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Potential Effect of Air Pollution on the Urban Traffic Vitality: A Case Study of Nanjing, China

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Abstract: Studies on the vitality of urban residents' daily commuting and air pollution are scarce. Based on the cell phone mobile signaling data, urban air quality observation data, and urban transportation infrastructure environment data of Nanjing in 2019, and through the panel regression model and the standard deviation ellipse analysis (SDE) to measure the impact of air pollution on residents' daily traffic vitality, we construct the survey panel matrix data system with streets as spatial units. Through SDE and panel regression model analysis, we measured the restraining effect of air pollution on the traffic vitality. The scope of the traffic vitality area SDE was found to shrink as the air quality index (AQI) increases. The study found three main characteristics: (1) Under different transportation models and different location conditions, there are obvious differences in traffic vitality. The entire city presents a trend of "northeast-southwest" axial expansion in the spatial pattern of the traffic vitality. Compared with the urban core area, the traffic vitality of residents in the north-south areas of Nanjing's periphery has declined significantly. (2) The inhibitory effect of air pollution on public traffic vitality and self-driving traffic vitality are differences. Approximately one-tenth of traffic activities may be inhibited by air pollution. The weakening of traffic vitality greatly reduces the city's ability to attract and gather people, materials, and resources. (3) The inhibitory effect of air pollution on traffic vitality is heterogeneous under different transportation infrastructure environments. The higher the public transportation station density and public transportation frequency of the street, the more obvious the suppression effect of air pollution. The higher the parking density, station accessibility, road intersections density, and transportation facility diversity, the lower the suppression effect of air pollution. This study elucidates the relationship among air pollution, the transportation infrastructure environment, and the traffic vitality, and provides significant guidelines for optimizing the organization of elements in the transportation infrastructure environment, thereby mitigating the inhibitory effect of air pollution on traffic vitality.

Keywords: air pollution; traffic vitality; built environment; spatial correlation; spatial lag model; phone signaling data; air quality; behavioral habits; activity density; population distribution; land use mix

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1. Introduction

The traffic vitality of residents in the city directly reflects the attractiveness and diversity of the city, which is embodied in the intensity and type of resident activities in the urban space [1–3]. Improving the traffic vitality is conducive to improving the quality of life of residents and is significant to the sustainable development of the city [4,5]. In urban transportation planning, unanimous attention has been paid to the traffic vitality, particularly the impact of the built environment on the traffic vitality [6,7]. However, researchers have found it difficult to accurately measure the traffic vitality. Past studies are mostly based on observational surveys in small-scale spaces (such as streets) or use short-term (such as 1 week) resident activity logs for discussion. Describing commuting vitality distribution and change characteristics for large-scale spaces (such as the entire city) and long-term periods (such as spanning several weeks) is difficult [8,9]. Existing studies have identified the spatial displacement of residents over a period of time as traffic travel activities [10]. The frequency and density of traffic trips represent traffic vitality. We identify the people whose location changes in a relatively short period of time as the traffic travel crowd. We take the street as a unit to measure the density of traffic people per unit area as traffic vitality. Therefore, daily traffic vitality refers to the daily traffic density of residents in the street unit. Generally speaking, traffic behavior mainly refers to the traffic travel activities of individual residents, while traffic vitality is used to describe the frequency and density of group traffic travel at the medium and macro spatial level (such as streets and larger spatial scales). Following the continuous development of information and communications technology (ICT) in recent years, mobile phones record the activities and travel behaviors of residents in all aspects of daily life. These geographically attributed location big data are real-time, continuous, and accurate among other characteristics, making them a suitable data source for the study of residents' transportation activities [11]. Past studies collected mobile phone signaling data [12,13], LBS positioning data [14], GPS data [15,16], and social media sign-in data (such as Weibo and Twitter) [17–20] among others to measure residents' commuting activities. The specific spatial dimensions involve three levels of streets, cities, and regions; the time dimension is accurate to the hour as the unit; and the intensity of commuting activities and temporal and spatial characteristics are recorded [21–24].

Atmospheric particles have multiple impacts on human health and the environment. Studies have shown that PM10 adversely affects human health and increases mortality; while fine particulate PM2.5 and ultrafine particles are at higher risk [24–26]. At the same time, there is a correlation between air pollution and traffic vitality. Atmospheric particles can absorb and scatter solar radiation, and particulate matter greatly reduces the visibility of surface traffic [27]. In addition, studies have shown that there are positive and negative effects between transportation infrastructure and air pollution. On the one hand, with the continuous improvement of transportation infrastructure, the transportation structure is increasingly optimized. A new generation of transportation infrastructure facilitates low-energy, low-polluting modes of transportation. A developed urban transportation system can significantly reduce traffic congestion, shorten the waiting time caused by road congestion, and increase the frequency of traffic travel. In addition, good transportation infrastructure can also reduce the level of exhaust emissions when vehicles are idling, thereby improving the overall level of urban haze pollution. On the other hand, from the perspective of the utilization of transportation infrastructure, the improvement of transportation infrastructure conditions will increase the scale of urban transportation. The improvement of transportation infrastructure will increase the daily commuting frequency and vitality of residents to a certain extent, which is conducive to the formation of more commuting needs and longer commuting distances [28].

In the past three decades, China's urbanization level has developed rapidly, and the urban population agglomeration also enhanced the traffic vitality. However, industrialization and the rapid development of motor vehicles have caused increasingly severe air pollution problems. Smog, PM2.5, and air quality are common in government and media reports and have become some of the main limitations of the sustainable development of cities [29]. Traffic sources are significant to urban air quality as they could impact the air quality along highways and streets. For example, black carbon PM is emitted primarily by traffic sources and affected the air pollutants' distribution [30–32]. Presently, urban geographers mainly focus on the temporal and spatial evolution characteristics and driving factors of air pollution, the impact of air pollution on the physical and mental health of residents, the differences between residents in different regions and different socioeconomic backgrounds, and the governance of air pollution areas [33]. At the same time, certain scholars focus on urban residents' exposure to air pollution, and use GPS, portable environmental monitors, and other tools to determine the impact of air pollution on residents' travel (such as travel trajectories, traffic ways) [34,35]. These studies have shown that following the popularization of health awareness, air quality affects residents' activities in urban spaces (whether to go out for activities, travel modes, and choice of location and time of activities), and thereby affecting residents' traffic vitality.

