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Travel before, during and after the COVID-19 pandemic: Exploring factors in essential travel using empirical data

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ABSTRACT

The COVID-19 pandemic has a significant impact on daily life, leading to quarantines and essential travel restrictions worldwide in an effort to curb the virus's spread. Despite the potential importance of essential travel, research on changes in travel patterns during the pandemic has been limited, and the concept of essential travel has not been fully explored. This paper aims to address this gap by using GPS data from taxis in Xi'an City between January and April 2020 to investigate differences in travel patterns across three periods pre, during, and post the pandemic. Spatial statistical models are used to examine the major supply and demand-oriented factors that affect spatial travel patterns in different periods, and essential and nonessential socioeconomic resources are defined based on types of services. Results indicate that the spatial distribution of travel demand was highly correlated with the location of socioeconomic resources and opportunities, regardless of the period. During the "Emergency Response" period, essential travel was found to be highly associated with facilities and businesses providing essential resources and opportunities, such as essential food provider, general hospital and daily grocery supplies. The findings suggest that local authorities may better identify essential travel destinations by referencing the empirical results, strengthening public transit connections to these locations, and ultimately promoting traffic fairness in the post-pandemic era.

1. Introduction

The COVID-19 pandemic, caused by the infectious coronavirus, has had an unprecedented impact on the world since early 2020 (Zhang et al., 2020). This impact is significant and varied, affecting social operation, environment, economic growth, energy consumption, and other aspects (Rahman et al., 2021). One of the most noticeable manifestations is the changes in travel patterns. Due to restrictions on mobility, many industries, businesses, and households have been greatly affected. Global road transportation and aviation activities have dropped by an average of 50% during COVID-19 compared to 2019 (IEA, 2020). A report by Marchant on the effects of COVID-19 lockdowns on transport showed that the top 10 cities around the world saw reductions in travel by over 80% (Marchant, 2020). In fact, many of the reductions were due to non-essential travel, which governments encouraged people to avoid.

The COVID-19 pandemic has highlighted the importance of understanding essential travel and its impacts on travel behaviors, not only during the pandemic but also in the post-pandemic era (Chen et al., 2021). Defining essential travel is crucial for policymakers to reconsider the most basic needs of citizens, especially during extreme circumstances like the COVID-19 pandemic. Although many countries and regions have advocated for only essential travel, the specific definition varies due to regional and cultural background differences. This concept has in general been defined as travel that is fundamental to daily life (Chen et al., 2021). In this paper, we created an operational definition of essential travel as travel that is still going on during the period of "Emergency Response to Public Health Emergencies" (hereinafter referred to as "Emergency Response") when non-essential activities were largely constrained by the government to control the spreading of the virus. Under such definition, essential travel includes but not limited to work, buying necessities and food, and seeking healthcare, etc. This study aims to answer several questions regarding essential travel. How did daily travel patterns differ pre, during, and post the "Emergency

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Response"? What factors influenced people's travel behavior during different periods? How did these factors vary across different regions? The answers to these questions can provide valuable insights into understanding essential travel. He et al. (2021) pointed out that the concept of essential travel is useful for identifying the basic travel needs of different groups, especially socially disadvantaged groups. However, existing research has failed to provide sufficient empirical evidence to justify the definition of essential travel, which is difficult to observe directly during normal times.

In this study, we aim to examine travel patterns during different periods of the COVID-19 pandemic using taxi travel data, and discuss how the results can inform decision-making for public transit services in the post-pandemic world. We employ spatial models to analyze the impact of essential and non-essential points of interest (POIs) on travel during the Pre, During, and Post periods. Our findings suggest that the influence of essential POIs on travel does not show a significant decrease in the During period and even slightly increases, with the coefficient of essential shopping showing a positive significance in this period only. On the other hand, the impact of non-essential POIs on travel decreases in the During period, with non-essential catering and non-essential education becoming non-significant. Furthermore, the spatial spillover effects of essential catering, essential healthcare, and y-lag indicate that in the During period, people may travel more directly to their destinations, and the influence of the surrounding areas on their destinations significantly decrease.

A more comprehensive comprehension of essential travel can enable planners to estimate the demand for essential travel more precisely and make recommendations for enhancing the public transit system to provide people in different locations with more equitable access to essential goods and services. This level of equity could have a significant impact on daily life and various stages of personal development, as it is necessary to have access to various socioeconomic resources and opportunities, such as employment, healthcare, and social connections.

The article will be organized as follows. Section 2 displays a careful literature review on the impact of COVID-19 on travel and the definition of essential travel in existing studies. Details about the research design, including methodologies and data will be presented in Section 3. Results are shown and discussed in Section 4. We will summarize the major findings and policy implications in the final section of the article.

2. Literature review

2.1. Individual travel during quarantine

The outbreak of the COVID-19 pandemic has a significant impact on travel activities and behaviors. Past studies on infectious diseases have shown that travel restrictions play a crucial role in controlling the initial spread of such diseases (Aldila et al., 2020; Beck and Hensher, 2020; Chinazzi et al., 2020; de Bruin et al., 2020; De Haas et al., 2020). Sharkey and Wood (2020) estimated a difference-in-difference model and found that a 1% decrease in non-essential travel would result in a 6.4% reduction in new cases on average. Villas-Boas et al. (2020) reported similar conclusions. As a result, many countries and regions implemented corresponding travel restrictions and advocated only "Essential Travel". These restrictive policies resulted in a year-on-year decline of more than 50% in global road transportation and air travel during the same period in 2020 (IEA, 2020). Despite the negative impacts of the pandemic, researchers have also discovered some positive effects of the COVID-19 pandemic on individual travel. For instance, the pandemic has resulted in shorter travel times for public transit and a reduction in accidents. The congestion index of cities worldwide has decreased to varying degrees as well (Clarke, 2020; Hurley, 2020).

The current body of research has predominantly focused on the changes in travel preferences, patterns, and means brought about by the COVID-19 pandemic. On one hand, due to various travel restrictions and the potential risk of virus transmission during travel, people's willingness to travel has decreased significantly, particularly for non-essential travel. Cui et al. (2021) reported a severe decline in the output of all transport sectors in China. Beck and Hensher (2020) observed the largest drop in outdoor recreational activities in Australia. On the other hand, in order to maintain social distancing during travel, some individuals who previously relied on public transit have shifted to using private cars (Campisi et al., 2020; Labonté-LeMoyne et al., 2020; Shakibaei et al., 2021; Zhang et al., 2020) or non-motorized modes of transportation (Bergantino et al., 2021; Teixeira and Lopes, 2020; Zhang and Fricker, 2021). Moreover, another study found that pre-existing disparities in travel behavior across socioeconomic status (SES) clusters were exacerbated during the pandemic lockdown (Kara et al., 2021). Meanwhile, recent studies have indicated that individuals are willing to travel more if the safety and health risks of travel can be mitigated and public transit can be restored. However, the recovery has fallen far short of expectations (Beck and Hensher, 2020; Przybylowski et al., 2021).

The COVID-19 pandemic and the resulting quarantine measures have presented both challenges and opportunities in the field of transport planning. On the one hand, the restricted mobility caused by quarantine orders has made it difficult for people in certain areas to access essential supplies and resources. For instance, residents in suburban areas have had to rely more on nonmotorized modes of transportation to obtain what they need than their urban counterparts. Policymakers must take appropriate actions to address potential disparities in individuals' travel choices during the pandemic and ensure that everyone has equal access to necessary goods and services. On the other hand, the quarantine measures have provided a valuable opportunity to study the fundamentals of transport services under extreme circumstances. Although travel is a means of accessing socioeconomic resources, some types of travel are more essential to daily life than others. By restricting non-essential travel during the Emergency Response period, the contrasts between essential and non-essential travel have become more apparent and can be studied more closely.

While previous research provided significant contributions to understanding how the pandemic has impacted travel behavior, there remains a need for more detailed and nuanced analysis to fully grasp the implications of these changes. In particular, there has been a lack of research that explores the interconnectivity between travel restrictions, quarantine orders, and the overall decrease in travel demand in relation to how it affects access to essential goods and services. Understanding this connection could prove useful for urban transport planners as they strive to address potential disparities in accessibility among individuals residing in different areas of cities.

2.2. A closer look at essential travel

During the Stay-at-Home policy period, there was a significant decrease in travel demand and activities. People were advised to travel only for essential purposes. However, the definition of essential travel varied across policies, orders, and guidelines, as well as across cultures and countries. In its guidelines, the World Health Organization (WHO) recommended that individuals only undertake essential travel and noted that different countries may have varying definitions of essential travel. The WHO's definition of essential travel included travel in emergency situations and humanitarian activities, such as the travel of vital personnel, returning to one's country of origin, and obtaining essential supplies such as food, medicine, and fuel (WHO, 2020). Table 1 presents the definitions of essential travel adopted by various institutions worldwide during the COVID-19 pandemic (C.D.C.P, 2022; C.D.P.H, 2021; E.U, 2020; Government, 2020a; Health, 2021; Immigration, 2021; University, 2021). The definitions of essential travel varied across institutions and the pandemic's different periods. Governments at higher levels were less likely to define essential travel for specific purposes and impose detailed travel restrictions.

It is worth noting that even before the COVID-19 pandemic, researchers had been discussing essential travel. Some studies have examined the characteristics of essential travel and have used this concept to evaluate whether transport planning is adapting to travel demand, ensuring fairness, and optimizing resource allocation efficiency (Krumdieck et al., 2010; Laube et al., 2007). These studies defined essential travel as travel that contributes to people's health, work, income, and other basic needs, but relied mainly on small-scale surveys or subjective observations and explanations. Gordon et al. (1988) is one of the few quantitative studies that used the National Personal Transport Research (NPTS) in the 1980s to demonstrate that non-essential personal travel accounted for about 30% of its total travel. Krumdieck et al. (2010) categorized travel purposes into three categories: 50% for essential, 20% for necessary, and 10% for optional. However, empirical evidence is still limited at present.

