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How does air pollution affect travel behavior? A big data field study

Yuquan Xu [a], Yuewen Liu [a,*], Xiangyu Chang [a], Wei Huang [a,b]

[a] School of Management, Xi'an Jiaotong University, No. 28 Xianning West Road, Xi'an 710049, China
[b] College of Business, Southern University of Science and Technology, No. 1088 Xueyuan Avenue, Nanshan District, Shenzhen 518055, China

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ABSTRACT

Exposure to ambient air pollution causes 4.2 million deaths worldwide every year; thus, people may avoid traveling on polluted days. However, the extant studies have mixed findings of the travel behavior on polluted days, caused by the shortcomings of survey data and specific activity data. In order to fulfill this research gap, this study evaluates the relationship between air pollution and travel behavior based on approximately 4.6 billion mobile positioning records in Xi'an, China. Moreover, this study also investigates how different demographic groups travel differently on polluted days. The results indicate that air pollution has a significantly negative correlation with travel behavior. Specifically, (1) people reduce travel distance slightly but reduce travel area greatly; and (2) younger people (50 and under) reduce more travel area while older people (over 50) reduce more travel distance on polluted days.

1. Introduction

Industrialization and urbanization have intensified fossil fuel consumption and caused severe air pollution problems, especially in developing countries (Horton et al., 2014). According to a World Health Organization (WHO) report, 91% of the world's population is exposed to air quality below WHO limits, and the exposure to ambient air pollution causes 4.2 million deaths every year (WHO, 2016). To avoid exposure to air pollution, people may undertake avoidance behavior, such as wearing anti-smog face masks and decreasing outdoor travel activities (Carlsten et al., 2020; D'Antoni et al., 2017). Numerous extant studies examine the effect of air pollution on travel behavior, but the research findings are mixed (e.g., Laffan, 2018; Liu & Salvo, 2018; Yan et al., 2019). Some show that travel activities may be reduced on heavily polluted days (e.g., Chen et al., 2018; Ward & Beatty, 2015); others show that air pollution has no significant effect on travel behavior; and still others argue that air pollution may increase travel activities as people leave polluted cities (e.g., Haddad & de Nazelle, 2018; Tribby et al., 2013).

The mixed findings may be caused by the datasets used in the extant literature. Some extant studies use surveys to collect data (e.g., Lu et al., 2017; Ma et al., 2019; Zhao et al., 2018). The survey methodology has several shortcomings: biased survey sample, small sample size, low participate rate, and self-report bias (Liu et al., 2018; Wesolowski et al., 2014). Some of these studies use online surveys, which may further bias the survey samples (Ma et al., 2019; Zhong et al., 2020). Moreover, the self-report travel intentions or behaviors are hard to validate, so the accuracy of the findings may be doubtful (Wesolowski et al., 2014). Some other extant studies use specific activity data (such as school absence records and zoo visiting records), focus on specific travel activities (such as cycling and

* Corresponding author.
E-mail address: liuyuewen@mail.xjtu.edu.cn (Y. Liu).

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driving), and relate to some segments of the population (such as students and households). Since people with different demographic characteristics may have different reactions to air pollution, the findings based on specific activity data may not be generalized (Ma et al., 2019; Zivin & Neidell, 2009). In summary, there lacks research to evaluate the relationship between air pollution and travel behavior using comprehensive datasets.

In order to fulfill the research gap, this study attempts to evaluate the relationship between air pollution and travel behavior on a large population via a big data field study in Xi'an, a representative city that suffers air pollution problems in winter in northern China. Unlike the extant research, this study uses mobile positioning data to verify people's travel behavior. The mobile positioning dataset has a full coverage of the mobile phone users, thus can avoid the problems mentioned above in the extant studies (Reif & Schmücker, 2020; Wesolowski et al., 2014; Xu et al., 2021). Specifically, this study collects approximately 4.6 billion mobile positioning records of 813,360 people (roughly 10% of Xi'an's population) during 61 winter days from a telecommunication company in Xi'an and examines travel behavior under different air pollution (measured by the Air Quality Index, AQI). Two indicators of travel behavior are carefully adopted: the Radius of Gyration (RG) that reflects people's travel distance, and the Number of visited Places (NP) that reflects people's travel area. Moreover, this study also analyzes how different demographic groups travel differently on polluted days. The results show that (1) while the RG reduces slightly on heavily polluted days, the NP reduces greatly. Specifically, as the AQI increases by 100 points, the average RG reduces by 0.76% while the average NP reduces by 6.57%, and (2) different demographic groups travel differently on polluted days. The younger people aged 50 and under reduce their NP more than the older people over 50, while the older people reduce their RG more than the younger people.

To the best of our knowledge, this is the first big data field study examining the travel behavior on polluted days, rather than focusing on a particular travel mode or specific population. Based on our huge dataset, this study provides a solid and comprehensive understanding of travel behavior on polluted days. Moreover, this study also shows how people in different demographic groups travel differently on polluted days, which could be the reason for the mixed findings in the literature. The research methodologies, including the indicators of travel behavior and the calculation method of mobile positioning data, have some referential value for future research. Our findings inform the policymakers to notice the importance of environmental protection and air pollution mitigation, understand the relationship between air pollution and travel behavior, and enact appropriate healthcare and transportation policies, such as legislating vacations and promoting effective public transportations on heavily polluted days (Basagana et al., 2018; McLaughlin, 2016).

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 introduces the research design, the datasets, and the data analysis methods. Section 4 presents the findings. Section 5 discusses the results as well as the policy implications and Section 6 concludes the paper.

2. Literature review

The extant literature studies the effect of air pollution on travel activities but generates mixed findings. This section summarizes the mixed findings and analyzes the possible reasons.

2.1. *The effect of air pollution on travel activities*

There are contradictory findings of the effect of air pollution on travel activities. It is commonly believed that people's avoidance behavior leads to reduced travel activities on heavily polluted days. For example, Liu and Salvo (2018) surveyed the absence rate at international schools and found that air pollution causes an increase in absenteeism. Chen et al. (2018) found that air pollution has a considerable detrimental negative effect on school attendance using student illness and absence records. Based on geotagged check-in data from Weibo (a Chinese social media website), Yan et al. (2019) showed that as air pollution increases, people's travel activities (including tourism, work, public transportation, and leisure) decrease. Laffan (2018) found that air pollution reduces the frequency of individual sports and outdoor activities. Ward and Beatty (2015) analyzed the behavioral response to air quality alerts through detailed time diary data. They found that people reduce the time spent on intense outdoor activities by an average of 18% (approximately 21 min). D'Antoni et al. (2017) reviewed the literature and summarized that people reduce or rearrange outdoor activities from 9.7% to 57% in cases of poor air quality.