Overall, current empirical research on the impact of air pollution on the traffic vitality is lacking. Owing to the development of information technology in recent years, the trajectory of residents' activities can be more accurately determined. A small number of studies have collected micro-blog sign-in data and used the city as a spatial unit to reveal that air pollution inhibits residents' activities (sign-in scale) [36], thereby affecting their happiness (emotions expressed in the sign-in text) [37]. In addition, certain scholars have focused on the impact of air pollution on specific types of activities, such as determining whether air pollution will inhibit residents from eating out based on changes in the number of online reviews on food and beverages [38]. However, these studies did not clearly distinguish and quantify related factors such as air pollution, built environment, and traffic vitality. Past studies have not analyzed the differential impact of air pollution on traffic activity under different transportation infrastructure environments. On the one hand, the studies that consider cities as the research unit disregard the spatial imbalance of air pollution and mobility in large cities [39]. On the other hand, current researchers have difficulty measuring the impact mechanism of built environment factors such as density, mixing degree, and location (distance) on air pollution's inhibition of traffic travel activities.

The differences among the inhibitory effects of air pollution on the traffic vitality vary for cities at different stages of social and economic development [36]. On the other hand, the built environment significantly influences residents' activities. The inhibitory effect of air pollution on the traffic vitality may be heterogeneous in the built environment. For example, although air pollution generally reduces residents' willingness to go out, in places where the built environment is relatively attractive, the reduction in residents' willingness to travel may be relatively low. To better measure the impact of built environment elements on the traffic vitality in an air-polluted environment, an analysis of the micro- and medium-scale space within the city is required [37]. In addition, to control the impact of hidden variable factors that may exist in the observation on traffic travel, it is necessary to obtain long-term panel data to improve the accuracy of model effect analysis [38]. Residents with different socioeconomic backgrounds live in different environments, and different residents have different perceptions of air pollution and outdoor activity habits [39]; this disparity exacerbates environmental injustice [40].

In recent years, the technical methods for measuring residents' daily traffic travel have constantly been updated. Following the popularization of mobile communication technology, local and international researchers use mobile phone signaling data to perform applied research on the urban center system, job–resident relationship analysis, and urban overall planning evaluation, and implement the urban system [41–43]. Mobile phone signaling data mainly extract the information exchange data and time stamp information between the base station and the mobile phone terminal in the mobile communication system to determine the spatial location and status of the phone user [44]. The identification of residents' travel behavior based on the travel laws of phone users has the advantages of presenting a large sample size, balanced sampling distribution, high spatial accuracy, and robust data timeliness. Scholars measure the built environment based on data sources such as points of interest (POI) and Open Street Maps. The specific influencing factors include urban structure, population density, street density, land use mix, and location [45,46]. These studies show that big data with geographic location attributes, such as mobile phone signaling check-in data, can reflect the daily commuting activities of residents in real time [47].

Based on the location data of mobile phone signaling, the urban air quality observation data, and the urban built environment data in Nanjing, 2019, this study comprehensively constructs the panel survey matrix data with the street as the spatial unit and the day as the time unit. The impact of air pollution on residents' daily traffic vitality is quantified through the panel regression model and standard deviation ellipse (SDE) analysis. According to existing research, people have expectations about the time spent on different types of travel activities. Generally speaking, in the urban road environment, the walking speed is 4–5 km/h, the bicycle speed is 15–20 km/h, the car speed is 60–80 km/h, the bus speed is 40–80 km/h, and the subway speed is 60–120 km/h [48]. Residents choose the exact traffic travel mode, and within a fixed travel time period, they will get a stable traffic travel range. Studies have shown that people's choice of long-distance transportation activities is affected by many factors, including atmospheric environment and urban built environment [49]. Different from the necessary activities within the 15 min daily life circle of residents, the traffic vitality pays more attention to the traffic travel behavior with a speed of more than 20 km/h and a travel time of more than 15 min. This paper takes 15 min as the minimum time unit and calculates the average displacement distance of mobile phone signaling location data within the urban area of Nanjing as the minimum activity radius of residents' travel. On this basis, this paper uses the standard deviation ellipse analysis model to measure the core range and direction distribution of large-scale residents' daily traffic travel. This study elucidates the relationships among air pollution, the built environment, and the traffic vitality through the statistical analysis of air pollution panel data at the street level. It also provides a theoretical basis for city managers to optimize the built environment to reduce the inhibitory effect of air pollution on the traffic vitality.