Since the outbreak of COVID-19, an increasing number of researchers have conducted quantitative studies on essential travel or non-essential travel in these unusual circumstances. Some scholars have evaluated the impact of non-essential travel on disease transmission. The results showed that for every 1% reduction in non-essential travel, there was an average reduction of 6.4% in new cases, but the definition of non-essential travel was uncertain (Sharkey and Wood, 2020). Another group of scholars linked essential travel to socio-economic status (SES). The research showed that COVID-19 exacerbated existing disparities in mobility between socioeconomic classes. The lower and middle socioeconomic groups mainly took long-distance and medium-distance trips for work, while the higher socioeconomic group mainly took short trips for recreational and other non-work purposes (Kara et al., 2021).

There is little quantitative research on essential travel, and a big obstacle lies in the source of data. On one hand, it is difficult to separate the essential travel and non-essential travel in daily situations. On the other hand, it is difficult to obtain the travel data of various modes at the city level. However, as one of the important components of the urban transport system, taxis have the characteristics of 24-h operation and the starting and ending points are completely determined by passengers, and people are more inclined to use taxis than public transit in extreme cases such as pandemic (Tong et al., 2012). In addition, Xie (2018) shows that the statistical law of taxi travel behavior obeys power law distribution, which is consistent with the power law distribution characteristics of residents' travel behavior in city level, further verifying the rationality of using taxi travel to analyze residents' travel. Therefore, this paper intends to use the GPS data of taxi operation to carry out the essential travel-related modeling analysis.

There is a lack of quantitative research on essential travel, and a significant challenge lies in obtaining suitable data sources. On the one hand, it is difficult to differentiate between essential and non-essential travel in everyday situations. On the other hand, it can be challenging to obtain travel data across different modes of transportation at the city level. However, taxis are a crucial component of the urban transport system due to their 24-h operation and the fact that their starting and ending points are entirely determined by passengers. Moreover, during exceptional circumstances such as a pandemic, people tend to prefer using taxis over public transit (Tong et al., 2012). Additionally, Xie (2018) shows that the statistical behavior of taxi travel conforms to a power law distribution, which is consistent with the power law distribution characteristics of residents' travel behavior at the city level. This finding further supports the rationality of using taxi travel data to analyze residents' travel patterns. Therefore, this study aims to utilize GPS data obtained from taxi operations to conduct modeling analysis on essential travel.

The literature on essential travel has been expanded as the COVID-19 pandemic goes on, but it has not adequately shown how such travel differs from other travel in terms of temporal and spatial patterns, and how such travel is made out of purposes to obtain unevenly distributed socioeconomic opportunities. After all, travel is to help people acquire resources at reasonable prices and costs, so essential travel may be conceptually critical in ensuring the minimum level of personal and family development. Therefore, more research is needed to help understand and utilize the concept in the practices of transport planning. As mentioned above, this paper defines that "Essential Travel" refers to the travel that is still going on during the period of "Emergency Response", so as to model it and quantitatively analyze its characteristics and influencing factors.

The literature on essential travel has grown during the COVID-19 pandemic, but it has not adequately explored how this type of travel differs from other travel in terms of temporal and spatial patterns, or how it is shaped by the pursuit of unevenly distributed socioeconomic opportunities. Travel is intended to help people acquire resources at reasonable prices and costs, and essential travel may play a crucial role in ensuring a minimum level of personal and family development. Therefore, additional research is necessary to better understand and utilize the concept of essential travel in transport planning practices. As stated earlier, this paper defines essential travel as travel that continues during the "Emergency Response" period. The goal of this study is to

Table 1
A summary of travel policies and definitions of essential travel by different institutions across the world.

Institutions	Time	Definition of Essential Travel
U.S. Centers for Disease Control and Prevention	August 2021	The CDC does not impose uniform restrictions on domestic travel, allowing states to adopt different travel restrictions. Regarding international travel, the CDC identified a notice–Warning Level 3: Avoid all non-essential travel to certain destinations.
California Department of Public Health	April 2021	Essential travel is travel associated with the operation, maintenance, or usage of critical infrastructure or otherwise required or expressly authorized by law, including work and study, critical infrastructure support, economic services and supply chains, health, immediate medical care, and safety and security.
Selected universities in the U.S.	May 2021	Essential travel in university is defined as those that are necessary and cannot be postponed or handled remotely. (i.e., for graduation, academic progress, core educational, business functions of the University, etc.)
New South Wales Government	July 2021	Although NSW does not provide a definition of essential travel, it does specify appropriate means of transport for certain people in its guidelines. In addition, the guide defines the people who are allowed to make essential travel, and provides recommended means of transport for different travel times. In particular, it mentions that public transit, taxis or carpooling are not allowed to travel.
European Commission	May 2021	The EU does not give the definition of essential travel, but gives the people whose travel belongs to it, including but not limited to: healthcare professionals; seasonal workers in agriculture; transport personnel; passengers in transit; passengers travelling for imperative family reasons; third-country nationals travelling for the purpose of study, etc.
Canadian Government	June 2021	Some of the travel purposes that are considered essential may be: economic services and supply chains; critical infrastructure support; health (immediate medical care), safety and security; supporting goods for indigenous communities; any other activities that are deemed non-optional or non-discretionary.
British Government	June 2020	Essential travel may include the following travel purposes: to obtain basic necessities, including food and medical supplies and supplies for the essential upkeep, maintenance and functioning of the household, or to obtain money; to seek medical assistance; to travel for work; to fulfil a legal obligation; to access critical public services, including educational facilities, social services, etc.

model and quantitatively analyze the characteristics and influencing factors of essential travel.

3. Research design

3.1. The study area

This study examines travel behaviors by taxi in the City of Xi ‘an between January and April 2020. Xi’an is one of the largest cities in China and a central city in the Northwest of the country. It has a population of 13 million and its built-up area reached 729 km^2 in 2019. Xi’an had long been a capital city in the ancient China and thus developed a largely monocentric urban form so far. Similar to other large cities, the urban core is highly dense, while population density decreases as distance to the urban core increases (Qin et al., 2023). Fig. 1 displays the spatial distribution of taxi destinations in a workday.

This research focuses on Xi’an, China, for several reasons. Firstly, during the spring of 2020, when most people were making essential travel due to strict quarantine measures, Xi’an provides an excellent opportunity to observe the behaviors of essential travel. Secondly, while the pandemic impact varied among cities in China, most cities adopted similar quarantine guidelines. As a representative city of China, Xi’an can provide empirical evidence regarding the demand and supply of essential travel during this special period. Lastly, Xi’an was chosen for this study because data was collected covering different periods of the “Emergency Response”, and microscopic taxi data made these studies possible. Furthermore, it is important to note the policy of stay-at-home orders were implemented under emergency response status in Xi’an. Based on the investigation of the pandemic and expert judgment, the pandemic prevention and control command department divided different regions of the city into high, medium, and low-risk areas according to the level of epidemic risk. Residents in low-risk areas could choose to make essential travel, while residents in other areas were advised to stay at home to control the transmission of the virus as much as possible. Urban rail transit and ground public transit were temporarily suspended during the period.

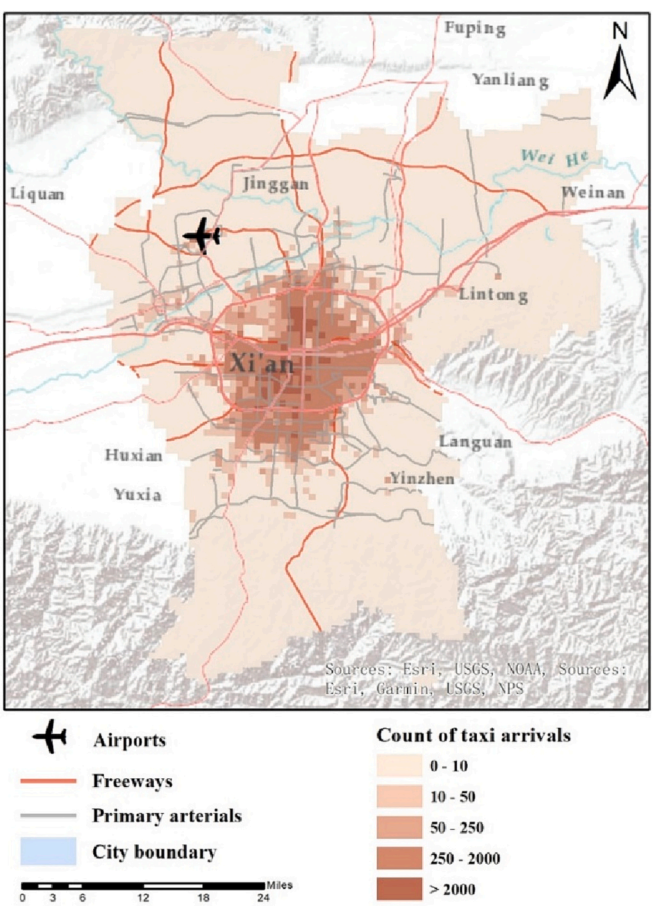

Fig. 1. Spatial distribution of taxi travel destinations.

The study area is divided into 1 km × 1 km grid cells, and both the dependent and independent variables will be calculated at this level. Based on the previously mentioned details, it is assumed that the travel patterns observed by taxis are representative of overall travel patterns. To protect individuals’ privacy, the original GPS data has been preprocessed, and travel tracks have been aggregated at the grid cell level (Zhou et al., 2022a). The dataset also includes information on travel start time, ending time, travel distance, and other relevant details.