However, other researchers have found that air pollution does not always have a negative effect or even has a positive effect on travel activities. For example, using survey and interview methods, Haddad and de Nazelle (2018) found that people's travel intentions are not significantly affected even if they are informed about air pollution. Ward and Beatty (2015) found that, when facing air pollution alerts with an AQI of more than 150, people aged 65 and under do not reduce their travel activities significantly. Noonan (2014) examined the travel behavior in Atlanta and found that the households do not travel less after a smog alert. Tribby et al. (2013) examined the effectiveness of air pollution alerts on traffic reduction using an automated traffic counter (ATC) dataset. They found that severe air pollution reduces traffic in urban centers but dramatically increases traffic near the edge of metropolitan areas.

2.2. *The gender and age disparities in the relationship between air pollution and travel behavior*

The mixed findings can be caused by the datasets used in the extant literature. Some studies use survey and interview methods to study the effect of air pollution on travel behavior (e.g., Cheng et al., 2019; Ma et al., 2019; Zhao et al., 2018). For example, Anowar et al. (2017) conducted a stated preference survey to evaluate the effect of air pollution on biking behavior, and Johnson et al. (2017) surveyed around one thousand Beijing residents about how they cope with air pollution. The survey methodology has several shortcomings: biased survey sample, small sample size, low participate rate, and self-report bias (Liu et al., 2018; Wesolowski et al., 2014). When the survey is conducted online (e.g., Ma et al., 2019), the participants could be biased because they are more likely to have higher education levels and have more disposable time (Zhong et al., 2020). Moreover, the respondents' self-report travel intentions and behaviors are hard to validate; thus, the accuracy of the findings based on survey datasets could be doubtful (Wesolowski et al., 2014).

Some other existing studies use specific activity data (such as school absence records and zoo visiting records), focus on specific travel activities (such as cycling and driving), and thus relate to some segments of the population (such as students and households). However, specific demographic groups may react to air pollution differently because the potential damage to their health, the benefits of travel, and their resources are different (Ma et al., 2019; Zivin & Neidell, 2009). For example, Zhou et al. (2015) found that air pollution has a more significant effect on older adults than young adults and has a stronger effect among older males than older females. Zivin and Neidell (2009) found that adults under 61 show a further diminished response (decreasing outdoor activities) to the air pollution alert, while seniors group aged over 61 and young children aged 2–12 ratchet up their response. Zhao et al. (2018) analyzed the effect of air pollution on cycling and found that males over 30 and low-income people continue to cycle during polluted days. Ward and Beatty (2015) found that, when facing air pollution alerts, although people under 65 do not reduce their travel activities significantly, older people aged 65 and over reduce their outdoor activities by 82%. Noonan (2014) found that people over 60 and those who exercise regularly reduce their outdoor activities after a smog alert while the households do not travel less. In summary, different segments of population react to air pollution differently, resulting in mixed findings in the extant literature (Ma et al., 2019; Zivin & Neidell, 2009).

In the literature, mobile positioning datasets have also been widely used to study social mobility (e.g., Raun et al., 2016; Wang et al., 2017; Xu et al., 2015). Compared to the specific activity datasets, the mobile positioning dataset collects spatiotemporal records automatically generated by mobile phones, thus has full coverage among mobile phone users and can avoid the problems mentioned above (Wesolowski et al., 2014). For example, Dewulf et al. (2016) studied air pollution exposure using a mobile positioning dataset, but they did not study the effect of air pollution on travel behavior.

In summary, the extant literature about the effect of air pollution on travel behavior generates mixed findings, which could be caused by the shortcomings of the survey data or specific activity data. There lacks research to evaluate the relationship between air pollution and travel behavior using comprehensive datasets. Inspired by the extant literature, this study uses a mobile positioning dataset to estimate the general effect of air pollution on travel behavior and compare the travel behavior differences among different demographic groups on polluted days.

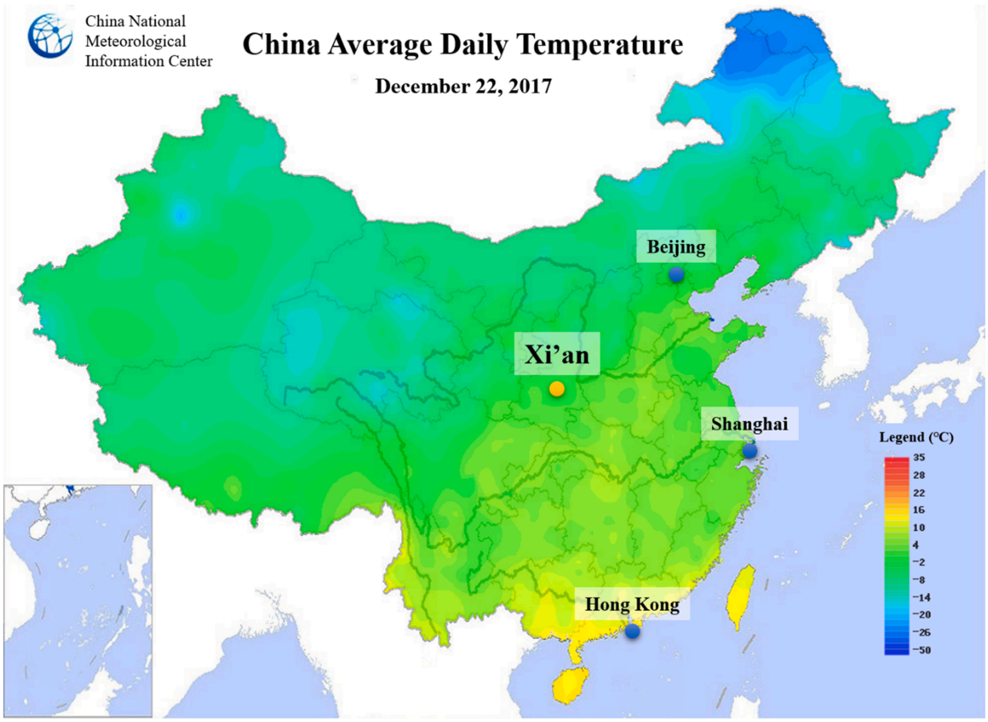

Fig. 1. The location of Xi'an. Source: China National Meteorological Information Center (http://data.cma.cn/data/online.html).

3. Research design

3.1. Study area

This study is conducted in Xi'an, one of the emerging megacities in China. As of 2015, Xi'an has a population of 8.7 million. The urban area of Xi'an is located at 34°16′N 108°56′E, nearly the center of China (as shown in Fig. 1). The winter in Xi'an (from December to the following February) is cold and dry. The average temperature in winter is approximately 4.2℃ or 39.6°F (Xi'an Municipal Bureau of Statistics, 2020). From November to the following February, the whole Xi'an city burns fossil fuel for central heating, which is the major reason for the air pollution problem. Xi'an is blanketed in a grey choky haze on some heavily polluted days, and the visibility is reduced to a few meters. On these days, the Xi'an city government issues air pollution alerts, and most of Xi'an residents wear breathing masks and may reduce their outdoor activities.

