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Foreign tourists' experiences under air pollution: Evidence from big data

Yang Yang [a], Xiaowei Zhang [b,*], Yu Fu [c]

[a] Department of Tourism and Hospitality Management, Temple University, 1810 N. 13th Street, Speakman Hall 111 (006-68), Hiladelphia, PA, 19122, USA
[b] School of Economics and Management, Beijing Jiaotong University, No. 3, Shangyuan Village, Haidian, Beijing, China
[c] School of Information Resource Management, Renmin University of China, 59 Zhongguancun Street, Haidian, Beijing, China

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ABSTRACT

Air pollution has become a major hurdle to tourists' experiences in many destinations. This study uses a large sample of TripAdvisor reviews for Chinese attractions and applies a five-way fixed-effects model to estimate the impact of air pollution on attraction ratings. Results show that an increase in the PM2.5 concentration led to a decline in foreign tourists' 5-point ratings of their experiences. Several factors appear to moderate this effect, such as tourists' past travel experience, year of travel, attraction types, tourists' national cultural traits, and air pollution in tourists' home countries. Tourists are more vulnerable to air pollution when coming from countries with more feminine and collectivist cultures and countries with lower air pollution. Across six air pollutants, only PM2.5 and PM10 concentrations are found to significantly influence foreign tourists' experiences. Lastly, practical implications are provided.

1. Introduction

Unprecedented urbanization within the last decade has drawn academic attention to various problems associated with cities, especially mega-cities (Chen et al., 2019). Air pollution is a key concern that has been covered by numerous media outlets (Mage et al., 1996). According to the 2014 environmental report from the World Health Organization, air pollution contributed to the deaths of approximately 7 million people worldwide in 2012 (World Health Organization, 2014). Affected cities, many of which are well-established urban destinations, have suffered gravely from typical air pollution indicators such as seasonal haze. Tourists often choose destinations for relaxation and expect a superior environment; poor air quality presents a major hurdle to tourist activities, especially those occurring outside (McKercher, Shoval, Park, & Kahani, 2015). Furthermore, tourists' psychological and emotional responses to air pollution can greatly compromise their destination experiences. As McKercher et al. (2015) noted, "air pollution emerged as the most significant factor that influenced [tourists'] behavior and satisfaction" (p. 453).

Many empirical studies have confirmed the impacts of air quality on tourism demand and the tourist experience (Deng, Li, & Ma, 2017; Yang & Chen, 2020). A thorough review by Eusébio et al. (2020) showed that two types of research prevail on this topic: studies focusing on tourism demand and studies examining effects on individual tourists. Regarding the first research stream, scholars have recognized the impact of air quality on tourism demand based on aggregate data (Deng et al., 2017; Xu & Reed, 2019; Zhou, Santana Jiménez, Pérez Rodríguez, & Hernández, 2019). Different econometric models have also been employed to estimate the effects of air quality measures or air pollutant measures on tourism demand indicators. The second research line complements demand studies by considering individual heterogeneity in empirical methods. Based on survey data (Yang & Chen, 2020), experimental data (Zhang, Hou, Li, & Huang, 2020), and social media data (Zhang, Yang, Zhang, & Zhang, 2020), such studies have explored people's responses to air pollution in terms of destination image (Becken, Jin, Zhang, & Gao, 2017), visit intentions (Peng & Xiao, 2018), travel perceptions and satisfaction (Yang & Chen, 2020), and activity patterns (McKercher et al., 2015). However, a main limitation of these micro studies is the limited variation in air quality/pollution levels when surveys are based on a handful of destinations over a short period. Moreover, to the best of our knowledge, past micro studies have disregarded heterogeneity in the impact of air quality/pollution and failed to disclose various factors moderating this effect on individual tourists.

To bridge this research gap, the present study considered 94,447 TripAdvisor reviews from foreign visitors at 2,324 tourist attractions across 110 destinations in mainland China between 2013 and 2019. Based on tourists' TripAdvisor profiles, travelers in the dataset hailed from 147 countries/territories worldwide. Note that we deleted all

* Corresponding author.
E-mail addresses: yangy@temple.edu (Y. Yang), zhxiaowei@bjtu.edu.cn (X. Zhang), yu.fu@ruc.edu.cn (Y. Fu).