3.2. The variables setting

The study analyzed travel behaviors during different periods of the pandemic, dividing the collected data into three periods based on the start and end of the “Emergency Responses” in Xi’an: Pre, During, and Post. The “Emergency Response” in Xi’an was implemented on January 25th, 2020 and lifted on February 28th, 2020 (Government, 2020b). Fig. 2 shows significant differences in travel volumes across the three periods. In the Pre period, the daily average number of taxi-riding trips remained stable between 480,000 and 550,000, except for holidays when it would fluctuate. The number of taxi-riding trips dropped rapidly in the During period from January 21 due to the potential risks in travel. By January 25, the number of taxi-riding trips had plummeted to about 100,000, representing a decrease of more than 80%, which may have been due to the implementation of the strict Stay-at-Home policy. Over the next 10 days, it continued to drop until February 20th. In the Post period, with the loosening of the policy, the number of taxi-riding trips gradually rebounded. By the end of April, the daily passenger travel had recovered and reached about 400,000 trips a day, representing a recovery rate of about 80% compared to normal days.

Assuming that the number of taxi-riding trips in each grid cell represents the actual taxi demand, we can consider it as a function of both travel demand and transport supply (see the function below Eq. (1)). Travel demands depend largely on the availability of socio-economic opportunities and resources such as restaurants, supermarkets, schools, hospitals, etc., in the vicinity of the destination. The density of each category of points of interest (POI) potentially affects an individual’s likelihood to make travel decisions. Accessibility to a place is also a crucial factor that influences travel choices. The location of major transport infrastructure can attract people to visit certain places. For instance, places located in close proximity to freeways will have an advantage in people’s travel choices.

$$Trip_i = f(TranSupply_i, TravDemand_i) \tag{1}$$

In the analysis, three independent variables are used: the average daily number of taxi-riding trips in each grid in the Pre, During, and Post periods. Table 2 describes the dependent variables. To compare the model coefficients across different periods, the dependent variables are normalized based on mean values.

The selection of independent variables is informed by prior research (Chung, 1997; Gutiérrez et al., 2011; Morrall and Bolger, 1996; Sung and Oh, 2011; Taylor and Fink, 2003; Taylor et al., 2009). Our focus is primarily on two dimensions of independent variables: travel demand and transport supply, and we choose appropriate forms of values for each variable. The specific variables are presented in Table 3.

We would like to provide further clarification on the choice of dependent and independent variables. Firstly, we choose workdays as the dependent variables for the three periods, as they can better capture the essential travel. Additionally, as depicted in Fig. 2, there is hardly any difference in the number of taxi-riding trips between workdays and weekends during the “Emergency Response” period. Secondly, we have

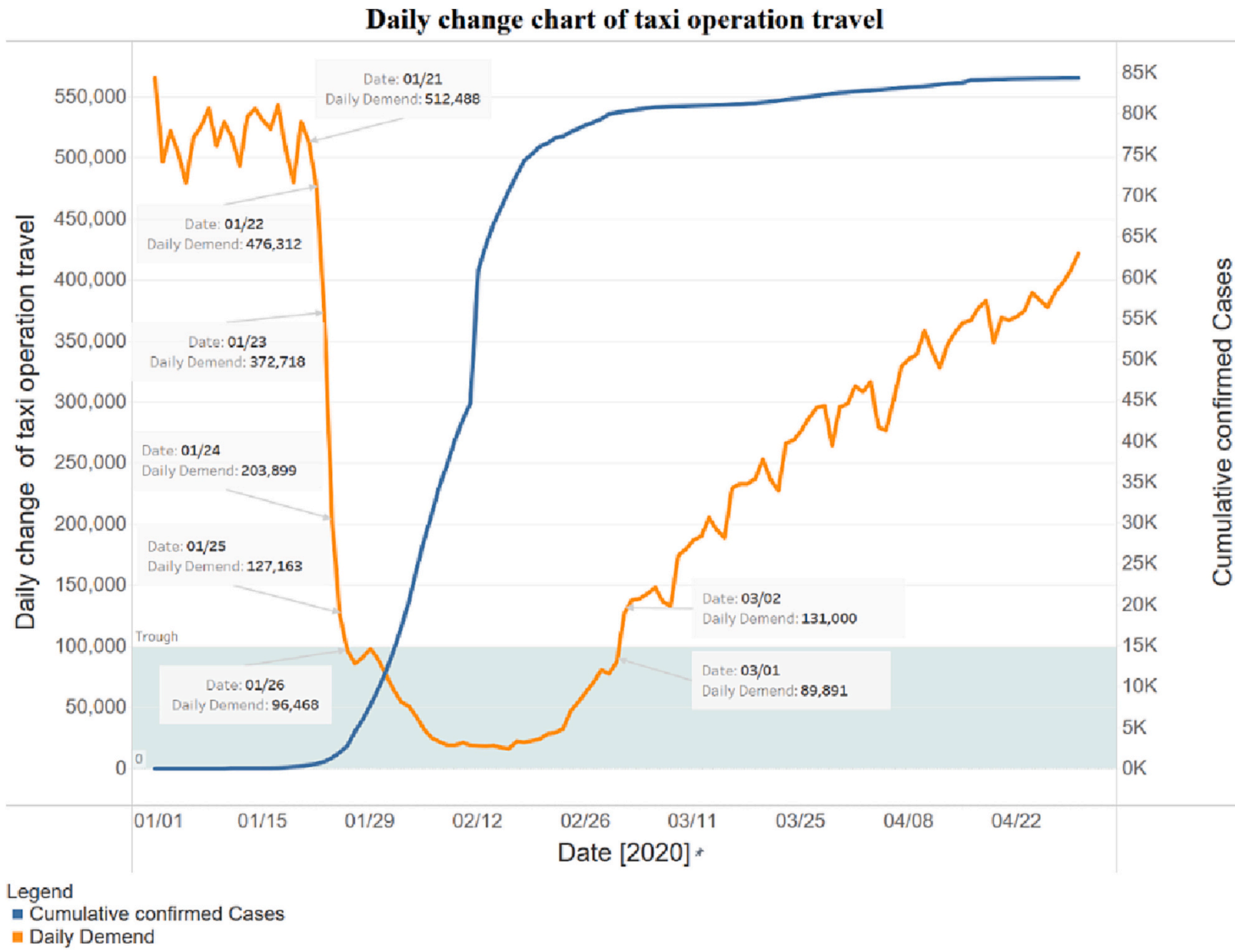

Fig. 2. Daily change of taxi-riding trips and Cumulative Confirmed Cases in China.

Table 2
Dependent variable.

Dependent Variables	Description
$Trip_{pre}$	Average number of trips on workday before pandemic, Jan.6-Jan.10
$Trip_{dur}$	Average number of trips on workday during pandemic, Feb.10-Feb.14
$Trip_{post}$	Average number of trips on workday after pandemic, Apr.20-Apr.24

not included variables such as bus stop or subway station density or distance as independent variables, as public transit was completely closed during the "Emergency Response" period, leading to different variables for each period. Lastly, while there are many other potential independent variables to consider, such as secondary road density and walking distance, we have not included them due to their strong collinearity, which would impact the modeling and were abandoned in the pre-modeling.

The travel demand variables used in this study serve as a proxy for localized resources and characteristics that attract travel. These variables provide an indication of how different types of socioeconomic opportunities can attract people to travel (Zhou et al., 2022b). Point of Interests (POI) data from Gaode Map Open Platform is used to measure these variables. Given the focus of this study on essential travel, we select four categories—catering, shopping, medical services, and science/culture & education—as major independent variables.

Table 3
Description of independent variables.

Type	Variables	Description
Travel demand	E_catering	Number of essential catering POI per km^2
	NE_catering	Number of non-essential catering POI per km^2
	E_shopping	Number of essential shopping POI per km^2
	NE_shopping	Number of non-essential shopping POI per km^2
	E_healthcare	Number of essential health care POI per km^2
	NE_healthcare	Number of non-essential health care POI per km^2
	E_education	Number of essential education POI per km^2
	NE_education	Number of non-essential education POI per km^2
	landuse_mix	Herfindahl-Hirschman index (HHI) of land use mixes
	popden	Population density (thousand person/ km^2)
Transport supply	Airport_distance	Distance to the nearest airport (km)
	Railway_distance	Distance to the nearest railway station (km)
	Ramp_distance	Distance to the nearest freeway ramp (km)
	Primary_density	Road network density of the primary roads (km/km^2)

Additionally, we matched the closest POI data of various types to the drop-off points of taxi passengers in the Pre and During periods, respectively (using the original latitude and longitude information of the drop-off point). Then, we associated their secondary POI classification attributes and grouped all POIs according to the secondary classification standard. The grouping statistical results are shown in Table 4. In this study, we defined POIs that did not decrease in proportion in the During period as Essential POIs, while the rest were classified as Non-Essential POIs. The specific division results and quantity of Essential and Non-Essential POIs are shown in Fig. 3.

The land use mix variable is derived from fine-grained land use information provided by the Gaode Map Open Platform. The Herfindahl–Hirschman index (HHI) is widely used to measure industry concentration in economics, and can be used to reflect diversity of land uses (Palan, 2010). The calculation formula of the HHI is shown in Eq. (2). A small HHI value indicates a greater mixability.

$$HHI_i = \sum_{j=1}^{N} \left(\frac{X_{ij}}{X_i} \right)^2 \tag{2}$$

Where X_i is the total number of POIs in grid i, and X_{ij} is the total number of POIs of category j in grid i.