3.2. Data collection and description

The data collection and calculation processes are illustrated in Fig. 2. By merging three datasets: the mobile positioning dataset (4.6 billion records), the demographics dataset (813,360 records), and the weather dataset (61 records), we generate the final experimental dataset (49.6 million records). Since the mobile positioning dataset is extremely large, we run all the data preparation steps mentioned above on a Spark distributed calculation platform with approximately 100 servers. Based on the final experimental dataset, we conduct descriptive analysis, visualization, and regressions.

3.2.1. Mobile positioning and demographics datasets

The mobile positioning dataset used in this study is collected from the dominant telecommunication company in Xi'an. When a mobile phone communicates with a communication cell tower, it generates a mobile positioning record. A typical mobile positioning record includes the mobile phone number (all the mobile phone numbers are encrypted to protect privacy), the location area code (LAC) and cell ID (CID) of the cell tower, and the communication time. In most cases, a mobile phone communicates with the nearest communication cell tower. Therefore, it is a common practice to use the position (in terms of longitude and latitude) of a cell tower as a proxy for the position of a mobile phone connecting with the tower (Wesolowski et al., 2014). Fig. 3 illustrates a sample of the mobile positioning data. The figure shows the positions of the towers with which the mobile phone user "0a3b127e" communicated, as well as the corresponding time on a particular day (November 18, 2017). Based on the records, we can draw a simulated travel route for the mobile phone user.

The mobile positioning dataset used in this study logs all of the mobile positioning records of 813,360 local mobile phone users (roughly 10% of residents) in November and December of 2017. The reasons November and December are chosen for this study include: (1) Xi'an and other northern cities in China begin burning fossil fuels for central heating in November (Ebenstein et al., 2017), which is a significant reason for the air pollution problem in winter (Zhang et al., 2015); (2) there were no public holidays during these two months; and (3) there was no snow during these two months in 2017. Both public holidays and snowy days can strongly influence travel behavior. With no public holidays or snowy days, we are able to focus on the travel behavior on polluted days.

To study the travel behavior of different demographic groups, we also collect a corresponding demographic dataset from the telecommunication company. That dataset has only three dimensions: user ID, age, and gender. Among the 813,360 mobile phone

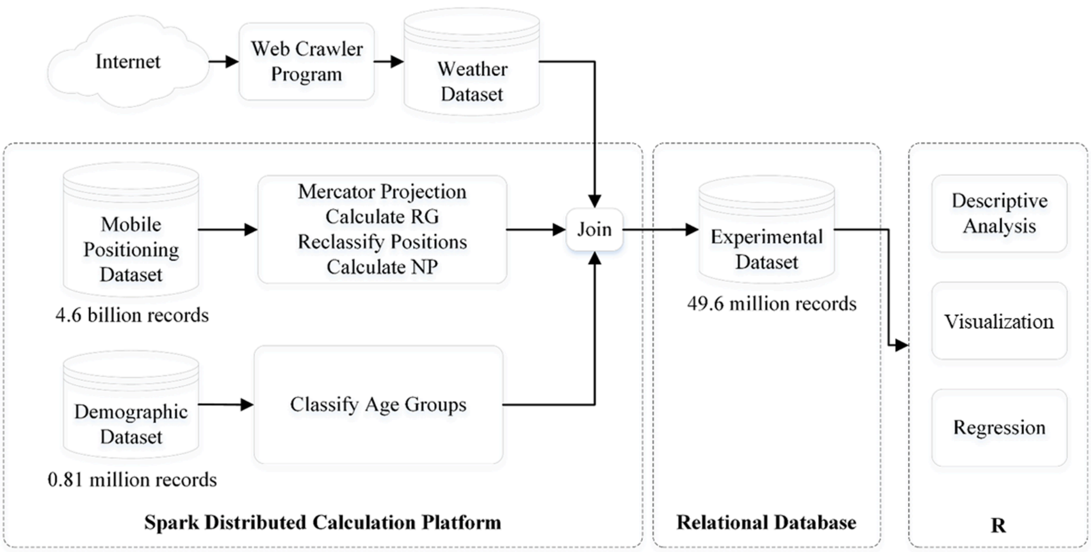

Fig. 2. The research framework.

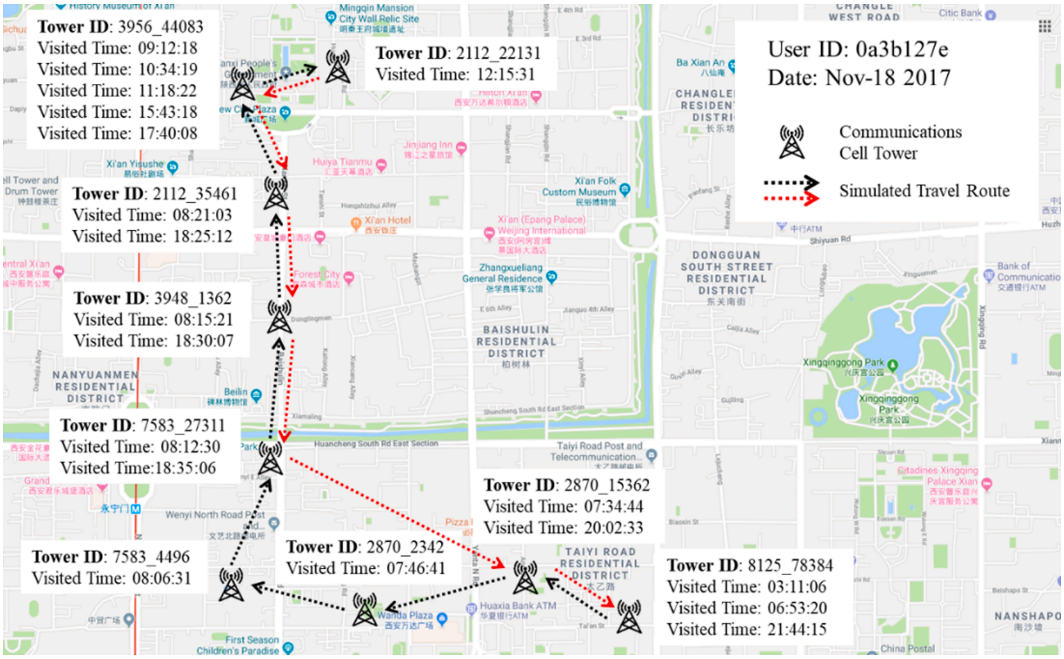

Fig. 3. An illustration of mobile positioning data.

users, there are 457,828 males (56.3%) and 355,532 females (43.7%). Following the common practice in extant literature (e.g., Figueroa et al., 2014; Klein et al., 2018; van den Berg et al., 2011), we classify the mobile phone users into five age groups: “(17-25)”, “(26-35)”, “(36-50)”, “(51-60)”, and “(61-)”. Mobile phone users under 17 are removed from our dataset because most of them are school students and are commonly banned from using mobile phones at school.