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reviews from domestic Chinese tourists, as TripAdvisor is less popular in the Chinese market compared with other online travel review platforms. We proposed and estimated a five-way fixed-effects model to scrutinize the impact of air pollution, measured by the daily PM2.5 concentration at a given destination, on tourists' TripAdvisor attraction ratings. After that, multiple moderators, including trip-specific, time-specific, attraction-specific, and country-of-origin–specific variables, were tested, based on their interaction terms with air pollution measures. By doing so, we have made several contributions to the literature. First, our comprehensive dataset consisted of destinations covering a broad geographical and temporal scope, ensuring sufficient variation in air pollution levels in the data to produce more generalizable results. Second, we examined various moderating factors on the air pollution–tourist experience relationship. In particular, we determined whether national cultural factors explained such vulnerability among foreign tourists. Scholars have identified associations between national cultural factors and tourists' behavior and satisfaction (Huang & Crotts, 2019), and our study adds valuable evidence to further explain this association in cross-cultural tourism studies. Third, online review data constitute a type of revealed preference data that are free from the laboratory manipulations typical of other forms of empirical data (Gerdt, Wagner, & Schewe, 2019).

2. Literature review and hypotheses

2.1. Air pollution and tourism demand

The severe consequences of air pollution pose myriad threats to human health and everyday life, leading air quality to be regarded as one of the world's most serious pollution problems (Evans & Jacobs, 1981). Prolonged exposure to air pollution, especially high particulate matter (PM) levels, may influence the central nervous system by activating reactive oxygen species and pro-inflammatory pathways (Fonken et al., 2011). Because individuals' perceptivity relies heavily on the central nervous system, the neuropsychological effects of air pollution have been studied extensively. More recent clinical and psychological research has shown that exposure to ambient air pollution can increase the risk of "low happiness" (Zheng, Wang, Sun, Zhang, & Kahn, 2019), anxiety (Power et al., 2015), depressive symptoms (Zijlema et al., 2016), and even suicide (Kim et al., 2010). In addition to contributing to physical illness, short-term exposure to air pollution can easily affect one's daily mood (Bullinger, 1989). Air pollution can thus be interpreted as a psychosocial stressor (Astell-Burt et al., 2013).

As air pollution involves health-related hazards for incoming tourists, it can impede tourism demand. Such pollution jeopardizes a positive destination image. In a survey, American and Australian tourists expressed negative attitudes about China's air quality in a travel context (Becken, 2013). Air pollution can also limit the scale and scope of tourism activities, particularly those held outdoors; for example, impaired visibility associated with air pollution may discourage tourists from sightseeing activities (Poudyal, Paudel, & Green, 2013). Furthermore, health and hedonic risks from air pollution are likely to evoke anxiety and potentially alter tourists' visit intentions (Williams & Baláž, 2015). A case study in Beijing indicated that haze pollution could even compel some potential tourists to cancel their travel plans altogether (Zhang, Zhong, Xu, Wang, & Dang, 2015).

Many empirical studies have confirmed the negative effects of air pollution on tourism demand. Anaman and Looi (2000) found that haze-related air pollution reduced inbound tourism to the country of Brunei Darussalam. Later, Poudyal, et al. (2013) noted that impaired visibility from air pollution inhibited travel demand to America's Great Smoky Mountain National Park. Zhou et al. (2019) explored the impact of air pollution on tourism in Beijing; findings from their gravity model suggested that the impact was more extensive for inbound tourists than domestic ones. Xu and Reed (2019) examined the consequences of air pollution on inbound tourism to Shanghai, and their econometric results showed that actual and perceived levels of air pollution tempered tourism demand. In addition to the direct negative impacts of air pollution, Xu, Huang, Hou, and Zhang (2019) identified corresponding negative spillover, implying that tourism demand is influenced by the air quality of neighboring areas. In a more recent study, Wang and Chen (2020) identified an inverted U-shaped relationship between PM2.5 concentration and inbound and domestic tourist arrivals to Chinese cities.