2. Data and Methods

2.1. Data Collection

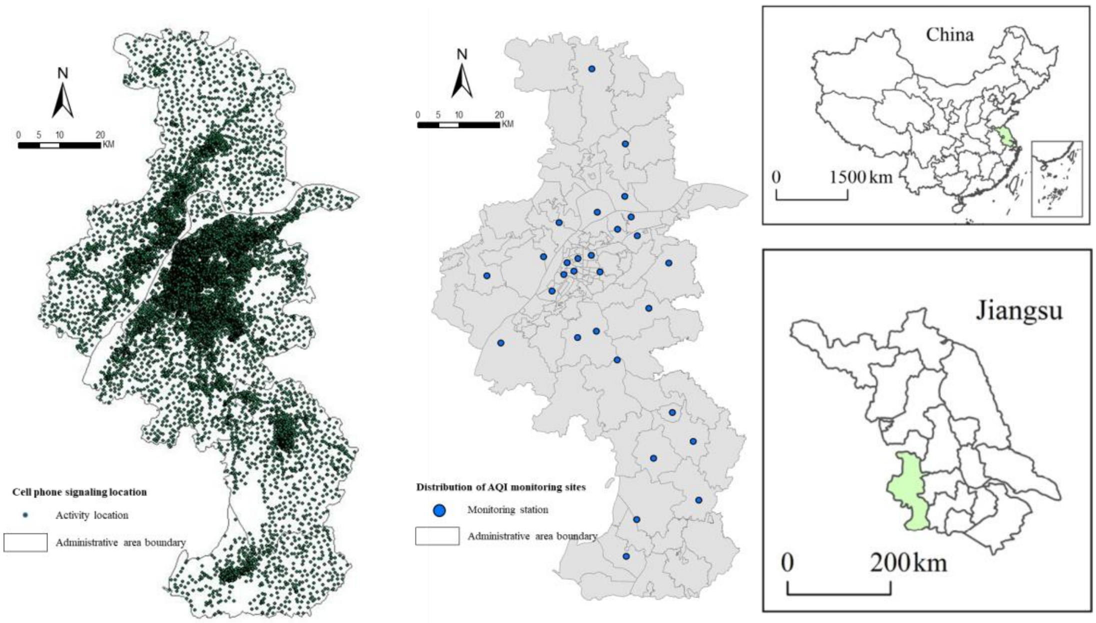
2.1.1. Mobile Phone Signaling Data

This study regards the street as the basic spatial unit and the day as the basic time unit for investigation. Specifically, mobile phone signaling data are used to measure the intensity of residents' commuting connections to reflect the traffic vitality [37–39]. In 2019, we obtained 60 days of mobile phone signaling data for 2 consecutive months from Chinese mobile operators in Nanjing, Jiangsu Province (Figure 1). On the one hand, the data provider had deleted private information such as the resident's name, age, work unit, and residential address from the original data submitted. On the other hand, we focused on analyzing the change characteristics of large-scale residents' traffic travel location and did not undertake in-depth analysis of individual residents' information. We were not involved in the description of individual private information of residents. We have supplemented the characteristics of Nanjing's social environment in this section and the details are as follows: Nanjing is the capital city of Jiangsu Province, with a land area of 6587.02 km^2. The urban area is 868.28 km^2. In 2019, the population of Nanjing was 9.282 million. There are 11 subway lines, 8395 buses, and more than 3 million cars in Nanjing. According to the data in the report "2019 Nanjing Environmental Status Bulletin", the main source of air pollutants in Nanjing is industrial production, not motor vehicle emissions [45]. Therefore, the built environment factors have a greater impact on the air quality in Nanjing. According to the Bulletin on traffic transportation in Nanjing in 2016, the residents transported by private cars take a percentage of 11.89% and those transported by public ways were 26.86% [46].

First, the user's residence and work place, and commuters were identified based on the staying time and recurrence rate of mobile phone users in different urban spaces. We determined the residents' movement trajectories based on cell phone signaling locations and timestamps. In addition, we judged land use attributes based on the information of points of interest on the network electronic map. Combining residents' travel trajectories and land use attributes, we can determine the types of residents' daily activities. Specifically, we collected cell phone signaling data between 22:00 at night and 5:00 a.m. the next day. Residents were generally sleeping during this time period, and we then confirmed the place of residence. Additionally, we collected cell phone signaling data between 10 a.m. and 5 p.m. We combined it with industrial land, commercial land, public service land, etc., to determine where residents work and the activity types. In addition, we took 15 min as the minimum time unit to further measure the movement range of the resident's mobile phone signaling position during this period. We determined the residents' traffic pattern.

Second, considering limitations such as the sample representativeness of mobile phone signaling location data (significant difference between the signaling check-in frequency of active commuter users and inactive users), data cleaning, and integration were carried out through methods reported in past studies [32,39]. Specifically, cell phone signaling records outside the scope of Nanjing were excluded. For multiple check-ins at a fixed location over a long period, this study records the value of traffic vitality as 1. Furthermore, according to the land development attributes of the user's place of residence, this study divides the urban functional space into seven types of labels, including workplaces, residences, public transportation, public services, leisure and entertainment, and tourist destinations [36].

Based on mobile phone signaling data, the working population in Nanjing accounts for 43.2% of the total population. The commuter population was compared with the most recent census data in Nanjing, and the consistency test was carried out in the city street unit. The two data results were linearly correlated, and the model results passed the 99% confidence interval test, with an R^2 value of 0.86, which indicated strong correlation. The results show that there is no significant difference between the two sets of data and predicting the commuter population based on mobile phone signaling data is reliable. Regardless of air pollution, residents have to commute to work; however, transportation for other activities is greatly affected by residents' subjective wishes. Therefore, this study focuses on the activities of commuters in five other functional spaces other than the work place and residence. These five activity tags accounted for 62.45% of all check-in records. The data reflect that in addition to the daily commute to work, more than half of the residents access urban public services, leisure, tourism, and other functions through daily commuting [22,36]. Finally, this study obtained more than 5.63 million mobile phone signaling records in the five functional spaces mentioned above. This study calculated the sign-in density of residents' activities in Nanjing, comprising 95 streets of 11 jurisdictions in 2019. The average daily check-in density was 17.9 times per 10 km^2.



(**a**) (**b**) (**c**)

Figure 1. Distributions of mobile phone sign-in locations (**a**), and AQI monitoring stations (**b**) and the case site location (**c**).

2.1.2. Air Pollution and Meteorological Data

Owing to the concern regarding air pollution, each city has set up air monitoring stations, and declared the city's AQI and the concentrations of 6 types of pollutants ($PM_{2.5}$, PM_{10}, CO, NO_2, O_3, SO_2) in real time. The standard of the AQI is the Technical Regulation on Ambient Air Quality Index of China, which is a national standard. It can be found on the website of the Ministry of Ecology and Environment of the People's Republic of China.

The data acquisition time was from 20 October 2019 to 20 December 2019, for 60 consecutive days, including 17 non-working days and 43 working days. This time period was the alternating period of autumn and winter, and the AQI changes obviously, which can support the research on the influence of AQI concentration changes on traffic vitality in this paper. This paper focuses on the general impact of air pollution on the urban traffic vitality. Therefore, in terms of data collection time, we avoided traditional holidays such as National Day, Labor Day, and Spring Festival, and tried our best to avoid the unstable impact of the high traffic density during holidays on the research results. Research data were obtained from the daily update data of the China Environment Ministry, which contain 29 air monitoring stations in Nanjing. This study continuously collected the daily AQI and 6 types of pollutant concentration data through the 29 air monitoring stations in 2019. We selected 342 observation days, which basically covered the meteorological observation data of a whole year. We obtained daily real-time meteorological observation data through the website of the Ministry of Environment of China (http://www.cnemc.cn/, accessed on 20 December 2019). We obtained multiple sets of meteorological observation data on each observation day, averaging 5–6 times a day, accumulatively obtained 1890 wind speed, temperature, and precipitation observation data, and correspondingly obtained 1890 AQI data. Studies have shown a significant high correlation between the AQI and the concentration of six types of pollutants [32]. Therefore, this study used the AQI data of each air monitoring station to represent the air pollution in the streets. According to Chinese national standards, air quality is divided into six levels: excellent (AQI $\leq$ 50), good (50 < AQI $\leq$ 100), light pollution (100 < AQI $\leq$ 150), moderate pollution (150 < AQI $\leq$ 200). As shown in Table 1, the average daily AQI of Nanjing in 2019 was 61.75 and the air quality was mainly excellent and moderately polluted. In addition, significant differences were observed among the AQI values of each monitoring station (F = 7.982, *p*-value = 0.000), indicating significant differences in air quality in various streets of Nanjing. According to our previous work [50–52], the stable boundary layer with less precipitation and high air pollutants emissions works together to make winter the most polluted season [53]. In the spring and summer, the enhanced convective activity of the atmosphere and increased precipitation created optimal weather conditions for diffusion, which was also beneficial for the removal of air pollutants. The dense population, large number of motor vehicles, industrial production, and human activities in the urban area also result in the urban area being more polluted than the suburbs [54,55].

Table 1. Variable definitions and summary statistics.

