perspectives 10, 100402.

Wang, S., 2020. Operation research and optimization of Meituan intelligent distribution system [WWW Document]. URL https://tech.meituan.com/2020/02/20/meituan-delivery-operations-research.html.

Wang, X., Kim, W., Holguín-Veras, J., Schmid, J., 2021a. Adoption of delivery services in light of the COVID pandemic: Who and how long? Transp. Res. Part A Policy Pract. 154, 270–286.

Wang, X., Wang, L., Wang, S., Chen, J.F., Wu, C., 2021b. An XGBoost-enhanced fast constructive algorithm for food delivery route planning problem. Comput. Ind. Eng. 152 https://doi.org/10.1016/j.cie.2020.107029.

Wang, Y., Lin, W., Feng, C., 2019. The Impacts of Information and Communication Technologies(ICT) on the spatial distribution of urban customer services: a case study of online takeaway industry in Beijing. Urban Dev. Stud.

Wang, Z., He, S.Y., 2021. Impacts of food accessibility and built environment on on-demand food delivery usage. Transp. Res. Part D Transp. Environ. 100, 103017 https://doi.org/10.1016/j.trd.2021.103017.

Wood, S.N., 2017. Generalized additive models: an introduction with R. CRC Press.

Xi, G., Cao, X., Zhen, F., 2021. How does same-day-delivery online shopping reshape social interactions among neighbors in Nanjing? Cities 114, 103219. https://doi.org/10.1016/j.cities.2021.103219.

Xi, G., Cao, X., Zhen, F., 2020. The impacts of same day delivery online shopping on local store shopping in Nanjing, China. Transp. Res. Part A Policy Pract. 136, 35–47. https://doi.org/10.1016/j.tranp.2020.03.030.

Xi, G., Zhen, F., Wang, X., Qin, X., 2014. Study on the influencing factors and spatial characteristics of residents’ online consumption in Nanjing. Geogr. Res. 33, 284–295. https://doi.org/10.11821/dlyj201402008.

Yang, F.X., Li, X., Lau, V.M.C., Zhu, V.Z., 2021. To survive or to thrive? China’s luxury hotel restaurants entering O2O food delivery platforms amid the COVID-19 crisis. Int. J. Hosp. Manag. 94, 102855 https://doi.org/10.1016/j.ijhm.2020.102855.

Zhang, F., Ji, Y., Lv, H., Ma, X., 2021. Analysis of factors influencing delivery e-bikes’ red-light running behavior: A correlated mixed binary logit approach. Accid. Anal. Prev. 152, 105977 https://doi.org/10.1016/j.aap.2021.105977.

Zhang, X., 2020. Nanjing’s take-out orders ranked first in the province in 2019 [WWW Document]. URL http://jsnews.jschina.com.cn/24hour/202001/1202000114_2458476.shtml.

Zhang, Y., Zhen, F., 2019. The influence of built environment on the choice of residents’ shopping modes: A case study of Nanjing. Geogr. Res. 38, 284–295. https://doi.org/10.1016/j.geolett.2018.06.004.

Zhen, F., Du, X., Cao, J., Mokhtarian, P.L., 2018. The association between spatial attributes and e-shopping in the shopping process for search goods and experience goods: Evidence from Nanjing. J. Transp. Geogr. 66, 291–299. https://doi.org/10.1016/j.jtrangeo.2017.11.007.

Zhu, P., Guo, Y., 2021. The Role of High-speed Rail and Air Travel in the Spread of COVID-19 in China. Travel Medicine Infectious Dis. 42, 102097.

Zhu, P., Tao, X., 2021. Is compulsory home quarantine less effective than centralized quarantine in controlling the COVID-19 outbreak? Evidence from Hong Kong. Sustain. Cities Soc. 74, 102222.

Zhu, Y., 2019. Analysis on the Spatial Pattern of Catering Facilities in Nanjing Based on POI data. Econ. Res. Guid.