Fig. 4 depicts the spatial distribution of catering POIs for both essential and non-essential types. It is evident from the figure that non-essential catering POIs are mainly concentrated in the urban core within the second Ring Road, while essential catering POIs are more widely distributed, covering almost all major urban subcenters (Giuliano et al., 2019). This could be because non-essential catering businesses such as tea houses and dessert houses tend to locate in densely populated areas where there is adequate demand to support their operations. Fig. 5 illustrates the spatial distribution of essential and non-essential types of shopping POIs. Although the distribution of both groups is generally similar, non-essential shopping businesses cluster in a few hotspots that are not shown in the essential shopping business map. For instance, agglomerations of home building materials markets can be easily seen in many cities due to the apparent advantages of agglomerative economies of scale. People tend to visit these agglomerations to purchase materials in bulk, and businesses located there can benefit from premium volumes of potential customers. Both figures demonstrate the different spatial patterns of essential businesses compared to non-essential ones, which could contribute to the wide spatiotemporal variations in travel demand during the COVID pandemic.

3.3. Spatial autocorrelation analysis

Because of spatial heterogeneity of socioeconomic opportunities, the spatial patterns of dependent variables and independent variables are both non-stationary across space. Travel by taxi is distributed along the road network, but the grid is artificially generated regardless of the network. Therefore, the travel demand by taxi can be highly subject of spatial autocorrelation: such demand in a grid cell may be highly correlated with its adjacent spatial units. As spatial autocorrelation can be classified into global spatial autocorrelation and local spatial autocorrelation, we examined them by calculating the Global Moran's I and local Moran's I respectively.

Global Moran's I calculated as Eq. (3), which is a global measure of spatial autocorrelation (Moran, 1950):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{X})(x_j - \overline{X})}{\sum_{i=1}^{n}(x_i - \overline{X})^2} \tag{3}$$

Where n is the number of spatial units, i and j are longitudinal and latitudinal indexes, x denotes the variable, $\overline{X}$ is the mean of x, and w_{ij} indicates the spatial weight between i and j. Global Moran's I index is a value ranging from −1 to 1. The spatial distribution is more similar to clustering of dissimilar values if Global Moran's Index approaches −1; otherwise, it would be more similar to clustering of similar values. The value tends to be randomly distributed in space if Global Moran's Index approaches 0.

In order to achieve two purposes, Anselin (1995) proposed Local Moran's I, which can be interpreted as indicators of local pockets of

Table 4
Group statistics of the nearest POI from the taxi drop-off point.

Primary Class	Secondary Class	POI Count		POI Proportion		Change Of Prop	Primary Class	Secondary Class	POI Count		POI Proportion		Change Of Prop
		Pre	During	Pre	During				Pre	During	Pre	During	
Catering	Chinese Food Restaurant	271,845	9402	63.34%	64.16%	**0.82%**	**Healthcare**	General Hospital	28,701	1367	6.56%	8.90%	**2.34%**
	Foreign Food	8598	237	2.02%	1.62%	−0.40%		Special Hospital	62,652	2045	14.31%	13.30%	−1.01%
	Fast Food Restaurant	84,553	3091	19.89%	21.09%	**1.20%**		Clinic	74,140	2455	16.94%	16.00%	−0.94%
	Leisure Food	1071	7	0.25%	0.05%	−0.20%		Emergency Center	1408	148	0.32%	1.00%	**0.68%**
	Coffee House	13,886	439	3.27%	3.00%	−0.27%		Disease Prevention Institution	1210	49	0.29%	0.29%	0.00%
	Tea House	13,243	408	3.11%	2.78%	−0.33%		Healthcare Products Store	259,805	8975	59.36%	58.40%	−0.96%
	Ice Cream Shop	17,060	522	4.01%	3.56%	−0.45%		Veterinary Hospital	9785	327	2.24%	2.10%	−0.14%
	Cake Shop	10,819	441	3.14%	3.01%	−0.13%		Others	102,237	3174			
	Dessert Sop	4108	108	0.97%	0.74%	−0.23%	**Education**	Museum	3867	77	1.15%	0.64%	−0.51%
	Others	114,755	3885					Exhibition Hall	4243	99	1.27%	0.83%	−0.44%
Shopping	Shopping Plaza	1676	52	0.56%	0.50%	−0.06%		Conference & Exhibition Center	2160	48	0.64%	0.40%	−0.24%
	Convenience Store	111,974	4049	37.70%	39.21%	**1.51%**		Art Gallery	2277	63	0.68%	0.53%	−0.15%
	Household Appliance	20,129	631	6.78%	6.11%	−0.67%		Library	4786	367	1.43%	3.07%	**1.64%**
	Supermarket	29,096	1198	9.80%	11.60%	**1.81%**		Science & Technology Museum	545	16	0.16%	0.13%	−0.03%
	Plants & Pet Store	14,475	479	4.87%	4.64%	−0.23%		Cultural Palace	2535	77	0.76%	0.64%	−0.12%
	Home Building Materials	33,806	1114	11.38%	10.79%	−0.59%		Archives	359	16	0.12%	0.12%	0.00%
	Comprehensive Market	30,951	1214	10.42%	11.76%	**1.34%**		Arts Organization	2529	92	0.76%	0.76%	0.00%
	Stationary Store	6329	206	2.13%	1.99%	−0.14%		Media Organization	9481	288	2.83%	2.41%	−0.42%
	Sports Store	3253	90	1.10%	0.87%	−0.22%		School	79,837	3048	23.82%	25.48%	**1.66%**
	Commercial Street	4387	101	1.48%	0.98%	−0.50%		Scientific Research Institution	22,533	911	6.72%	7.61%	**0.89%**
	Clothing Store	32,894	920	11.07%	8.91%	−2.17%		Training Institution	168,721	5770	50.33%	48.23%	−2.10%
	Special Trade House	788	19	0.27%	0.18%	−0.08%		Driving School	31,343	1092	9.35%	9.13%	−0.22%
	Cosmetics Store	7260	253	2.45%	2.44%	−0.01%		Others	204,722	6576			
	Others	242,920	8214										

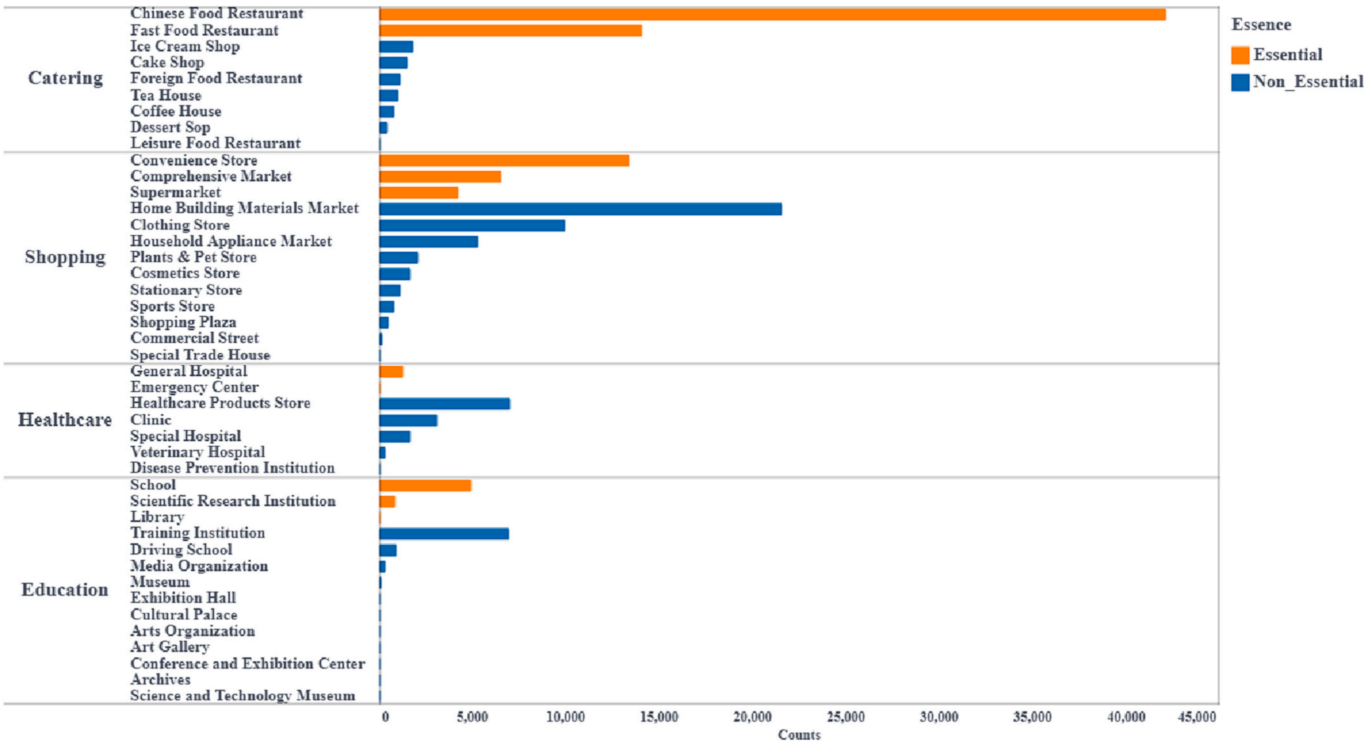

Fig. 3. POI category and quantity.

nonstationarity or hot spots, and be used to assess the influence of individual locations on the magnitude of the global statistic and to identify “outliers”. The expression is shown as Eq. (4):

$$I_i = \frac{n(x_i - \overline{X})}{\sum_{i=1}^{n}(x_i - \overline{X})^2}\sum_j w_{ij}(x_j - \overline{X}) \tag{4}$$

When Local Moran’s I index>0, it means that surrounding units have similar values to the unit; When Local Moran’s I index<0, it indicates surrounding units have dissimilar values to the unit. And when Local Moran’s I index = 0, it implies that surrounding units have no relationship with the unit.