Variable		Description	Observation	Min	Max	Mean	Variance
Explanatory variables (air quality)	AQI	Daily Air Quality Index	1890	20.08	61.75	27.44	161.19
Explanatory variables (transportation facilities)	Parking density	$\text{paking density} = \frac{\text{parking numbers}}{\text{Street area } (\text{km}^2)}$	132	0.49	15.47	15.27	82.88
	Station accessibility	$\text{station walkability} = \frac{\text{walking distance}}{\text{Street area } (\text{km}^2)}$	132	0.06	14.73	17.84	81.74
	Metro/Bus station density	$\text{station density} = \frac{\text{subway/bus stations}}{\text{Street area } (\text{km}^2)}$	132	0.00	0.71	1.17	6.26
	Transportation facility diversity	$X_i = \frac{\text{Area of Type i transportaion facility } (\text{km}^2)}{\text{Total land area } (\text{km}^2)}$ $P_i = \frac{X_i}{\sum_{i=1}^{n} X_i}$ $\text{Facility Diversity Index} = \frac{(-1)\left(\sum_{i=1}^{n} P_i \ln(P_i)\right)}{\ln(n)},\ n = 6$	132	0.27	0.68	0.09	0.83
	Road intersection density	$\text{Road intersection dense} = \frac{\text{street road intersections}}{\text{Street area } (\text{km}^2)}$	132	0.00	12.74	14.82	63.79

Table 1. *Cont.*

Variable		Description	Observation	Min	Max	Mean	Variance
Dependent variable	Traffic vitallity intensity	Activity intensity $= \frac{\text{Daily signaling check-in}}{\text{Street area } (10\ \text{km}^2)}$	49,831	0.00	17.83	50.58	3014.00
Control variable (weather)	Precipitation	Daily precipitation, dummy variable: 1 = heavy rain and above, 0 = other	1890	0	0.02	0.12	1
	Wind speed	Daily average wind speed (m/s)	1890	0.45	1.72	0.76	6.82
	Temperature	Daily average temperature (°C)	1890	6.94	22.65	5.32	32.76
Control variable (date attributes)	Date	Non-working days, dummy variables: 1 = non-working days, 0 = working days	342	0	0.27	0.38	1

Note: Transportation facility diversity index are closely related to resident traffic activities, including bus stops, subway stations, bicycle stops, car parking spaces, bus parking stations, gas stations, etc.

Studies have shown that meteorological conditions affect the choice of residents' activities [35]. The China Meteorological Administration updates the data daily. This study collected data on the daily average wind speed, average temperature, and rainfall in 2019 released by 29 meteorological monitoring stations in Nanjing. This necessitates control of the impact of meteorological and environmental factors when measuring the air pollution impact on traffic vitality. We regarded heavy and extra heavy rain (precipitation $\geq$60 mm/d) are as extreme weather conditions in cities. This situation is likely to cause urban waterlogging and affect residents' traffic activities [39] and was regarded as a dummy variable in the model in this study (Table 1). Based on the monitoring data of each meteorological station, we take the average recorded data of the meteorological stations in the street as the street meteorological measurement result. Based on the results of descriptive statistical analysis, we can find that there are significant differences in temperature, humidity and wind speed among streets (F = 33.72, p-value = 0.000; F = 175.83, p-value = 0.000), but no significant differences in rainfall between streets (F = 1.548, p-value = 0.119).

2.1.3. Transportation Infrastructure Elements Data

This study considers the streets as the survey unit, and measures the impact of the built environment on the vitality of residents' transportation through five variables [6,7,9,13]: parking density, subway station density, road intersection density, transportation facility diversity, and spatial location (Table 1). We use streets as spatial units to measure indicators such as traffic stops, road intersections and AQI. We take the average AQI within the street as the street's AQI value. In addition, we calculate the average number of road intersections per unit area within the street. In short, the three indicators of transportation infrastructure, air quality, and traffic vitality are all statistically calculated on the street as the spatial unit. The population data were obtained from the database of the seventh national census in 2020. The data on subway/bus/parking stations and road intersections were obtained from the facility points of interest and road network database in Baidu electronic map. The calculation of the transportation facility diversity index was mainly based on the land use classification data of Nanjing in 2020. The location distance specifically refers to the straight-line distance from the city's geometric center to the administrative center. Xi refers to the ratio of the land use area of category i in a street to the land area of the street. This indicator is used to measure the degree of transportation facility mixing, which indirectly reflects the intensity of transportation facility and the maturity of block development. The type of transportation facility directly affects the types of residents' traffic activities. The higher the degree of transportation facility mixing, the richer the types of residents' traffic activities, and the higher the density of residents' activities, the stronger willingness of residents to travel.

2.2. Research Methods

2.2.1. Spatial Panel Regression Model

The study involved 60 days of survey panel data on 95 streets. To better reveal the restraining effect of air pollution on the traffic vitality, we selected the fixed effects model for controlling the unobservable time and individual effects [42]. The basic panel regression model is expressed as follows:

$$Y_{it} = \gamma_0 + \gamma_1 X_{it}^a + \gamma_2 X_{it}^w + \gamma_3 X_t^d + \eta_t \ + u_i + \varepsilon_{it} \quad (1)$$

where the dependent variable Y_{it} is the activity intensity of street i on day t, reflecting the traffic vitality. X_{it}^a refers to the AQI of street i on day t, and encompasses wind speed, temperature, and precipitation. X_{it}^w refers to the variable group of the meteorological conditions of the i street on the t day, including meteorological data such as wind speed, temperature, and precipitation. X_t^d refers to a dummy variable that distinguishes between working days and non-working days. Studies show a significant difference between the residential activity spaces of working and non-working days (including rest days and holidays) [18,22]. Therefore, this study controlled for the working and non-working day factors, and then analyzed the impact of air pollution on the traffic vitality. η_t is a time-fixed-effect variable. u_i is the street fixed effect variable. This variable is a dummy variable for streets that controls for unobservable differences in streets that do not change over time. ε_{it} is the error term. γ_0 is the variable coefficient adjustment variable, which represents the influence weight of each variable.

Furthermore, we explore the impact of air pollution on the traffic vitality and the heterogeneity of different transportation infrastructure environments, and based on the panel regression model (Equation (1)), interaction terms between built environment variables and air pollution variables were introduced and expressed as follows:

$$Y_{it} = \gamma_0 + \gamma_1 X_{it}^a + \gamma_2 X_{it}^w + \gamma_3 X_t^d + \gamma_4 X_i^b X_{it}^a + \eta_t \ + u_i + \varepsilon_{it} \quad (2)$$

where X_i^b refers to the streets' built environment variable, including population density, subway station density, road intersection density, land use mix, and location variables. The traditional panel data regression model does not consider the spatial autocorrelation of the elements, which may cause errors in the regression coefficients.