3.2.2. Weather dataset

The weather data are collected from a public weather data website (http://tianqi.2345.com) using a Python program developed by the authors. The weather data contain the minimum temperature, the maximum temperature, the AQI, and the weather (such as sunny, cloudy, or rainy).

The AQI is an index of daily air quality, calculated from five major air pollutants: ground-level ozone (O_3), particulate matter (PM), carbon monoxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (SO_2) (AirNow, 2019). The higher the AQI is, the worse the air quality will be. In the winter of Xi’an, particulate matter is the dominant pollutant because of the burning of fossil fuel (Huang et al., 2014; Xu et al., 2017; Yang & Wang, 2017). When AQI is high (e.g., greater than 200), the polluted air smells unpleasant and

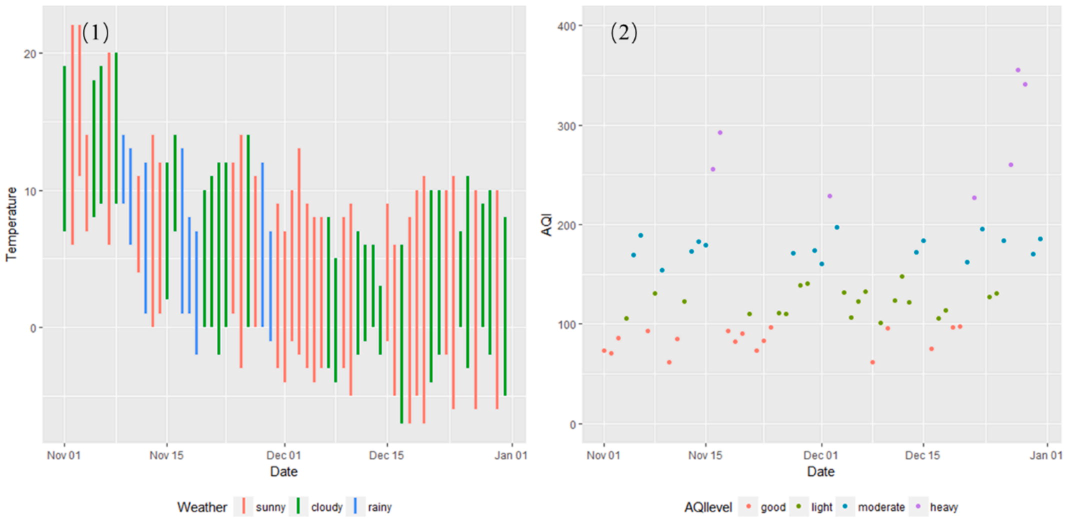

Fig. 4. Visualization of weather data.

significantly reduces visibility. The citizens in Xi'an can obtain official air quality information through smartphone applications. Moreover, on heavily polluted days, the Xi'an government also issues air pollution alerts to protect its citizens.

Following the extant literature, we transform AQI to AQI/100 so that the regression coefficients are more easily interpreted (Yan et al., 2019). We also categorize AQI into different AQI levels, following the official classification methods in China and the USA (AirNow, 2019; Ministry of Ecology and Environment, 2016). AQI is classified as "good" when it is below 100, "light" when between 100 and 150, "moderate" when between 150 and 200, and "heavy" when higher than 200. Among the 61 days in our sample, there are 17 air quality "good" days, 20 "light" days, 17 "moderate" days, and 7 "heavy" days.

The weather data of Xi'an in the 61 observed days are illustrated in Fig. 4. Subfigure 4(1) shows the temperature range and weather conditions. The upper and lower bounds of each bar represent the maximum and minimum temperature, and the color of each bar represents the weather condition. The temperature decreases in November and is relatively stable in December. The weather conditions are mainly sunny or cloudy. In our dataset, there are only seven rainy days, concentrated in November. Subfigure 4(2) shows the AQI and AQI levels. There is no obvious pattern in the AQI sequence.

3.2.3. *Measurements of travel behavior*

The "travel behavior" should be appropriately measured before conducting any further analysis. Following the literature (e.g., Barbosa et al., 2018; Hasnat & Hasan, 2018; Pappalardo et al., 2015), we adopt two indicators: the Radius of Gyration (RG) and the Number of visited Places (NP).

The RG is formally defined as $r_g = \sqrt{1/n\sum_{i=1}^{n}(p_i - p_c)^2}$, where p_i is the ith place traveled and p_c is the center of the places. In other words, the RG measures the average distance of the visited places to the center of the places. In the literature, RG is used to reflect the travel distance. For example, Hasnat and Hasan (2018) used the RG to indicate how far people move, and Barbosa et al. (2018) used the RG to indicate the typical travel distance from the center of mass trajectory. Moreover, to give the RG value a direct interpretation, we implement the Mercator projection method before calculating the RG (Farman, 2010). After the Mercator projection, the unit of RG becomes kilometers, i.e., if the RG equals one, the average distance of the visited places from the center of the places is one kilometer.

The NP is defined as the number of places people visit. In the literature, the NP is interpreted as the travel area (e.g., Barbosa et al., 2018; Qin et al., 2012). For example, Papandrea et al. (2016) showed that a higher NP reflects a larger travel area. Pappalardo et al. (2015) also measured the travel area through the NP: if people visit more places, they cover a larger geographic area. In this study, it is incorrect to measure NP using the number of distinct communication cell towers. The reason is that when a mobile phone stays in one place, the mobile phone signal may shift between several nearby communication towers as the signal intensity varies, and thus may result in the overestimation of NP (see Fig. 5). Subfigure 5(1) gives an example of communication cell towers used during calls. Each point represents a used cell tower. As illustrated by the dashed circle, we can see that some cell towers are close to each other. To avoid this error, following Wang and Chen (2018), we divide the map into 100-meter squares and merge the cell towers in each square to one point. Subfigure 5(2) shows the merged result of the cell towers.

In summary, we use the RG and NP to reflect two different dimensions of travel behavior: RG reflects the travel distance, while NP reflects the travel area. Fig. 6 illustrates some examples. The person has high NP but low RG in subfigure 6(1); has both high NP and RG in subfigure 6(2); has both low NP and RG in subfigure 6(3); and has low NP but high RG in subfigure 6(4). The figure shows that if a person travels long distances, the person will have a high RG; if a person visits many places, then the person will have a high NP.

Table 1 summarizes all the variables used in this paper. The independent variables include age, gender, AQI, the highest temperature of a day, weather, and day of the week; the dependent variables (DV) include RG and NP. There are five numerical variables (age, AQI, the highest temperature, RG, and NP) and three categorical variables (gender, weather, and day of the week).