2.2. Air pollution and tourist behavior

Air pollution also has far-reaching effects on the tourist experience at the micro level. First and foremost, short-term exposure to air pollution leads to health issues such as coughing (Sato, Gui, Ito, Kohzuki, & Ebihara, 2016). Tourists thus consider destinations with heavy air pollution risky to visit, and this perceived risk dictates their travel decisions (Mawby, 2000). Air pollution has become one of the most prominent travel-related risks in recent years. Tourists' risk evaluations of air pollution largely depend on their awareness and understanding of environmental hazards (Law & Cheung, 2007). For example, although haze pollution represents a long-term environmental problem, Chinese tourists did not respond notably to such pollution until this issue attracted considerable public attention in 2013 (Sun, Yang, Sun, & Wang, 2019). Inbound tourists are especially sensitive to haze-related threats because they can become easily overwhelmed by the impacts of air pollution on their travel experiences as well as health (Zhang et al., 2015). Yet compared with local residents who are exposed to long-term air pollution, tourists who only encounter pollution temporarily tend to be less sensitive to haze (Yan, Duarte, Wang, Zheng, & Ratti, 2019).

The perceived risk of air pollution can trigger tourists' protective behavioral intentions in a destination (Ruan, Kang, & Song, 2020). Given the consequences of air pollution on the destination experience and human health, tourists usually engage in protective behavior to mitigate associated risks (Peng & Xiao, 2018). For instance, visitors may avoid destinations with severe air pollution in favor of less-polluted areas (Denstadli, Jacobsen, & Lohmann, 2011; Ruan et al., 2020). To reduce environmental risks, tourists may prefer activities in which pollution hazards are less pervasive (Zhang et al., 2020b). Because air pollution reduces a location's aesthetic value and diminishes the pleasure of natural attractions, tourists exposed to poor air quality often seek out indoor environments over outdoor settings (Choi, Yoon, & Kim, 2019; Poudyal et al., 2013). Recreational and leisure activities are also preferred among tourists who encounter heavy air pollution (Wang, Zhou, Lu, & Cui, 2020). For instance, scholars have found that tourists spend less time in areas affected by air pollution and more time at multi-complex shopping malls (McKercher et al., 2015), art galleries, and museums (Choi et al., 2019; Yan et al., 2019).

2.3. Hypothesis development

In the social media era, tourists have started using online travel agents (e.g., TripAdvisor) to describe, praise, or criticize their travel experiences by leaving online ratings and evaluations (Kwok, Xie, & Richards, 2017). Thus, understanding the factors of tourists' satisfaction reflected in these online ratings is of great importance for the tourism industry. These determinants of online ratings can be broadly divided into two categories: tourist-specific and destination-specific ones. Existing literature noted that tourists-specific factors are crucial in shaping tourists' satisfaction with destinations, and these factors include age, gender, income, occupation, educational achievement, and cultural background (Danaher & Arweiler, 1996; Žabkar, Brenčič, & Dmitrović, 2010). Meanwhile, factors of the destination environment on tourists' satisfaction are also highlighted by many studies, such as attraction types, activities and events participated, environmental quality, price level, destination culture, climate and image, service and sanitation (Chi & Qu, 2008; Kozak & Rimmington, 2000). Furthermore, psychological factors like perceived value and emotion help shape online tourist ratings as well (Hu & Yang, 2020).

Pollution poses multiple risks to tourists' trips such as health hazards, poor visibility, and emotional damage (Peng & Xiao, 2018). Zhang et al. (2020a) showed that in the presence of pessimism in an environment featuring high air pollution, tourists may reduce their consumption and be less likely to become committed to a destination, resulting in lower revisit intentions. A pleasant environment in tourism destinations may lead to a favorable perception of travel experience; on the contrary, air pollution restricts destination selection and can lead to disappointing travel experiences, compromising tourists' happiness and satisfaction (Nawijn & Peeters, 2010; Zhang, Zhang, & Chen, 2017). Moreover, traveling in a polluted environment can evoke depression and stress (Sass et al., 2017), and these negative emotions may promote tourists' unethical behavior (Lu, Lee, Gino, & Galinsky, 2018).