2.2.2. Spatial Lag Model (SLM) and the Spatial Error Model (SEM)

Studies show an obvious spatial dependence in the traffic vitality space, and there may be a significant correlation between the intensity of residents' activities in adjacent spatial units [3]. Moran's I test identified a spatial autocorrelation ($p < 0.05$) of street traffic vitality. Therefore, we used GeoDa software to obtain the spatial matrix that measures the neighborhood relationship between streets and introduced the spatial lag model (SLM) and the spatial error model (SEM) to measure the impact of air pollution on the traffic vitality and the heterogeneity in the built environment. SLM and SEM are two spatial econometric regression models commonly used to calculate spatial correlations [43,44]. SLM is expressed as follows:

$$Y_{it} = vKY_{it} + \gamma X + \varepsilon \quad (3)$$

where K is an exogenous spatial weight matrix (150 $\times$ 150) reflecting the neighboring relationships among spatial units. KY_{it} refers to a lagging dependent variable that reflects spatial autocorrelation. v is a parameter of spatial dependence, and its absolute value represents the strength of spatial relevance. γ is the parameter vector. X is the independent variable measured by the model. ε refers to the error term that satisfies the spatial autocorrelation. In contrast with SLM which measures the spatial correlation through the spatial lag of the dependent variable, SEM measures the spatial correlation in the error term, and is expressed as follows:

$$Y_{it} = \gamma X + \beta W \varepsilon + u \quad (4)$$

where u is the error term, and its distribution conforms to a normal distribution with a mean value of 0 and a fixed variance. β is the spatial dependency parameter for filtering the spatial relevance of the error term.

2.2.3. Standard Deviational Ellipse Model

The standard deviational ellipse (SDE) model was used to describe the directionality and range characteristics of the spatial distribution of urban geographic elements [24]. It has been widely used in activity space analysis [26]. In this study, the SDE tool in ArcGIS software was used to visualize the characteristics and variations of residents' traffic vitality space under different air quality levels, and then quantitatively analyze the impact of air pollution factors on the traffic travel space vitality.

3. Results

3.1. Spatial Change Characteristics of Traffic Vitality under Air Pollution

This paper measures the trajectory position coordinates of residents' traffic travel through mobile phone signaling data. Based on the mobile phone signaling data, this paper uses the standard deviation ellipse model for spatial fitting, and then obtains the core area and distribution direction of residents' traffic vitality. Population data comes from the seventh national census, and the statistical unit is the street. We verified and corrected the distribution of the permanent population in the census through mobile phone signaling data. Generally speaking, 10:00 p.m. to 6:00 a.m. is the time for residents to rest and sleep, which can reflect the actual spatial location of residents. Based on the census data, we use the distribution of mobile phone signaling data during sleep as a correction index to finely measure the spatial distribution of the daily urban population. Therefore, the area and direction of the urban population distribution ellipse will change slightly on different survey days. To visualize the spatial changes in traffic vitality under the air pollution environment, this study separately calculates the residents' average traffic vitality under the air quality of each street in four levels: excellent (AQI $\leq$ 50), good (50 < AQI $\leq$ 100), light pollution (100 < AQI $\leq$ 150), and moderate pollution (150 < AQI $\leq$ 200). The vitality distribution of traffic space is shown in Figure 2. Moreover, based on the data from the 7th census of Nanjing City and the land use survey data in 2019, this study presents a map of the spatial distribution characteristics of the population and facilities. It further reflects the relationship between the traffic vitality (red circle) and the distribution of population (green circle) and facilities (blue circle) (Figure 2 and Table 2).

Table 2. Standard deviation ellipse features of urban vibrancy under different air quality levels (i.e., AQI $\leq$ 50, 50 < AQI $\leq$ 100, 100 < AQI $\leq$ 150, and 150 < AQI $\leq$ 200) and its comparison with the SDE of population and facilities.

	Traffic Pattern	Longitude of Center Point (°)	Latitude of Center Point (°)	Long Axis Radius (km)	Short Axis Radius (km)	Direction (°)	Area (km^2)
Traffic vitality ellipse (excellent)	Public traffic	118.37	31.17	35.29	19.59	30.73	548.97
	Self-driving	118.23	30.06	31.29	18.32	28.65	482.32
Traffic vitality ellipse (good)	Public traffic	118.36	31.12	30.62	18.13	29.22	477.15
	Self-driving	118.13	28.33	28.53	17.42	27.51	433.56
Traffic vitality ellipse (light pollution)	Public traffic	118.22	30.42	21.75	17.86	38.82	392.25
	Self-driving	118.19	29.57	20.33	16.92	37.65	388.78
Traffic vitality ellipse (moderate pollution)	Public traffic	118.28	31.11	13.39	13.72	42.68	332.23
	Self-driving	118.26	32.19	12.76	13.65	40.72	297.84
Population ellipse	-	118.31	31.17	33.57	21.23	37.21	528.13
Facilities ellipse	-	118.32	31.19	27.50	21.17	32.29	526.82