3.3. *Regression models*

To examine the relationship between air pollution and travel behavior, we run regression models controlling the impacts of the other variables such as day of the week, weather, and temperature. Moreover, since the RG and NP follow the log-normal distribution, we conduct the "log-level" regression model (Wooldridge, 2015), as follows:

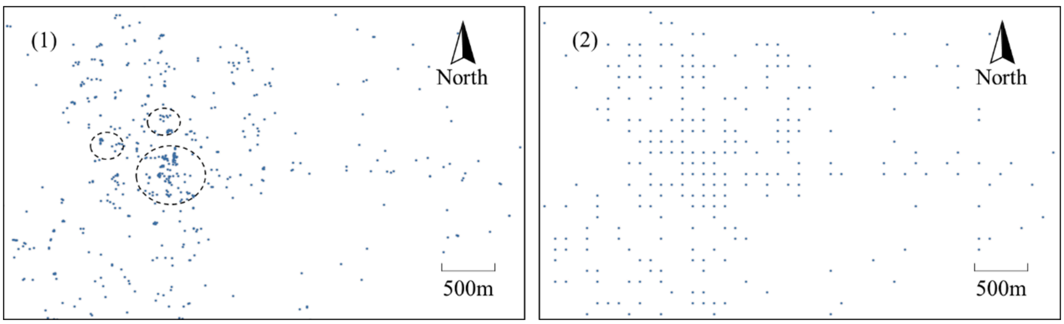

Fig. 5. The illustration of merging telecommunication cell towers.

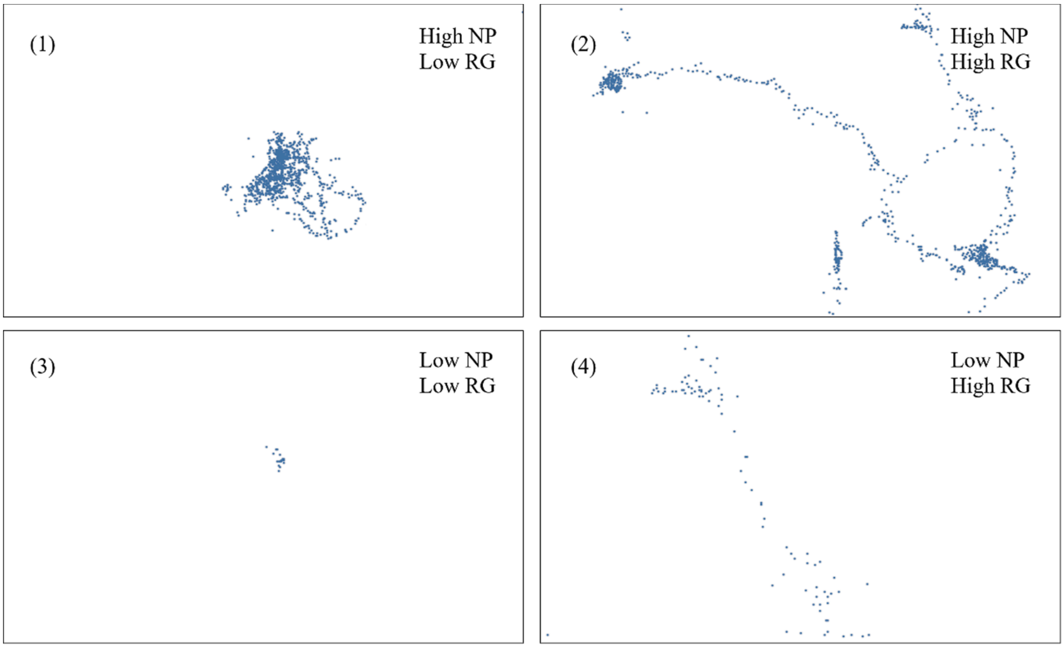

Fig. 6. Samples of different RG and NP.

Table 1
Descriptive characteristics of variables.

Variable	Description	Mean	SD.	Min.	Max.
Age	Mobile phone users' age, classified into five groups: (17-25)*, (26-35), (36-50), (51-60) or (61-)	42.80	13.80	18.00	129.00
Gender	Mobile phone users' gender: male or female*	–	–	–	–
AQI	The daily Air Quality Index, classified into four groups: good*, light, moderate, or heavy	144.54	63.22	62.00	355.00
Highest temperature	The daily highest temperature (°C)	11.00	4.10	3.00	22.00
Weather	The weather of a day: sunny*, cloudy or rainy	–	–	–	–
Day of the week	The day of the week: Monday* Tuesday, Wednesday, Thursday, Friday, Saturday, or Sunday	–	–	–	–
RG	The radius of gyration, reflecting the travel distance (kilometer)	1.94	2.86	0.00	80.66
NP	The number of visited places, reflecting the travel area	27.49	37.55	1.00	1264.00

* This category is the benchmark group in the regression models.

$$\log Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \varepsilon$$

In a log-level regression model, the coefficient β_i of an independent variable X_i indicates the percentage change of the dependent variable Y given one unit increase of the independent variable (Wooldridge, 2015). Previous studies have also used the log-level model to analyze travel issues (e.g., Miranda-Moreno & Lahti, 2013; Nosal & Miranda-Moreno, 2014). Following the literature (Ma et al., 2019), the independent variables and control variables used in this study include the AQI, maximum temperature, weather condition (including sunny, cloudy and rainy), age, gender, and weekday. Moreover, we study the different demographic groups' travel differences on polluted days using the interaction term in the regression model (Yoon et al., 2017).

4. Results

In this section, we first present the comparisons of the average RG and NP values in each category of demographics and AQI levels; then, we run regressions to examine the relationship between air pollution and travel behavior; afterward, we investigate whether people with different demographics travel differently on polluted days.

4.1. Descriptive results

Table 2 presents the comparisons of the descriptive statistics of RG and NP in each category of demographics, AQI levels, weather conditions, and day of the week. As shown in Table 2, days with "good" AQI levels are associated with the biggest RG (1.981) and NP (29.895), while the "heavy" AQI level days are associated with the smallest RG (1.903) and NP (25.904). The results of ANOVA analysis also show that the average values of RG and NP are statistically different among the AQI level categories ($p < 0.001$).

Fig. 7 shows a scatter plot of AQI and daily average values of RG and NP. As shown in Fig. 7, in general, as the air pollution becomes

Table 2
Comparisons of RG and NP in different categories.