3.4. Regression models

If there are different degrees of spatial correlation, the traditional panel model can not be used in setting model, such as the Ordinary Least-Squares (OLS) regressions (Elhorst, 2014). Because spatial correlation will lead to the correlation of error terms in linear regression model, or will lead to biased estimation results, thus spatial regression model should be chosen. The commonly spatial models contain the spatial lag model (SLM), the spatial lag of X model (SLX) and the spatial Durbin model (SDM).

The SLM model is suitable for the endogenous spatial correlation between dependent variables, focusing on the spatial spillover effect of dependent variables. The SLX model is suitable for the endogeneity of independent variables, and the adjacency matrix W in the model can be parameterized to better adapt to different spatial distributions (Vega and Elhorst, 2015). The SDM model is a general form of spatial model, which can be simplified to the first two under certain conditions, including not only the spatial lag of the dependent variable, but also the spatial lag of the independent variable. Its original form is shown as Eq. (5).

$$y = \lambda Wy + X\beta + WX\theta + \varepsilon = (I - \lambda W)^{-1}X\beta + (I - \lambda W)^{-1}(WX\theta + \varepsilon) \tag{5}$$

Where, y is a vector (n*1) of observations of the dependent variable; X is matrix(n*k) of observations of the independent variables; λ, β and θ are vector(k*1) of regression coefficients; W is spatial weight matrix and ε is a vector(n*1) of error terms.

SDM model theory holds that the observed values of dependent variables are influenced not only by the dependent variables in the surrounding areas, but also by the independent variables in the surrounding areas, so the key factors affecting the dependent variables can be observed more comprehensively from the endogenous and exogenous perspectives (Borst and McCluskey, 2007; Elhorst, 2014). Therefore, the total marginal effect of independent variables on dependent variables can be further divided into direct effect and indirect effect. Through Taylor expansion, it’s easy to verify that $(I - \lambda W)^{-1} = I + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + \dots$. Suppose that X contains k explanatory variables and the $r-th$ explanatory variable is $X_r = (x_{1r}, x_{2r}, \dots, x_{nr})(n \times 1)$, then we can get $X\beta = (x_1 \dots x_k)(\beta_1 \dots \beta_k) = \sum_{r=1}^{k}\beta_r x_r$, so Eq. (5) can be rewritten as Eq. (6):

$$y = \sum_{r=1}^{k}\beta_r(I - \lambda W)^{-1}x_r + (I - \lambda W)^{-1}(WX\theta + \varepsilon) \tag{6}$$

Suppose $S_r(W) = \beta_r(I - \lambda W)^{-1}$, then Eq. (6) can be expanded into Eq. (7):

$$\begin{matrix} y_1 \\ \vdots \\ y_n \end{matrix} = \begin{pmatrix} S_r(W)_{11} & \cdots & S_r(W)_{1n} \\ \vdots & \ddots & \vdots \\ S_r(W)_{n1} & \cdots & S_r(W)_{nn} \end{pmatrix}\begin{pmatrix} x_{1r} \\ \vdots \\ x_{nr} \end{pmatrix} \tag{7}$$

According to Eq. (7), it can be seen that $\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij}$. This indicates that the variable x_{jr} in region j may have an impact on the dependent variable in any other region i, which is the spatial autocorrelation effect of the spatial model. Specifically, if $j = i$, then $\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii}$, which corresponds to the diagonal element of Eq. (7). This can be understood as the direct effect of the independent variable x_{ir} in region i on the dependent variable y_i in the same region. Therefore, the direct effect of the independent variable x on the dependent variable y is the average of all diagonal elements in Eq. (7), while the indirect effect is the average of all non-diagonal elements (Chen, 2010).

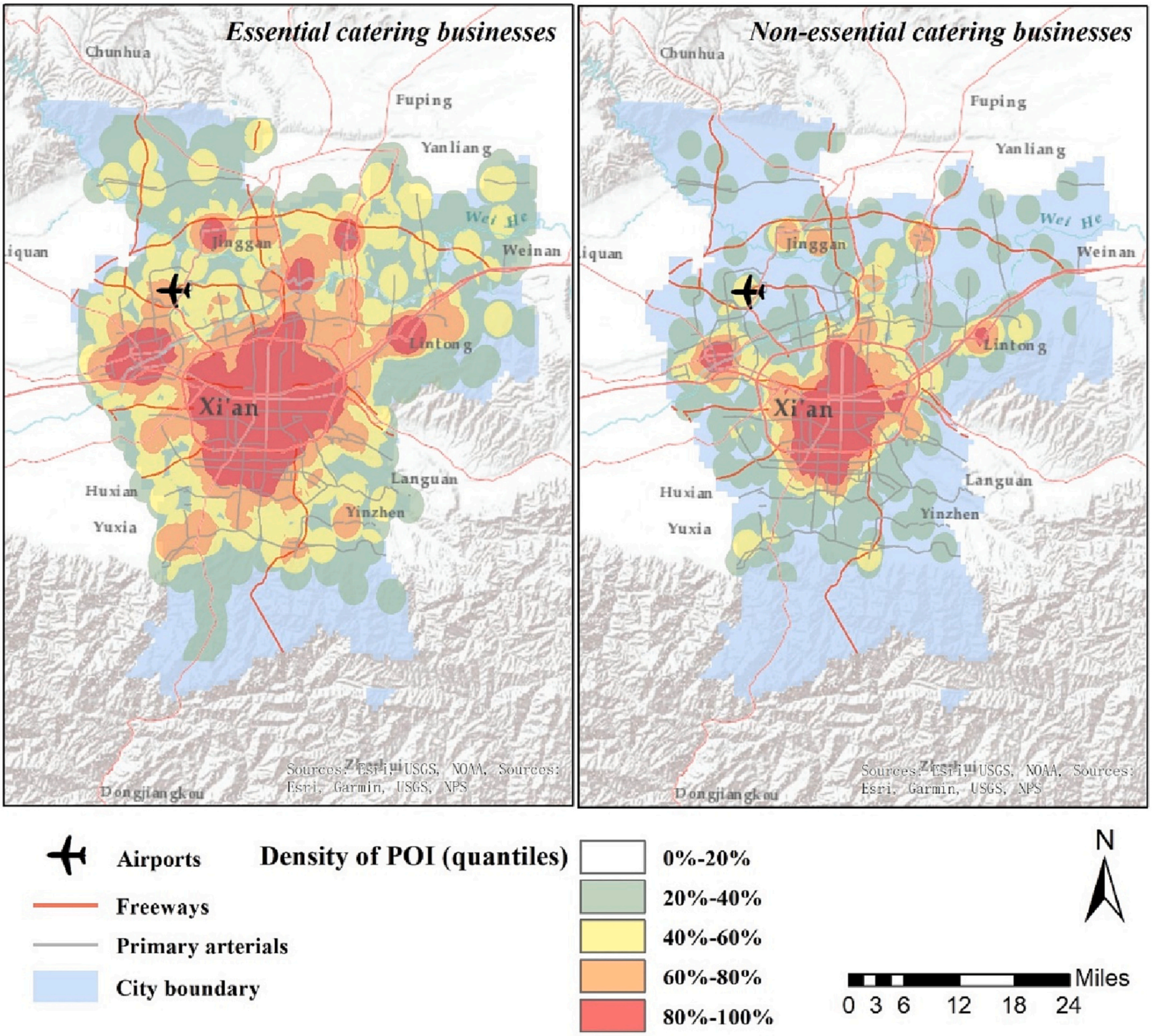

Fig. 4. Spatial distribution of POIs in essential and non-essential catering businesses.

There are two parameter estimation methods for spatial models, one is generalized two-stage least-squares cross-sectional regression method (gs2sls), the other is maximum likelihood estimation method (ML). The main difference between them is that it is more effective when the error obeys the assumption of normal distribution, otherwise it is not as robust as the former, for example, in the presence of heteroscedasticity. The heteroscedasticity of the dependent variable in this paper is proved by using White test, so the parameter estimation method of gs2sls is used in this paper.

4. Results

4.1. Spatial analysis: overall distribution and autocorrelation

Fig. 6 illustrates the spatial distribution of taxi travel demand in the different periods of the pandemic, revealing significant disparities in demand across the three periods. In the Pre period, taxi travel was primarily concentrated within the beltway, with numerous hotspots in the urban core. However, as a result of the Stay-at-Home policy, almost all hotspots disappeared in the During period, and travel intensity declined precipitously. In the Post period, travel demand had rebounded and had nearly returned to pre-pandemic levels.

Table 5 displays the global Moran's I index for the number of taxi-riding trips in the three periods. The results indicate that the global Moran's I index for all three periods is significantly greater than 0, which suggests that the number of taxi-riding trips is spatially autocorrelated. Furthermore, we calculated the local Moran's I index for the number of taxi-riding trips in each period. The results show that the spatial distribution of the local Moran's I index is similar across all three periods. Specifically, the index is mostly significant within the second Ring Road, characterized by a High-High Cluster. Outside the second Ring Road, the index is generally not significant, with only a few areas exhibiting a Low-High Cluster, such as the airport and the edge of the second Ring Road.