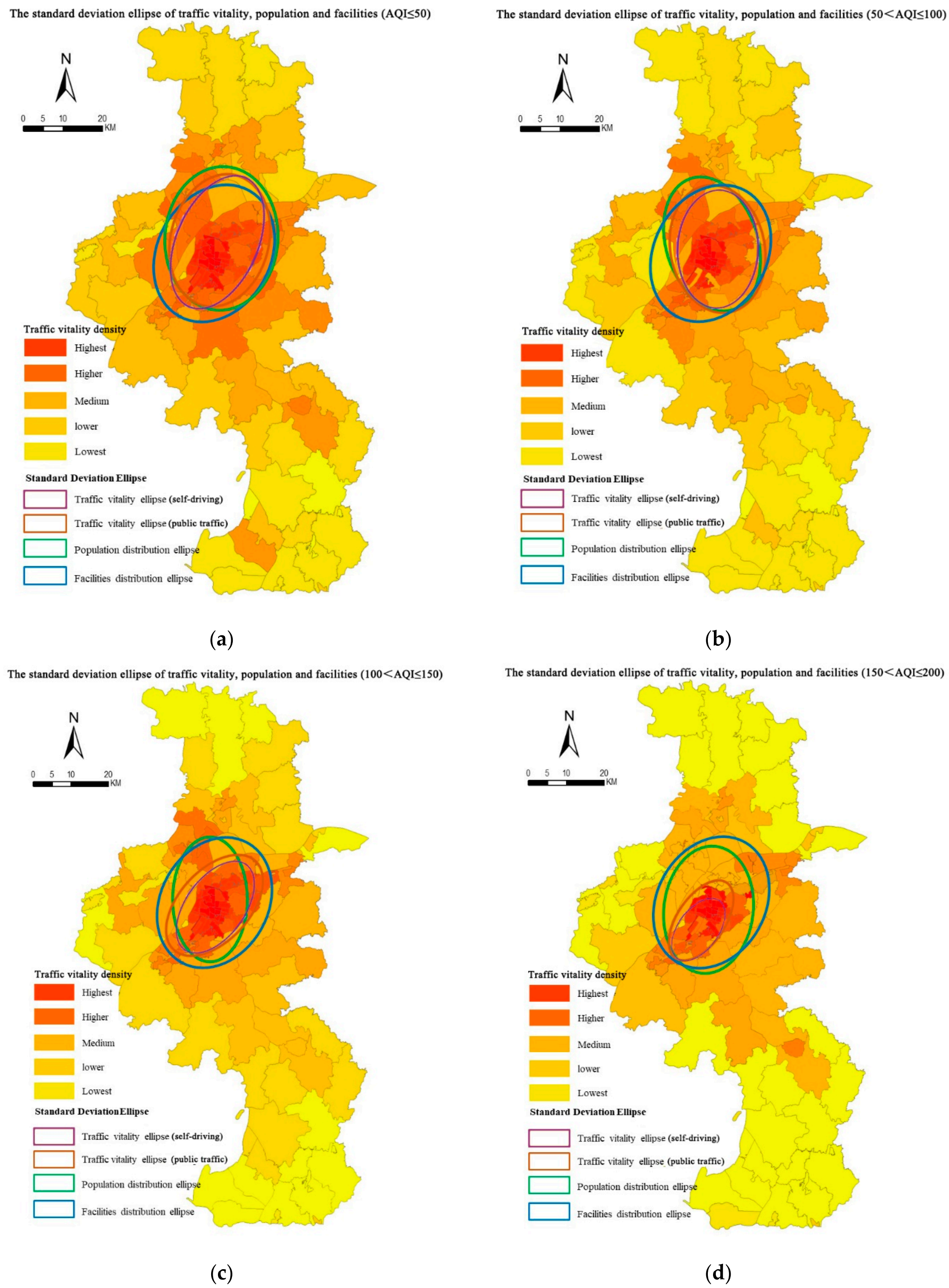


Figure 2. Standard deviation ellipse (SDE) features of traffic vitality under different air quality levels (i.e., (**a**) AQI $\leq$ 50, (**b**) 50 < AQI $\leq$ 100, (**c**) 100 < AQI $\leq$ 150, and (**d**) 150 < AQI $\leq$ 200) in Nanjing.

Under good air quality, Nanjing's traffic vitality is obviously consistent with the spatial direction of population and distribution of facilities. This confirms that mobile phone signaling check-in data can accurately reflect the spatial distribution of residents' commuting travel activities [19–22]. The traffic vitality space in Nanjing presents the spatial characteristics of "one core–multiple centers–multiple nodes", and areas with a high degree of travel activity are located along the Yangtze River. The core of residents' activities is located in the main urban area of Nanjing, and there are many hot spots for travel activities in the periphery of the urban area. The entire city presents a trend of "northeast–southwest" axial expansion in the spatial pattern of the traffic vitality. The "multi-node" refers to high-density area nodes with multiple traffic trips within the city.

The model results show that the influence of air pollution degree on residents' willingness to travel is not a simple linear relationship, but a fluctuating relationship, which drops sharply upon reaching a certain level. When the air quality is moderately polluted, the latitude and longitude of the SDE center point and the long and short axes change significantly. The direction of traffic vitality SDE changed from "Southwest-Northeast" to "East-West". This indicates that as the risk of air pollution exposure increased, although the intensity of traffic vitality in the urban core area declined, it remained the main choice for residents' travel activities. Compared with the urban core area, the traffic vitality of residents in the north-south areas of Nanjing's periphery has declined significantly.

In addition, the model results show that air pollution significantly compresses the size of the active area for residents' traffic and travel, and changes the distribution direction of the active area. When air quality is excellent, the SDE area of traffic vitality between the population and the distribution of facilities, indicating that residents are more willing to go to the outer areas of the city to carry out activities. As the risk of exposure to air pollution increases, when air quality is good, the SDE area for traffic vitality decreases to 71.3% of the excellent air quality. When air quality is light pollution, the SDE area for traffic vitality decreases to 47.8% of the excellent air quality. As the air quality transformed into moderate pollution, the area of the SDE for traffic vitality is significantly reduced to 34.2% of the area when the air quality is excellent. The SDE area of traffic vitality is significantly lower than the SDE area of population distribution, showing significant spatial shrinkage.

3.2. Inhibitory Effect of Air Pollution on Traffic Vitality

Table 3 shows the results of the panel regression model of the impact of air pollution on traffic vitality. Model 1 is a basic panel regression model. We used Model 1 as the base control model, Model 2 represented SLM panel regression models, and model 3 represented SEM panel regression models.

(1) Air pollution significantly inhibits the traffic vitality. After controlling the weather conditions, whether it is working day or not, and the spatial correlation conditions, AQI shows a significant negative correlation with traffic vitality. The weakening of traffic vitality greatly reduces the city's ability to attract and gather people, materials, and resources. Based on models 4 and model 5, each increase of 10 unit in the AQI value reduces the public traffic vitality intensity by approximately 0.46 times/10 km^2. Therefore, as the air quality decreases by one level (AQI increases by 50 units), the activity intensity decreases by 2.3 times/10 km^2. Based on models 6, each increase of 10 unit in the AQI value reduces the public traffic vitality intensity by approximately 0.52 times/10 km^2. Therefore, as the air quality decreases by one level (AQI increases by 50 units), the activity intensity decreases by 2.6 times/10 km^2. The daily average of 19.7 times/10 km^2 of mobile phone signaling sign-in intensity in Nanjing 2019. A change in the air quality in Nanjing from good to light pollution causes public traffic vitality to drop by 11.67% and self-driving traffic vitality to drop by 13.19%. Therefore, approximately one-tenth of traffic travel activities may be inhibited by air pollution. However, a shift on the air quality in Nanjing from good to moderate pollution (AQI increase by 100 units) inhibits nearly 23.35% of traffic travel.

Table 3. Results of the basic panel regression and spatial panel regression models.