		RG				NP			
		Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Age group	*(17-25)*	1.88	2.97	0.00	62.28	27.63	34.27	1	1,002
	(26-35)	2.12	2.96	0.00	66.97	32.60	40.85	1	1,132
	(36-50)	2.02	2.93	0.00	80.66	28.90	39.72	1	1,264
	(51-60)	1.80	2.71	0.00	70.49	21.89	30.79	1	950
	(61-)	1.41	2.30	0.00	67.24	15.87	24.68	1	1,073
Gender	*Male*	2.11	3.01	0.00	80.66	29.81	41.62	1	1,264
	Female	1.74	2.63	0.00	70.35	24.50	31.31	1	1,150
AQI level	*Good*	1.98	2.88	0.00	63.84	29.90	41.10	1	1,264
	Light	1.93	2.84	0.00	80.66	27.13	36.69	1	1,166
	Moderate	1.94	2.87	0.00	70.49	26.16	35.36	1	1,106
	Heavy	1.90	2.82	0.00	63.85	25.90	35.83	1	1,196
Weather	*Sunny*	1.97	2.89	0.00	70.35	28.02	37.72	1	1,264
	Cloudy	1.89	2.78	0.00	70.49	25.66	34.92	1	1,196
	Rainy	2.01	2.95	0.00	80.66	31.35	43.99	1	1,234
Day of week	*Monday*	1.89	2.72	0.00	67.24	28.35	38.27	1	1,134
	Tuesday	1.87	2.69	0.00	64.17	27.31	36.82	1	1,088
	Wednesday	1.85	2.68	0.00	66.52	27.05	37.31	1	1,123
	Thursday	1.83	2.67	0.00	63.84	27.28	37.41	1	1,196
	Friday	2.01	2.90	0.00	63.85	29.13	38.93	1	1,264
	Saturday	2.08	3.11	0.00	70.35	27.66	38.05	1	1,234
	Sunday	2.06	3.15	0.00	80.66	25.74	35.92	1	1,150

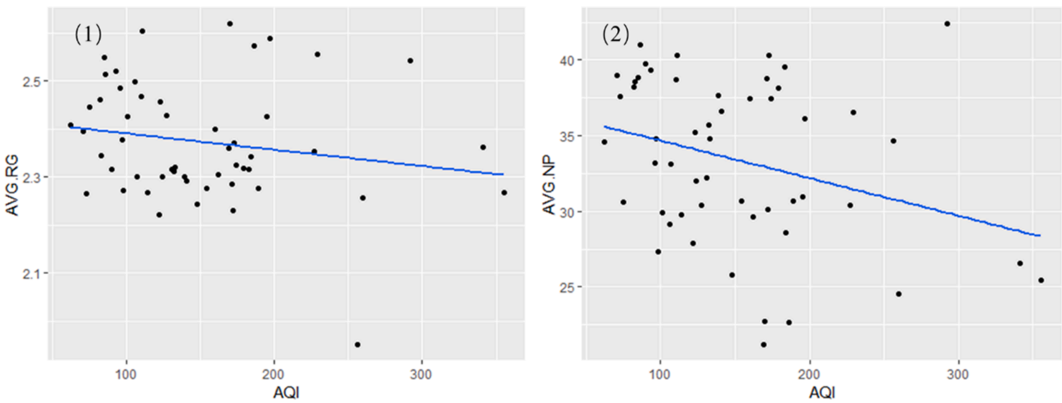

Fig. 7. The relationships between AQI and the daily average of RG and NP.

heavy, the average values of both RG and NP become lower, reflecting reduced travel during those days.

4.2. The association between air pollution and travel behavior

The regression results are reported in Table 3: Model 1 and 2 study the relation between AQI and RG. We first put AQI/100 in Model 1 and then replace it using AQI levels in Model 2. The regression coefficient of AQI/100 in Model 1 is −0.0076 ($p < 0.001$), which means that for every 100-point increase in AQI, RG drops by 0.76%. The regression coefficients of each AQI level variable in Model 2 mean that compared with "good" days (baseline), RG decreases by 0.56% on the "light" pollution days, decreases by 0.7% on the "moderate" pollution days, and decreases by 2.29% on the "heavy" pollution days. Although the regression coefficients are significant at the 0.001 level (benefiting from our huge sample size), the effect of air pollution on RG is relatively small. Considering the average value of RG on "good" days is 1.86 km, a 0.76% drop (when AQI increases by 100) represents merely 14.1 m, and a 2.29% drop (when air quality turns from "good" to "heavy") represents 42.6 m. The results show that, although people reduce their travel distance on polluted days, the reduction is relatively small.

Similarly, we study the relation between AQI and NP in Model 5 and 6. The regression coefficient of AQI/100 in Model 5 is −0.0657 ($p < 0.001$), i.e., for every 100-point increase in AQI, NP drops by 6.57%. The regression coefficients of each AQI level in Model 6 show that, compared with "good" days (baseline), NP decreases by 3.31% on the "light" pollution days, decreases by 8.08% on the "moderate" pollution days, and decreases by 13.27% on the "heavy" pollution days. Considering the average NP on "good" days is roughly 30 places, a 6.57% drop (when AQI increases 100) represents two fewer places and a 13.27% drop (when air quality turns from "good" to "heavy") means four fewer places. Compared to the effect size of air pollution on RG, the effect size of air pollution on NP is

Table 3
The regression results.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
DV	RG		RG		RG		RG		NP		NP		NP		NP	
(Intercept)	0.9590	***	1.0664	***	0.8551	***	0.9477	***	3.4216	***	3.5426	***	2.9825	***	3.4413	***
AQI/100	−0.0076	***	–		−0.0076	***	0.0003		−0.0657	***	–		−0.0657	***	−0.0794	***
Light	–		−0.0056	***	–		–		–		−0.0331	***	–		–	
Moderate	–		−0.0070	***	–		–		–		−0.0808	***	–		–	
Heavy	–		−0.0229	***	–		–		–		−0.1327	***	–		–	
Age	−0.0044	***	−0.0044	***	–		−0.0041	***	−0.0161	***	−0.0161	***	–		−0.0166	***
(AQI/100)*age	–		–		–		−0.0002	***	–		–		–		0.0003	***
Male	0.1125	***	0.1125	***	0.1119	***	0.1131	***	0.1662	***	0.1662	***	0.1655	***	0.1685	***
(AQI/100)*gender	–		–		–		−0.0004		–		–		–		−0.0016	**
ageGroup(26-35)	–		–		0.0919	***	–		–		–		0.1310	***	–	
ageGroup(36-50)	–		–		0.0483	***	–		–		–		−0.0318	***	–	
ageGroup(51-60)	–		–		−0.0162	***	–		–		–		−0.3006	***	–	
ageGroup(61-)	–		–		−0.1427	***	–		–		–		−0.6353	***	–	
Highest temperature	0.0011	***	0.0011	***	0.0011	***	0.0011	***	0.0052	***	0.0052	***	0.0052	***	0.0052	***
Tuesday	−0.0078	***	−0.0080	***	−0.0078	***	−0.0078	***	−0.0575	***	−0.0620	***	−0.0575	***	−0.0575	***
Wednesday	−0.0151	***	−0.0142	***	−0.0151	***	−0.0151	***	−0.0796	***	−0.0828	***	−0.0796	***	−0.0796	***
Thursday	−0.0154	***	−0.0147	***	−0.0154	***	−0.0154	***	−0.0438	***	−0.0424	***	−0.0438	***	−0.0438	***
Friday	0.0266	***	0.0284	***	0.0266	***	0.0266	***	0.0140	***	0.0121	***	0.0140	***	0.0140	***
Saturday	0.0253	***	0.0270	***	0.0253	***	0.0253	***	−0.0995	***	−0.0955	***	−0.0995	***	−0.0995	***
Sunday	0.0155	***	0.0154	***	0.0155	***	0.0155	***	−0.1447	***	−0.1440	***	−0.1447	***	−0.1447	***
Cloudy	−0.0095	***	−0.0085	***	−0.0095	***	−0.0095	***	−0.0750	***	−0.0765	***	−0.0750	***	−0.0750	***
Rainy	0.0058	***	0.0062	***	0.0058	***	0.0058	***	0.0705	***	0.0657	***	0.0705	***	0.0705	***
Observation	49,614,960		49,614,960		49,614,960		49,614,960		49,614,960		49,614,960		49,614,960		49,614,960	
Adj. R^2	0.0169		0.0169		0.0202		0.0169		0.0471		0.0471		0.0519		0.0470	