4.2. Inferential analysis

4.2.1. Model comparison

The study utilizes both global OLS regression model and spatial

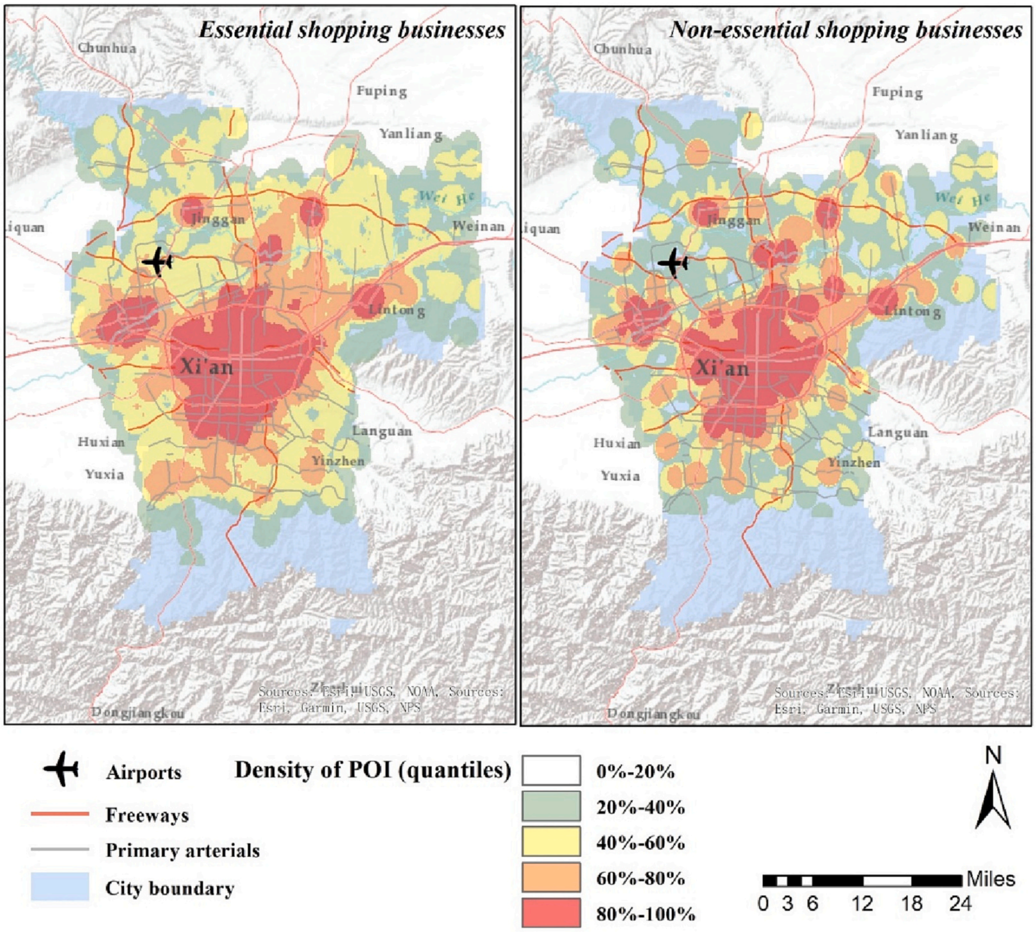

Fig. 5. Spatial distribution of POIs in essential and non-essential shopping businesses.

regression models to examine the relationship between the number of taxi-riding trips and various independent variables in different pandemic periods. Table 6 provides a comparison of the models to show how the coefficients change when controlling for the spatial autocorrelation of the dependent and independent variables. The results indicate that the Pseudo R-squared of the SLX and SDM models is larger than that of the global OLS model. Additionally, the two indexes of Log-Likelihood and AIC suggest that all three spatial models are superior to the OLS model. These findings suggest that incorporating spatial dimensions is necessary to more accurately estimate relationships of interest.

Table 6 reveals differences among the spatial models as well. SLM (Y-Lag only), SLX (X-Lag only), and SDM (X-Lag & Y-Lag) exhibit a gradual increase in R-squared and Likelihood, and a corresponding decrease in AIC. The results indicate that the SDM model performs the best, implying that controlling the spatial autocorrelation of both dependent and independent variables can effectively help estimate taxi travel demand in different pandemic periods. Compared to the global OLS model, the coefficients of several variables in the SDM model exhibit different statistical significance, while the signs of coefficients remain the same. These findings suggest that the importance of a certain variable in predicting the number of taxi-riding trips may change when the spatial autocorrelations are controlled. Moreover, the results reveal that the number of taxi-riding trips in a certain spatial unit is not only related to the influencing factors of this unit, but also to the influencing factors in adjacent units. Hence, the SDM model can better reflect the degree of influence of different variables on the dependent variable.

4.2.2. *Variable association analysis*

According to the results in Table 6, the factors affecting the number of taxi-riding trips in different periods show substantial differences in terms of their coefficients. In the Pre and Post periods, the impacts of the independent variables are similar to a large extent, with some notable differences. Firstly, in the Post period, there is a significant suppression of travel demand for essential healthcare, which may be due to people's fear of potential risks during the pandemic. Secondly, non-essential education strengthens its impact in the Post period, likely because people choose to use taxis as a more private and safer travel option for that purpose. In contrast, the influencing factors of taxi travel demand in the During period are significantly different from those in the other two periods. Firstly, the importance of E_catering, E_shopping, and E_education does not significantly decrease and even slightly increases, as evidenced by the significant positive coefficient of E_shopping in the During period only. This strongly confirms the hypothesis of this study that essential travel is closely associated with basic socio-economic providers, such as local food stores, convenience stores, and important educational facilities. Secondly, the transport supply type variables, such as landuse_mix and Primary_density, are no longer significant in the During period. It is possible that during the Emergency Response periods, when the main purpose of travel is essential, people may not be concerned about building characteristics such as land use patterns and road network accessibility, which led to the disappearance of the effects of these variables.

The SDM model also reveals the spatial spillover effects of variables, which vary across different pandemic periods. Firstly, the spillover effect of E_shopping is negative in the Pre and Post periods, but positive in the During period. This suggests that in the Pre and Post periods, the

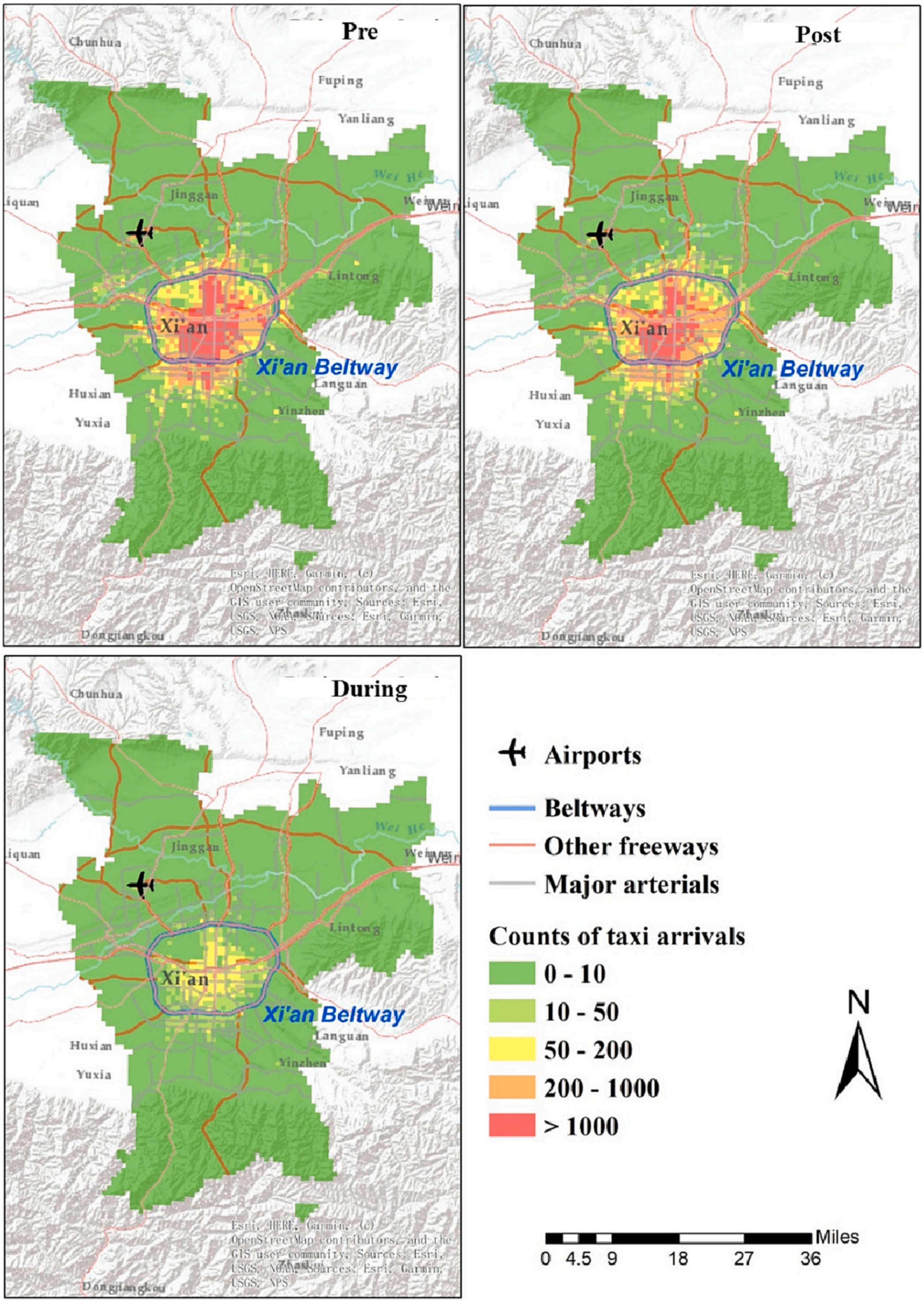

Fig. 6. Hotspots of taxi destinations in different periods.