In terms of the expectation–disconfirmation theory (Oliver, 1997), tourists' satisfaction is considered to be a cognitive state and influenced by previous cognitive experiences, especially depending on the disconfirmation result of comparison between subjective experience and previous reference basis. In the presence of air pollution, disconfirmation exists when the experience is inferior to expectation, leading to negative impacts on experience (Spreng, MacKenzie, & Olshavsky, 1996). When air pollution covers the foreign tourists' experience, gray sight or health risks will generate substantial discrepancies and disconfirmation with their original expectations, which may directly cause unpleasure and dissatisfied (Schiffman & Williams, 2005). Therefore, we propose the following Hypothesis:

H1. A higher level of air pollution leads to a less satisfactory level of foreign tourist experience.

Tourists' level of experience is likely to influence travel satisfaction. More expertised tourists tend to have more questions about the destination attributes like local attractions, risk, security, weather, facilities, stability, and so on (Brucks, 1985). As travel knowledge increases, tourists become more sensitive of destination attributes, attractions, and other concrete information that is relevant to the travel details (Zhang, Zhang, & Yang, 2016). According to the past literature, expertised customers are more demanding when evaluating the service and experience in the tourism context (Park, Yang, & Wang, 2019). Therefore, these tourists with a higher expertise level are more likely to witness an exaggerated negative effect of air pollution on travel experience by being more sensitive to air quality. Therefore, we propose the following Hypothesis:

H1a. The expertise level of foreign tourists moderates the effect of air pollution such that the effect is larger for more expertised tourists.

In the early years of air pollution, a sudden environmental deterioration would largely magnify the disconfirmation of foreign tourists' experience. The disparity between cognitive knowledge and actual experience makes it challenging for foreign tourists to get used to a polluted environment in the short term, leading to a more substantial effect of air pollution compared to later years. Over time, foreign tourists are increasingly knowledgeable about the expectation when traveling in China with regard to air pollution hazards, which make the tourists more prepared for air pollution. All the above may help reduce the disconfirmation between expectations and actual travel experiences in the presence of air pollution. Therefore, we propose the following Hypothesis:

H1b. Year of travel moderates the effect of air pollution such that the effect is larger in earlier years.

The pleasure and arousal dimensions by outdoor sightseeing activities may lead to a favorable perception of travel quality (Gascon et al., 2015). Outdoor attractions, such as mountains, national parks, and waterfront parks, are highly reliant on air quality (Abdurahman et al., 2016; Böhm & Pfister, 2011). Impaired visibility associated with air pollution has largely limited the expected natural sight. Some negative emotions like anxiousness and depression are common responses to gray cityscapes and unpleasant odors associated with air pollution (Schiffman & Williams, 2005; Yang et al., 2021). Moreover, health risks from air pollution also obviously stimulated tourists' outdoor experience (Evans & Jacobs, 1981). For example, respiratory and visual systems can be stimulated by pollutants in the air, and physical discomfort and agony may directly cause unpleasure (Bullinger, 1989). Unlike indoor activities, tourists are more threatened by air pollution when participating in activities in an outdoor environment (Mace, Bell, & Loomis, 2004). Therefore, we propose the following Hypothesis:

H1c. Attraction type moderates the effect of air pollution such that the effect is larger in outdoor attractions.

Tourists' satisfaction is culturally constrained because tourists evaluate the same experience differently according to their unique and distinct cultural background (Torres, Fu, & Lehto, 2014). Cultural psychologists suggested that national cultural differences, such as "masculinity versus femininity" and "individualism versus collectivism" (Hofstede, 2011), can influence tourists' evaluations (Huang & Crotts, 2019). Hofstede (1980) pointed feminine cultures might contribute a high level of environmental consciousness and sensitivity because due to the pursuit of life details. On the contrary, people in masculine cultures are generally pressured by the results of material gains and, therefore, are more likely to overlook the environmental risks and judge them as less problematic. We propose the following Hypothesis:

H1d. The national cultural dimension of "masculinity versus femininity" moderates the effect of air pollution such that the effect is larger for tourists from more feminine national cultures.