Notes: *** indicates significance at $p < 0.001$ level. ** indicates significance at $p < 0.01$ level.

much larger.

To further explain the results, we illustrate the regression coefficients of AQI levels on RG and NP in Model 2 and 6 in Fig. 8, which visually shows that the NP drops much more than RG when air pollution becomes heavier. An intuitive explanation is that people may have to travel to work regardless of the level of air pollution (Zhao et al., 2018), so the correlation between air pollution and travel distance is relatively small. However, people might protect themselves from air pollution by avoiding outdoor activities (Wang and Zheng, 2020; Yoo, 2021), so the correlation between air pollution and travel area is relatively large. These results lead us to compare the travel behavior of different demographic groups, especially the younger people who have to travel to work and the older people who are retired.

4.3. The different travel behavior of demographic groups on polluted days

The demographics variables studied in this paper are age and gender. Model 1, 2, 5, and 6 report the regression coefficients of gender and age on travel behavior variables. The regression coefficients of age show that for every one-year age increase, the average RG drops 0.44% ($p < 0.001$), and the average NP drops 1.61% ($p < 0.001$). The regression coefficients of gender show that males travel much more than females in terms of both RG and NP. Males' average RG is 11.2% ($p < 0.001$) more than females, and males' average NP is 16.6% ($p < 0.001$) more than females.

It is possible that the correlation between age and travel behavior is non-linear. For example, middle-aged people may have the highest RG and NP. Therefore, we also study the correlations between age groups and travel behavior (see Model 3 and 7). We illustrate the regression coefficients of age groups in Fig. 9. The figure clearly shows that both the correlations between age and RG and NP have an inverted U-shape. As age grows, both the average RG and NP first increase and then drop. The average NP varies much more than RG. Specifically, the "(26–35)" group has the highest RG and NP while the "(61-)" group has the lowest RG and NP. The results are easily interpreted: the younger people aged 50 and under travel more widely and frequently than the older people over 50 (Frandberg & Vilhelmson, 2011).

To analyze how different demographic groups travel differently on polluted days, we introduce the interaction term of AQI and age (AQI/100*age) and the interaction term of AQI and gender (AQI/100*gender) in Model 4 and 8, respectively. Interestingly, the regression coefficients of AQI/100*age on RG is −0.0002 ($p < 0.001$), while the regression coefficients of AQI/100*age on NP is 0.0003 ($p < 0.001$). The negative regression coefficient of AQI/100*age on RG means that the negative correlation between air pollution and RG becomes stronger (more negative) as age grows, while the positive regression coefficient of AQI/100*age on NP means that the negative correlation between air pollution and NP becomes weaker (less negative) as age increases. The results are intuitive. First, people aged 50 and under have to travel to work and thus cannot reduce their travel distance much on polluted days, while people over 50 are more likely retired and thus can reduce their travel distance more (Hjorthol et al., 2010). Second, people aged 50 and under have a longer expected future life and are more sensitive to environmental issues (McCunn & Gifford, 2012), so they are more likely to reduce the number of visited places on polluted days to protect themselves.

Model 4 and 8 study the interaction between AQI and gender. The regression coefficient of the interaction term AQI/100*gender on RG is non-significant, while the regression coefficient of AQI/100*gender on NP is −0.0016 ($p < 0.001$). Controlling for other variables, the non-significant coefficient on RG means that males' and females' differences of travel behavior on polluted days in terms of RG are negligible. The negative coefficient on NP implies that the correlation between air pollution and males is stronger (more

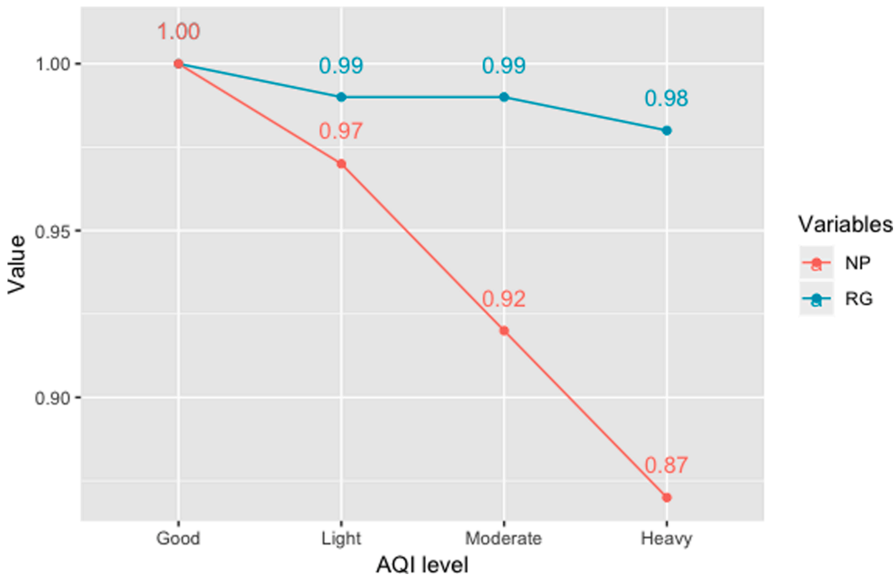

Fig. 8. The coefficients of AQI levels.