Table 5
Global Moran's I index of the number of taxi-riding trips in three periods.

Period	Moran's I	z-score	*p*-value
Pre	0.80	81.31	0.00
During	0.69	70.58	0.00
Post	0.81	82.30	0.00

surrounding areas suppress E_shopping in a region, while in the During period, they drive E_shopping in a region. This may be due to limited supply of necessary goods during the Emergency Response period, leading people to travel to areas with concentrated convenience stores, thus increasing the probability of completing essential shopping. Secondly, in the During period, the spillover effects of E_catering, E_healthcare, NE_education, and Y-lag are no longer significant. This may indicate that, in the case of virus transmission, people directly go to their destination without the need for more contact with nearby facilities. For example, under normal circumstances, a person may not only look for restaurants in the geographic unit where the taxi arrives but also look for drinks in nearby units after dinner. However, during the Emergency Response period, they may only focus on the unit where the target restaurant is located. Thus, spillover effects are greatly compromised in the During period. Based on these findings, the SDM model can better reveal the complex relationships of variables that change over different periods.

4.2.3. Combined spatial effect analysis

Appendix A presents the direct, indirect, and total marginal effects of each independent variable in the SDM model across three different periods. The marginal effects of the independent variables on the dependent variables can be divided into two parts: direct effects from local units and indirect effects from surrounding geographical units. It is important to note that direct impact and indirect impact should be treated independently since they may represent localized impact and sub-regional impact, respectively, in the urban environment. Therefore, when the direct effect is offset by the indirect effect and the total effect may not be significant, it does not necessarily mean that the variables are irrelevant. On the contrary, the influence of the variables varies within and outside geographical units.

The results presented in Appendix A reveal several key findings. Firstly, in the Pre and Post periods, the direct effects of the independent variables on taxi travel demand are notably smaller than the indirect effects (which are an order of magnitude larger). This indicates that the demand for taxi travel in a given grid cell is significantly influenced by the demand from its surrounding region. In contrast, in the During period, only direct effects are observed while indirect effects are not statistically significant. This suggests that the demand for taxi travel during this period was more constrained to the destination, with little spillover effect to the surrounding areas. Secondly, for variables such as essential shopping, healthcare, and essential education, the direct effect is generally positive, but the indirect effect is strongly negative or insignificant. As a result, the total spillover effect is negative or insignificant. This finding highlights the complex spatial relationships among different variables at the regional level, which cannot be adequately captured by a simple OLS model. Hence, a more sophisticated spatial model like SDM is required for accurate analysis. Overall, the results demonstrate the importance of considering both direct and indirect effects when examining the impact of independent variables on taxi travel demand. Moreover, the findings underscore the need for a spatially explicit model that can account for the complex spatial relationships among variables.

5. Discussion and conclusion

The empirical spatial model has demonstrated that taxi travel is influenced by various factors, such as individual travel demands and transport supply. Building on the existing literature, this paper specifically investigates the shifts in taxi travel demand during different pandemic periods and identifies unique travel patterns during the Emergency Response period, which helps redefine essential travel in a more precise manner. Additionally, by examining the travel disparities across different pandemic periods, we can provide more effective optimization strategies for public transit to better serve essential travel in the post-pandemic era.

First, the SDM model proves to be a better method for characterizing the relationship between taxi travel demand and various factors. Given that taxi travel demand is influenced by numerous factors and its spatial distribution is highly uneven, this paper compares the global OLS model to a range of spatial models. The SDM model, which demonstrates superior performance, not only estimates the spatial relationship between taxi travel demand and various factors, but also calculates the spatial spillover effect between local and surrounding regions. As a result, public administration officials may need to take into account neighboring units when predicting travel demand in each geographic unit. For example, in order to estimate travel demand for healthcare services, facilities within a certain distance should be considered to account for spillover effects, although such effects could vary across different periods.

Secondly, this paper provides a clearer definition of essential travel by contrasting travel differences across pandemic periods. The contribution of essential travel purposes to taxi travel demand do not decrease significantly and even slightly increase, while that of non-essential travel purposes dropped significantly. This indicates the critical role of essential travel during the extreme conditions of society-wide quarantine. People prioritize visiting resources and facilities that provide the most vital services, such as convenience stores to obtain daily supplies, rather than purchasing luxury goods in large shopping plaza. These differences have been identified through empirical analysis, leading to a more explicit concept of essential travel.

Thirdly, in the During period, taxi travel demand was found to be highly associated with localized resources, while the impact of surrounding areas was significantly reduced compared to the Pre and Post periods. Therefore, essential travel during this period is closely related to local businesses and facilities that provide essential services. Consequently, addressing travel demand from a spatial perspective during the pandemic requires a context-based approach. While socioeconomic resources can typically be accessed over a wide geographic area during normal times, this is much less feasible during events like the COVID-19 pandemic. Similarly, post-pandemic, the differences in mobility between individuals will also need to be considered when planning for essential resource provision. Ensuring local access to essential resources should be the primary focus of facility planning by public administration in order to enhance the welfare of those in need.

The findings of this study can inform the optimization of public transit services in a hierarchical manner during the post-pandemic period. In order to ensure that all citizens have access to essential resources, it is crucial to accurately identify the destinations of essential travel and efficiently connect individuals to these locations. To assess the adequacy of the current public transit system in meeting this demand, we further analyzed the coverage of major essential travel destinations by bus in a grid cell-based manner (Table 7 and Fig. 7). Table 7 indicates that the bus system can meet 66.32%, 77.22%, and 65.29% of travel demand in the Pre, During, and Post periods, respectively. In the During period, bus services can cover more travel destinations than the other two periods, regardless of grid cell category. These results suggest that the current public transit system has done a relatively good job in matching essential demand as compared to non-essential demand. However, the findings also highlight the need to prioritize improving transit services, particularly by expanding the bus network to grid cells with the highest quartiles of essential travel demand but without a current bus line. For instance, Fig. 7 illustrates that the grid cells with red boundaries in the first two quartiles have high essential travel

Table 6
Results of models.

Independent variables	OLS			SLM			SLX			SDM		
	Pre	During	Post	Pre	During	Post	Pre	During	Post	Pre	During	Post
E_catering	0.254***	0.197***	0.486***	0.140***	0.123***	0.330***	0.103**	0.137***	0.292***	0.110**	0.136***	0.302***
NE_catering	2.079***	1.052***	2.722***	1.804***	0.887***	2.338***	1.039***	0.233*	1.204***	1.046***	0.234*	1.206***
E_shopping	0.238**	0.546***	0.239*	−0.065	0.278***	−0.174	0.013	0.183**	−0.105	0.009	0.182**	−0.116
NE_shopping	0.0242	0.0186	0.042	−0.008	−0.002	−0.002	0.021	0.029	0.035	0.019	0.030	0.034
E_healthcare	0.610*	0.676**	0.451	1.178***	1.034***	1.203***	0.006	0.225	−0.447	−0.1787	0.251	−0.692*
NE_healthcare	0.2262	0.1587	−0.045	0.377**	0.279*	0.164	0.675***	0.510***	0.565**	0.671***	0.514***	0.558**
E_education	1.943***	1.437***	2.350***	1.079***	0.814***	1.161***	0.694***	0.318***	0.536***	0.654***	0.323***	0.475***
NE_education	0.855***	−0.009	1.380***	0.400**	−0.286**	0.757***	0.244*	−0.101	0.574***	0.258*	−0.106	0.595***
landuse_mix	5.301***	5.207***	6.555**	16.888***	12.912***	22.523***	3.399*	1.540	3.562	4.001**	1.453	4.279*
Airport_distance	0.159***	0.105**	0.226***	−0.107**	−0.065*	−0.147**	0.943***	1.130***	1.240***	1.100***	1.090***	1.440***
Railway_distance	−0.191***	−0.138***	−0.259***	0.726***	0.514***	0.997***	−1.48***	−1.050***	−1.900***	−1.350***	−1.080***	−1.720***
Ramp_distance	−0.227*	−0.170	−0.359**	0.453***	0.319***	0.587***	0.151	−0.432*	0.224	−0.008	−0.404*	0.016
Primary_density	5.475***	2.087***	6.390***	1.921***	−0.181	1.593**	1.963***	0.742	1.750**	2.019***	0.731	1.784***
Popden	2.150***	2.300***	2.850***	1.070***	1.360***	1.360***	0.252*	−0.048	0.049	0.146	−0.021	−0.104
_cons	−7.523***	−6.249***	−9.309***	−65.486***	−47.878***	−88.473***	−16.676	−37.835***	−25.898***	−27.625**	−34.861***	−39.396**

Independent variables	OLS			SLM			SLX			SDM		
	Pre	During	Post	Pre	During	Post	Pre	During	Post	Pre	During	Post
W × E_catering							10.254***	−1.082	14.417***	12.172***	−1.243	17.010***
W × NE_catering							157.776***	92.046***	214.344***	177.457***	88.798***	242.104***
W × E_shopping							−17.962***	26.841***	−28.256***	−16.971***	25.608***	−26.495***
W × NE_shopping							−1.161	0.241	−0.454	−1.778	0.2953	−1.316
W × E_healthcare							−134.080***	−12.471	−148.218***	−182.545***	−5.786	−211.137***
W × NE_healthcare							−31.642***	−84.959***	−44.265***	−36.040***	*−83.107****	−50.862***
W × E_education							−82.778***	−34.020***	−108.264***	−82.146***	−34.052***	−107.944***
W × NE_education							21.401**	−7.110	20.129	30.372***	−7.626	30.845**
W × landuse_mix							24.744	67.831**	40.992	49.815	60.465**	72.699*
W × Airport_distance							−2.840***	−3.780***	−3.640***	−3.170***	−3.690***	−4.040***
W × Railway_distance							6.340***	4.730***	8.390***	5.720***	4.850***	7.590***
W × Ramp_distance							−2.690*	1.640	−4.330**	−2.290	1.600	−3.920*
W × Primary_density							−83.550***	−65.663***	−122.577***	−86.957***	−63.945***	−129.087***
W × popden							12.000*	26.600***	19.400***	18.500***	24.800***	27.500***
W × Y				2.664***	2.597***	2.706***				−1.795***	0.446	−1.802***
R-squared	0.594	0.548	0.603	0.522	0.451	0.529	0.740	0.662	0.756	**0.743**	**0.662**	**0.759**
Log-Likelihood	9373	10,271	7896	9998	10,666	8572	10,539	11,031	9175	**10,548**	**11,032**	**9179**
AIC	−18,717	−20,511	−15,761	−19,961	−21,298	−17,110	−21,018	−22,003	−18,289	**−21,036**	**−22,005**	**−18,299**
BIC	−18,618	−20,413	−15,663	−19,850	−21,186	−16,999	−20,820	−21,806	−18,092	**−20,839**	**−21,815**	**−18,102**
N of Obs.	5268											

Note: The dependent variable was transformed by multiplying the value by 1000. E.g.: 1000 essential catering POI is associated with 0.111 taxi trip arrivals in the SDM model.