In collectivistic cultures, people are interested in what is the best to share, cooperate and harmonize the group's aims (Praveen, Addae, & Cullen, 2012), while in individualistic cultures, people make behavioral decisions in a more independent and autonomous way by considering individual interests (Huang & Crotts, 2019). Tourists in collectivistic societies are more inclined to pay attention to environmental concerns, which aligns with pro-social attitudes and behaviors. Therefore, we propose the following Hypothesis:

H1e. The national cultural dimension of "individualism versus collectivism" moderates the effect of air pollution such that the effect is larger for tourists from more collectivist cultures.

Existing studies indicated that tourists from different origins would benchmark the destination's air quality with those of their residence to evaluate their experience of the destination (Yang & Chen, 2020). Based on the expectation–disconfirmation theory, the air quality of tourists' home country helps shape the expectation of air quality in a destination, and the relative air quality perception tends to play a role in evaluating tourist experience (Yang & Chen, 2020). Moreover, for a tourist from a less polluted country, their experience shock can be exaggerated in the presence of air pollution both physically and emotionally. Therefore, we propose the following Hypothesis:

H1f. Air pollution level of home countries moderates the effect of air pollution such that the effect is larger for tourists from countries with a lower level of air pollution.

3. Research method

3.1. Data collection

We collected travel ratings of Chinese attractions from TripAdvisor, a worldwide travel website containing more than 878 million reviews and posts on 8.8 million accommodations, restaurants, attractions, airlines, and cruises. TripAdvisor provides a list of destination cities ranked by travel popularity in each country; we selected the top 110 most popular cities in China and developed a Java-based web crawler to gather data using three steps. First, the crawler automatically entered the "popular city" list page and extracted the URLs of all attractions. Second, after entering the homepage of each attraction based on the URL, the profile information of the attraction was extracted automatically, such as the attraction name, address, and total number of reviews. Finally, automatic page-turning technology was applied to extract all review-related information, including the review text, reviewer's name, reviewer's home city, travel date, and review date.

Fig. 1 presents the locations of mainland Chinese destinations in our sample. As noted, our data consisted of attraction reviews from 110 destinations listed on TripAdvisor. Beijing and Shanghai were the two most popular Chinese destinations on the site, accounting for 30.99% and 21.82% of reviews in our final sample, respectively. As shown in Fig. 1, the selected destinations are dispersed across China. Several clusters denote potential tourism hotspots: the Yangtze River Delta near Shanghai; the Pearl River Delta near Guangzhou; and a southwestern cluster covering Chengdu, Chongqing, and the northwestern part of Yunnan. These tourism hubs mirror findings on inbound tourism clusters (Yang & Wong, 2013), confirming the representativeness of our sample. Fig. 2 presents the geographic distribution of reviewers' reported countries of origin in their TripAdvisor profiles. Among 147 countries/territories worldwide, the top three origin countries of tourists in our sample were the United States (26.74%), Australia (13.48%), and the United Kingdom (13.29%). According to Fig. 2, most foreign tourists were from North America, Western Europe, Southeast Asia, and Oceania.

We also collected historical weather information from TianQi (http://www.tianqi.com/), a popular website presenting comprehensive daily weather data for 2,290 locations in China. According to the descriptions on TianQi, original weather information is provided by the China Meteorological Administration. Similarly, historical air quality data were gathered from AQIStudy (www.aqistudy.cn), a website providing daily air quality/pollution data for 367 Chinese cities. Air quality information includes the daily average air quality index (AQI) and daily average concentration of pollutants such as PM2.5, PM10, SO_2, NO_2, O_3, and CO. Daily records are calculated based on hourly data provided by China's Ministry of Ecology and Environment. Notably, destination names from TripAdvisor covered multiple administrative levels (i.e., prefecture-level cities and counties under the jurisdiction of a prefecture-level city). Therefore, we transformed these names to their corresponding levels in line with TianQi and AQIStudy, respectively. Lastly, we collected the cultural score of each country from https://www.hofstede-insights.com/.