Variable	Model 1		Model 2		Model 3		Model 4 (Bus)		Model 5 (Subway)		Model 6 (Self-Driving)	
	Coef.	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**
Date (Non-working day = ref.)	0.761 *	0.453	0.792 *	0.383	0.862 *	0.408	0.738 *	0.373	0.738 *	0.398	0.743 *	0.477
AQI	−0.152 ***	0.024	−0.087 ***	0.024	−0.097 ***	0.024	−0.271 ***	0.063	−0.248 ***	0.063	−0.233 ***	0.063
Wind speed	−1.063 ***	0.142	−0.093 ***	0.142	−1.103 ***	0.152	−0.498 ***	0.142	−0.472 ***	0.142	−0.518 ***	0.15
Precipitation (Non-torrential rain = ref.)	−2.017 ***	0.351	−2.018 ***	0.35	−2.112 ***	0.375	−2.075 ***	0.35	−1.931 ***	0.35	−2.032 ***	0.371
Temperature	0.937 ***	0.126	0.664 ***	0.126	0.746 ***	0.135	0.672 ***	0.126	0.663 ***	0.126	0.724 ***	0.134
(Temperature)^2	−0.023 ***	0.019	−0.017 ***	0.019	−0.009 ***	0.019	−0.013 ***	0.019	−0.013 **	0.019	−0.010 **	0.019
AQI* Parking density	-	-	-	-	-	-	-	-	-	-	−0.001 **	0.000
AQI* Public transportation frequency							0.325 **	0.043	0.215 ***	0.037	-	-
AQI* Station accessibility	-	-	-	-	-	-	0.267 **	0.053	0.229 ***	0.053	-	-
AQI* Transportation facility diversity	-	-	-	-	-	-	−0.003 ***	0.000	−0.004 ***	0.000	−0.003 ***	0.001
AQI* Metro/Bus station density	-	-	-	-	-	-	0.024 **	0.007	0.025 **	0.006	-	-
AQI* Road intersection density	-	-	-	-	-	-	0.002 **	0.000	0.001 *	0.000	0.001 *	0.000
ρ	-	-	0.082 ***	0.008	0.075 ***	0.008	-	-	0.052 ***	0.007	0.069 ***	0.007
Location fixed effect							Control					
Street fixation effect							Control					
Season fixed effects							Control					
N							49,831					
					Model fit							
Adjusted R^2	0.076		0.076		0.082		0.274		0.218		0.235	
Log-likelihood	−276,912.2		−261,782.9		−252,838.2		−273,091.1		−292,071.3		−266,721.5	
AIC	438,912.2		462,295.9		462,276.5		463,212.2		473,118.6		456,115.1	

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

(2) At the same time, the model results also show that meteorological conditions have a significant impact on traffic vitality. Nanjing has a subtropical monsoon climate. The mild and humid climatic conditions are conducive to the transportation of residents, and eliminate the inapplicability of the model results caused by the drastic changes in outdoor temperature in different cities [44]. The regression model results show that there is a negative correlation between meteorological conditions (temperature, humidity, etc.) and traffic vitality (public traffic pattern, self-driving traffic pattern, etc.). The increase in temperature and wind speed, and heavy rain lead to a significant reduction in residents' activities, thereby reducing the traffic vitality. In addition, as the temperature and wind speed rises, the decreasing trend of traffic vitality in public traffic pattern gradually decreased, while the trend of decreasing traffic vitality in self-driving traffic pattern did not change significantly.

(3) Under different traffic patterns, the traffic vitality intensity between adjacent streets also shows spatially correlated. In general, the fit of the SLM and SEM panel regression models shows relatively accurate. As shown in Models 1–3, compared with the results of traditional regression models, the significance and influence trends of variables in the SLM and SEM models are more stable. In the SEM and SLM panel regression models, the spatial dependence parameter (ρ) value was positively significant, thereby indicating a significant positive correlation between the adjacent streets' traffic vitality. The model result also indirectly indicates that there is spatial heterogeneity in the inhibitory effect of air pollution on traffic vitality. In different streets, the differences in transportation infrastructure conditions will also indirectly affect the traffic vitality under different traffic patterns.

3.3. Impact of Air Pollution on Traffic Activity Is Heterogeneous in Different Transportation Infrastructure Environments

Models 4–6 further introduce interaction terms between transportation infrastructure environments and air pollution variables. Owing to the accuracy of model fitting, models 4–6 exhibit greater improvement than models 1–3, and the influence coefficients of the 6 interaction variables are all significant. Model 1, Model 2, and Model 3 analyze the correlation between air quality-related variables and traffic vitality, respectively. Among them, Model 2 focuses on the influence analysis of "rain or not" factor on traffic vitality. Model 3 focuses on the influence of "whether it is a working day" factor on traffic vitality. Model 4, Model 5 and Model 6 respectively measure the interaction impact between AQI index and transportation infrastructure environment factors on traffic vitality. Transportation infrastructure environment factors include parking density, public transportation frequency, station accessibility, road intersection density, transportation facility diversity, and subway station density. The model specifically analyzes whether there is a significant correlation between the interaction terms of different indicators and traffic vitality. Model 4–6 respectively measure the cross-influence effects of transportation infrastructure and air pollution level on urban traffic vitality under different traffic patterns of bus, subway and self-driving, etc. It proves that the inhibitory effect of air pollution on traffic vitality shows significant heterogeneity in different transportation infrastructure environments.

(1) The higher the public transportation station density and public transportation frequency of the street, the more obvious the suppression effect of air pollution. Generally speaking, the public transportation station agglomeration is conducive to promoting the accessibility of station and connection of urban elements, thereby enhancing the traffic vitality [36]. The results show that densely distributed public stations areas are more sensitive to air pollution, thus strengthening the inhibitory effect of air pollution on traffic vitality. The research results of the models are consistent with the past studies stating that air pollution has a significant inhibitory effect on traffic vitality [39]. Air pollution has a strong inhibitory effect on the vitality of traffic in densely distributed public stations areas. This inhibitory effect adversely affects the sustainable development of urban society and economy.

(2) The higher the parking density, station accessibility, road intersections density, and transportation facility diversity, the lower the suppression effect of air pollution. Compared

with public traffic such as buses and subways, the impact of air pollution on self-driving traffic pattern is relatively low. The higher the parking density in the street, the more the opportunities for residents to drive by themselves to reach their destination and carry out related activities. To a certain extent, the inhibitory effect of air pollution on traffic vitality is alleviated. When the density of road intersections is high, the road system in the street presents the spatial morphological characteristics of wide lanes, network interweaving, and small scale. Studies have shown that a road system with small scale, small road width, and network intertwined can help increase diversified traffic travel [26,31,37]. In addition, the higher the degree of transportation facility diversity, the more abundant the types of transportation provided. In addition, the diversification of activity types is considered to be an important aspect of improving the traffic vitality [32,35]. This study shows that the diversification of transportation facility types in built-up areas has alleviated the inhibitory effect of air pollution on traffic vitality.

(3) The inhibitory effect of air pollution on traffic vitality presents significant space heterogeneity. There is spatial heterogeneity in the inhibitory effect of air pollution on traffic vitality, which will weaken the enthusiasm of residents to use urban infrastructure and hinder the optimization and adjustment of urban functional spatial structure. If this air pollution situation continues to increase and does not improve for a long time, the disadvantage of the suburb's lack of attractiveness to the population will be further magnified. The model results are consistent with the distribution characteristics of traffic vitality space in the central urban streets and suburban streets under different air quality levels in the previous section. Under the increasingly serious of air pollution, the decline in traffic vitality in the suburbs of Nanjing is significantly higher than that of the central urban area. This will lead to the lack of suburban traffic vitality, which will further affect the layout strategy of suburban infrastructure. Therefore, urban management departments should pay more attention to the supervision of air quality in suburban areas, so as to alleviate the inhibitory effect of air pollution on traffic vitality as much as possible.