Table 7
Percent of travel demand covered by public transit.

Level	Pre			During			Post		
	Count	Covered	Percent	Count	Covered	Percent	Count	Covered	Percent
0	3053	317	10.38%	4153	925	22.27%	3015	315	10.45%
1	553	240	43.40%	278	163	58.63%	563	225	39.96%
2	554	356	64.26%	279	199	71.33%	563	338	60.04%
3	554	378	68.23%	279	232	83.15%	563	406	72.11%
4	554	495	89.35%	279	267	95.70%	564	502	89.01%
Overall	66.3%			77.2%			65.3%		

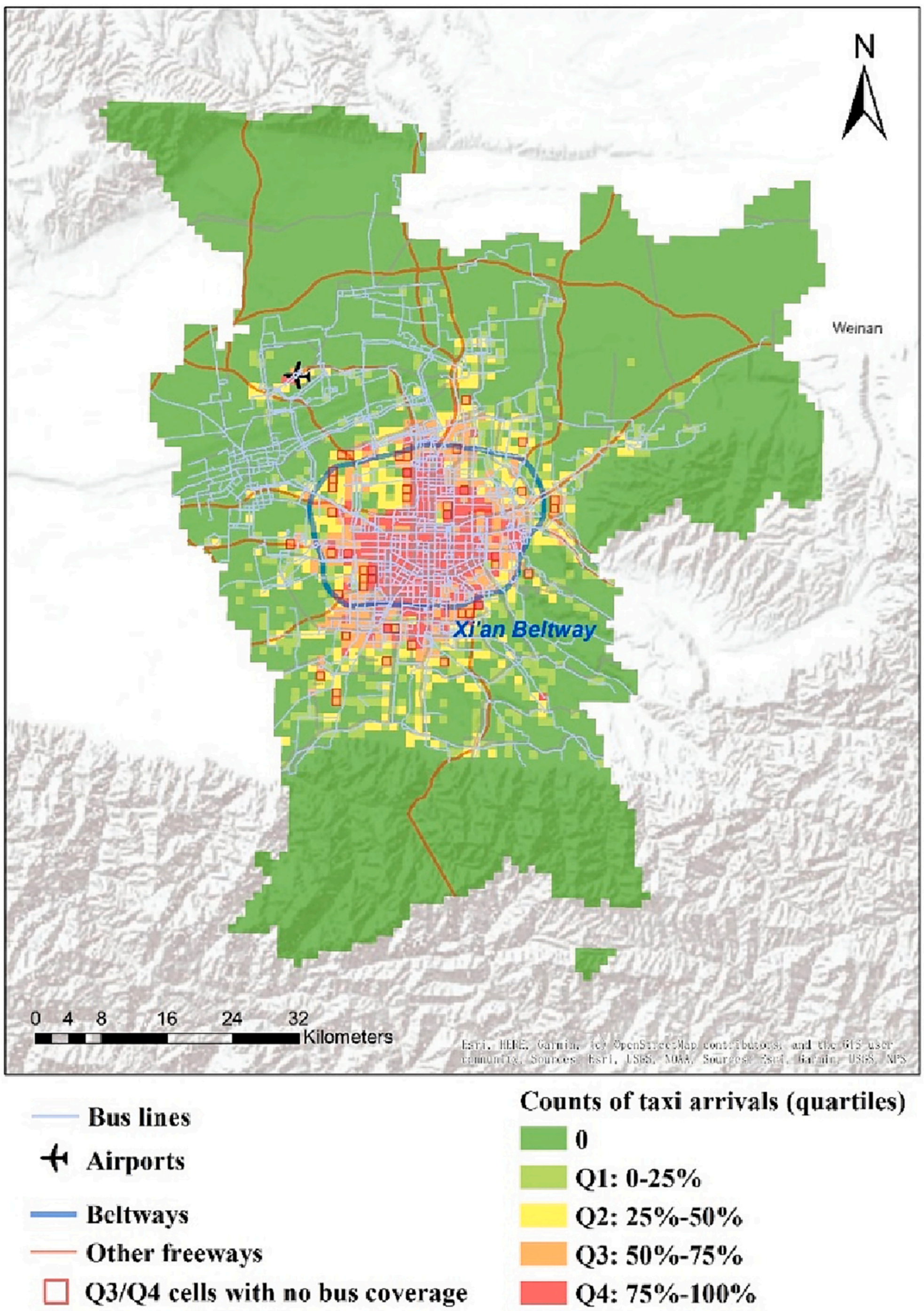

Fig. 7. Travel demand and public transport line coverage.

demand, but no public transit line passes through them. Therefore, these areas should be given priority consideration in the optimization of the public transit system.

The clarification of the concept of essential travel is a significant contribution of this study. The existing literature lacks a uniform standard for defining essential travel, which is typically associated with travel for food, work, medicine, etc. This paper proposes a novel approach to define essential travel based on local travel demand and transport supply, providing a decision-making basis for optimizing public transit that caters to essential travel in the post-pandemic era. The public administration has been increasingly concerned about the inequity in access to spatial opportunities among socially disadvantaged people. The findings of this research can provide evidence for identifying communities' capability of providing essential services.

At the end of this paper, we want to acknowledge some limitations of research design and data analysis. This paper focuses on the spatial distribution of taxi travel demand in different periods with regard to the pandemic, and mainly discusses its patterns relative to building environment, facility accessibility and population. Some more refined characteristics, such as population age structure, and family income were not included in this study due to the data unavailability. Admittedly, understanding these factors may be of great help to modeling and estimating essential travel demand. In addition, although spatial models are found to be one of the best choices in this study, we expect to see other advanced methods such as machine learning techniques to explore this topic in future research. Finally, due to the limited data, we failed to obtain data on all modes of travel in different periods and had to rely on taxi GPS tracks only. In addition, since the taxi data does not have the attributes of travel purpose, we cannot carry out statistics on whether the travel is essential or not according to the purpose. In the future, more research may be needed to apply the empirical model to other cities and countries, so as to explore essential travel from a more general perspective.

Author contributions

The authors confirm contribution to the paper as follows: Chao Yang: Conceptualization, Supervision, and Project administration; Zhiyang Wan: Data curation, Investigation, Methodology, and Writing-original draft; Quan Yuan: Conceptualization, Funding acquisition, Methodology, Writing-review & editing; Zhou Yang: Methodology, and Visualization; Maopeng Sun: Data curation and Resources.

Data availability

Data will be made available on request.

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Appendix A. Spatial effect analysis of SDM

Explanatory variables	Pre			During			Post		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
E_catering	0.103**	4.208***	4.311***	0.136***	−2.067	−1.931	0.293***	5.803***	6.096***
NE_catering	0.948***	61.700***	62.648***	0.261*	155.513	155.774	1.071***	84.096***	85.167***
E_shopping	0.019	−5.969**	−5.951**	0.190**	44.937	45.127	−0.101	−9.213***	−9.314***
NE_shopping	0.020	−0.637	−0.617	0.030	0.540	0.570	0.034	−0.483	−0.448
E_hospital	−0.077	−64.035***	−64.112***	0.249	−9.926	−9.677	−0.574	−73.567***	−74.141***
NE_hospital	0.692***	-13.088***	−12.396***	0.489***	−144.974	−144.486	0.587***	−18.180***	−17.592***
E_education	0.701***	−29.280***	−28.579***	0.313***	−59.313	−59.000	0.536***	−38.134***	−37.598***
NE_education	0.242	10.510***	10.752***	−0.108	−13.422	−13.530	0.578***	10.436**	11.014**
landuse_mix	3.977**	14.982	18.959*	1.472	106.903	108.375	4.242*	22.779	27.021**
Airport_distance	1.100***	−1.810***	−0.704***	1.090***	−5.610	−4.520	1.450***	−2.330***	−0.880***
Railway_distance	−1.350***	2.860***	1.510***	−1.080***	7.640	6.560	−1.730***	3.750***	2.020***
Ramp_distance	−0.007	−0.799	−0.806	−0.404*	2.480	2.070	0.018	−1.380	−1.370**
Primary_desity	2.070***	−31.831***	−29.761***	0.711	−111.285	−110.574	1.858***	−46.372***	−44.514***
Popden	0.136	6.420***	6.560***	−0.013	43.400	43.400	−0.120	9.690***	9.570***

Notes: for significant correlation '***' = 0.01; '**' = 0.05; '*' = 0.1.

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