3.2. Econometric method

In this study, we used a five-way fixed-effects model to unveil the impact of air pollution on tourists' experiences as reflected by TripAdvisor reviews. The model is specified as follows:

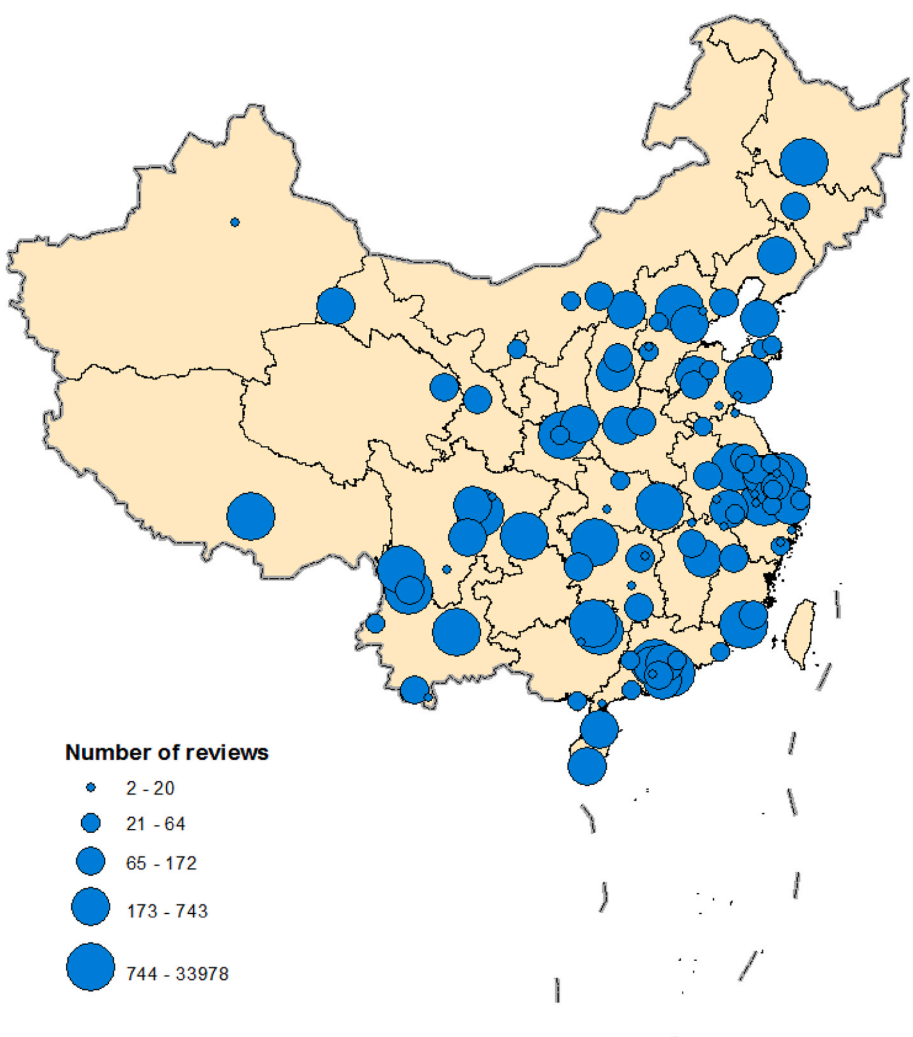

Fig. 1. Locations of Chinese destinations in TripAdvisor review sample.