4. Discussion

This study integrated mobile phone signaling data, weather, and air pollution among other multi-source data, and conducted panel statistical analysis at the street level. The research results have enriched the empirical research on the micro-spatial scale of traffic vitality in the city interior area, and will elucidate the relationship among air pollution, the built environment, and traffic vitality. In terms of the research content, this study measured the inhibitory effect of air pollution on traffic vitality and verified the heterogeneity impact under different transportation infrastructure environments. Considering China's current urban development stage of rapid urbanization, industrialization, and motorization, the urban management departments should strengthen pollution emission management to effectively reduce regional air pollution. In contrast, urban construction departments should strengthen the construction of urban rail transit systems with high coverage, high carrying capacity, and high operating frequency, optimize the layout of land use, fortify the construction of supporting facilities, and alleviate the inhibitory effect of air pollution on residents' transportation.

This study is limited in the following three aspects, which should be addressed in future. First, collecting the residents' activity data from multiple dimensions, combining the residents' daily life trajectories with the built environment attributes, and refining the relationship between different traffic modes and air pollution are necessary [23–25]. Second, in future research, we will try to integrate different types of data to enrich the measurement models and methods of traffic vitality. Third, people with different socioeconomic backgrounds have different views on transportation choices and air pollution tolerance. We need to study the differences in the inhibitory effects of air pollution on different population types to better address environmental equity issues [32,33]. Presently, certain theoretical studies have shown that air pollution has differentiated inhibitory effects and behavioral feedback on different types of people, but empirical research is required to verify the mechanism and quantitative feedback.

5. Conclusions

This study mainly obtains the location data of mobile phone signaling in Nanjing 2019, using the street as the space unit to calculate the traffic vitality in each street. Combining the air quality index, daily climate state, traffic commuting pattern and the characteristics of the street transportation infrastructure environment, we focus on exploring the inhibitory effect of air pollution on traffic vitality and the heterogeneous impact of different transportation infrastructure environments. The study found three main characteristics:

(1) There are obvious differences among traffic vitality under different air quality levels. Specifically, in different transportation models and different location conditions, there are obvious differences in traffic vitality. The traffic vitality space in Nanjing presents the spatial characteristics of "one core-multiple centers-multiple nodes", and areas with a high degree of travel activity are located along the Yangtze River. The core of res-idents' activities is located in the main urban area of Nanjing, and there are many hot spots for travel activities in the periphery of the urban area. The entire city presents a trend of "northeast-southwest" axial expansion in the spatial pattern of the traffic vitality. The "Multi-node" refers to high-density area nodes with multiple traffic trips within the city. This indicates that as the risk of air pollution exposure increased, although the in-tensity of traffic vitality in the urban core area declined, it remained the main choice for residents' travel activities. Compared with the urban core area, the traffic vitality of residents in the north-south areas of Nanjing's periphery has declined significantly.

(2) The inhibitory effect of air pollution on public traffic vitality and self-driving traffic vitality are differences. Specifically, each increase of 10 unit in the AQI value reduces the public traffic vitality intensity by approximately 0.46 times/10 km^2. Therefore, as the air quality decreases by one level (AQI increases by 50 units), the activity intensity decreases by 2.3 times/10 km^2. In addition, each increase of 10 unit in the AQI value reduces the public traffic vitality intensity by approximately 0.52 times/10 km^2. Therefore, as the air quality decreases by one level (AQI increases by 50 units), the activity intensity decreases by 2.6 times/10 km^2. Therefore, approximately one-tenth of traffic activities may be inhibited by air pollution. The weakening of traffic vitality greatly reduces the city's ability to attract and gather people, materials, and resources.

(3) The inhibitory effect of air pollution on traffic vitality is heterogeneous under different transportation infrastructure environments. The higher the public transportation station density and public transportation frequency of the street, the more obvious the suppression effect of air pollution. The higher the parking density, station accessibility, road intersections density, and transportation facility diversity, the lower the suppression effect of air pollution. Com-pared with public traffic such as buses and subways, the impact of air pollution on self-driving traffic pattern is relatively low. There is spatial heterogeneity in the inhibitory effect of air pollution on traffic vitality, which will weaken the enthusiasm of residents to use urban infrastructure and hinder the optimization and adjustment of urban functional spatial structure.

This paper introduces the Spatial Lag Model and Spatial Error Model to further investigate the impact of air pollution on traffic vitality and its heterogeneity in the built environment after controlling for spatial dependencies. The spatial matrix model of street adjacent relationship was constructed with the help of ArcGIS software. Specifically, the SEM model and the SLM model integrate the spatial element information, and integrate the spatial dimension effects such as the agglomeration and diffusion of elements in the space into the traditional regression model. This model is beneficial to analyze the interaction effect of spatial elements in the influence mechanism. However, the model used in this paper still needs to be further optimized, and it is necessary to study the inhibitory effect of air pollution on different populations and different types of activities. The optimized model can better respond to research on international environmental justice issues. People with different socioeconomic attributes, genders, and types of activities have different tolerances for air pollution. Under different circumstances, there are still large differences in the traffic vitality of residents, which needs to be further explored by empirical research.

The results of this study help to clarify the relationship between air pollution, the built environment, and the vitality of urban transportation. In general, air pollution significantly affects the vitality of urban traffic. Under different built environment conditions, the effect of air pollution on urban traffic vitality also showed significant differences. Therefore, the government needs to work with environmental protection departments, natural resource management departments, transportation management departments, and other departments to work together to improve the urban environment. On the one hand, environmental protection departments should strengthen the prevention and control of air pollution, including reducing pollutant emissions, and strictly controlling new production capacity in high-energy-consuming and high-polluting industries. Relevant departments need to vigorously promote clean production, speed up the adjustment of the energy structure, and increase the supply of clean energy such as natural gas and coal-to-methane. At the same time, the environmental protection department needs to strengthen the supervision and management of industrial projects, strengthen the constraints of energy conservation and environmental protection indicators, and shall not approve the construction of projects that have not passed the environmental assessment. On the other hand, the urban construction department should appropriately increase the scale of commercial land in the built-up area and increase the density of the road network and subway stations. In the urban area, the proportion of industrial land will be reduced, and the mixed degree of land use will be improved, thereby enhancing the traffic vitality of residents in the built-up area.

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