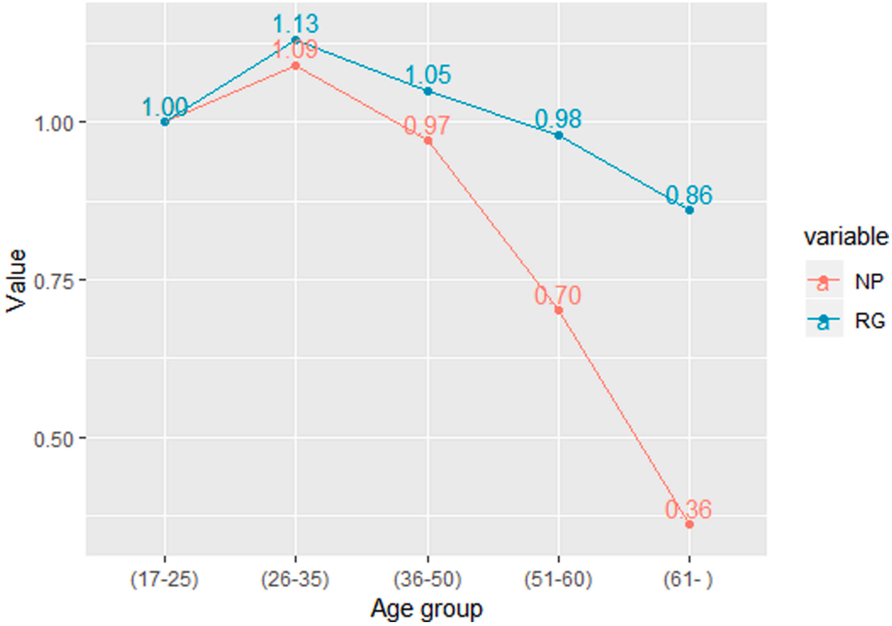

Fig. 9. The coefficients of age groups in Model 3 and 7.

negative) in terms of NP. The reason could be that males take part in more outdoor activities than females, and thus males' travel behavior is more likely to be influenced by air pollution (Hallal et al., 2012; Lottrup et al., 2012).

5. Discussions and policy implications

This research studies travel behavior differences among different demographic groups on air pollution days. It contributes to the existing literature by providing solid big data evidence that air pollution has a significantly negative relationship with travel behavior in RG and NP. It also enriches the existing literature by comparing travel behavior differences among different demographic groups on polluted days. In this section, several theoretical and policy implications are discussed.

First, the study demonstrates that air pollution does reduce travel activities using a large-scale dataset. Extant literature has inconsistent findings of the effect of air pollution on travel behavior because these studies either use special activity datasets, study particular travel modes, or focus on a specific population. With a big data source, our results show that air pollution has a general negative relationship with travel behavior. Moreover, air pollution has a stronger negative correlation on travel area than on travel distance. These results extend our understanding of the relationship between air pollution and travel behavior.

Since air pollution reduces travel activities, it also has a negative effect on the economy (Liao et al., 2021; Yang & Zhang, 2018). Therefore, our findings inform the policymakers to notice the importance of environmental protection and air pollution mitigation. According to our findings, the government should enact policies not only to control air pollution but also to protect residents' travel demands on air pollution days. On the one hand, the government should make administrative policies to reduce emissions from industries and fuel vehicles. The government should stop high air pollution industrial productions on heavily polluted days and replace the fossil fuel energy of the high air pollution industries with green energies. The government could also restrict the use of fuel vehicles via license-plate number restriction (drive restrictions according to the last digit of license-plate numbers), congestion charge, license-plate auction, and vehicle purchase taxes. These policies are implemented in some cities and achieve positive results. For example, London introduces a congestion charge in 2003 and has made significant reductions in pollutants (Green et al., 2020). Vehicle restrictions and stricter emission standards help Guangzhou achieve more than a 10% reduction of pollutant concentration (Liu et al., 2013). On the other hand, the government should also protect travel demand, especially on heavily polluted days. The government should make administrative policies to encourage public transportation, such as offering public transport fare subsidies, improving public transportation density and frequency, shortening route time-consuming, and even investing in new public transportation infrastructure and constructions. The government could also promote green travel ideas, lifestyle, and social atmosphere among the citizens.

Second, our research findings supplement the literature that different demographic groups travel differently on polluted days. In particular, we find that the decrease of travel area of younger people aged 50 and under is more than that of older people over 50. In comparison, the decrease of travel distance of older people over 50 is more than that of younger people aged 50 and under on polluted days. The reason may be that younger people still have to travel long distances for work while older people are more likely to be retired and just need short travel distances for exercises or entertainment on polluted days. Moreover, older people are more concerned about the harmful effects of air pollution on their health. With the consideration of these results, on the one hand, the government should make some economic and administrative policies to protect the relatively younger people, who are the primary labor force for economic development. For some pollution-exposed occupations, governments and companies should consider providing protective materials or even holidays on heavily polluted days. For example, McLaughlin (2016) reported that some primary and secondary schools cancel classes, and some factories are closed on heavily polluted days (McLaughlin, 2016). On the other hand, although people over 50 may not have to travel for work, they still need to travel for leisure activities such as exercise or square dancing (Wang, 2019). Government should build more indoor public service facilities, such as indoor gyms, indoor chess rooms, and indoor cardrooms, to meet the needs of people over 50 (Wu et al., 2018). Moreover, the government should educate people over 50 to pay attention to self-protection and to avoid outdoor activities on heavily polluted days.

6. Conclusions

Since exposure to ambient air pollution causes 4.2 million deaths worldwide every year, people may avoid traveling on air pollution days. However, the extant studies have mixed findings of the travel behavior on polluted days due to their specific activity data. To the best of our knowledge, this paper is the first attempt to study the travel behavior during polluted days on a large population's travel behavior via "big field data". This study collects more than 4.6 billion records of 813,360 people during 61 winter days. We study the relationship between air pollution (measured by AQI) and travel behavior (measured by RG and NP). We also investigate how different demographic groups travel differently on polluted days. The results show that air pollution is significantly negatively related to travel behavior. Specifically, (1) people reduce the average RG by 0.76%, but reduce their average NP by 6.57% as AQI increases by 100 points; and (2) the younger people aged 50 and under reduce their NP more than the older people over 50, while the older people reduce their RG more than the younger people.

There are several future research directions. First, this paper studies travel behavior on polluted days and the difference in travel behavior among different demographic groups using a huge dataset. However, limited by the dataset, the explanations of the results in this paper are still intuitive. Future studies may study the underlining mechanisms of our "big data" findings. Second, more datasets of years and cities would add to the robustness of the results. Third, a dataset in a more disaggregated form (e.g., at hourly intervals) or with more detailed information (e.g., precipitation) could be more meaningful to study the impact of weather on travel behavior. Last but not least, travel behavior may be influenced by many factors, and air pollution is only one among them (Kuhnimhof et al., 2012). In future research, if multi-source datasets can be collected, the results should be more comprehensive.

Declaration of Competing Interest

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

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