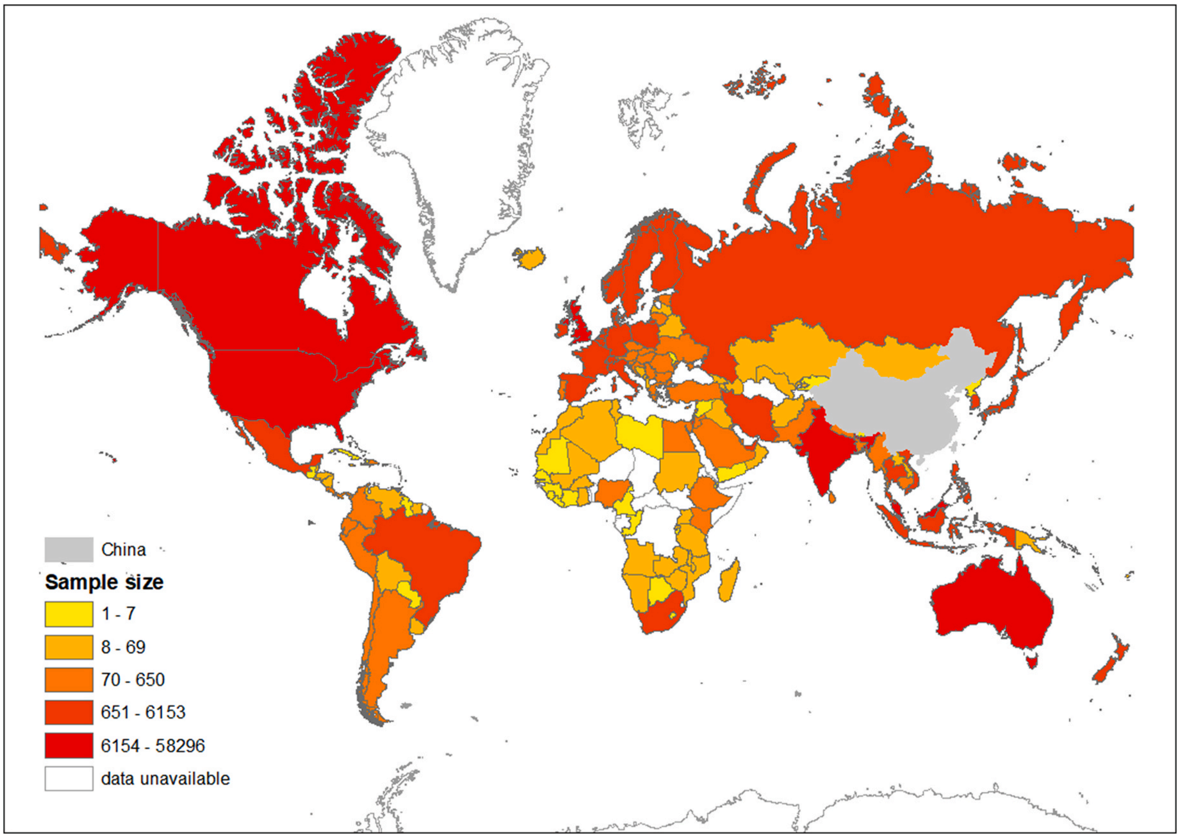

Fig. 2. Distribution of foreign tourists' countries of origin.

$$y_{i(k)jt} = lnpm25_{jt} \cdot \gamma + lnpm25_{jt} \cdot Z_{i(k)jt} \cdot \rho + \mathbf{X}_{it}\beta + \mu_k + \tau_j + \eta_t + \delta_t + \omega_t + \varepsilon_{i(k)jt}$$

where i indicates a single tourist from country/territory k; j indicates the attraction reviewed on TripAdvisor; and t indicates the date of travel. The dependent variable, y, denotes the 5-point tourist experience rating posted on TripAdvisor on a given attraction's webpage. Among various independent variables, *lnpm25* is our major variable of interest; it measures the log of the PM2.5 concentration (i.e., micrograms per cubic meter) in the city hosting a given attraction on the corresponding date. Among air pollutants, PM2.5 has been found to threaten human health more than other air pollutants. Individuals' perceptions of air quality are considerably influenced by PM2.5 due to heavy media coverage (Zhang et al., 2015). The estimated coefficient of *lnpm25*, γ, can be used to test H1. In our dataset, the distribution of the PM2.5 concentration was heavily left-skewed. We therefore took a logarithmic transformation of our original data. We also estimated models based on concentrations of different air pollutants to compare their effects on tourists' experiences. $\mathbf{X}_{it}$ represents a set of control variables expected to explain tourists' experiences, and $Z_{i(k)jt}$ is a variable that moderates the effect of the PM2.5 concentration on tourists' experiences. The model includes five fixed-effects terms as well: μ_k reflects origin-country–specific effects (for 147 countries/territories); τ_j reflects attraction-specific effects (for 2, 324 attractions); η_t reflects holiday-specific effects (i.e., from the New Year, Spring Festival, Tomb Sweeping Festival, Labor Day, Dragon Boat Festival, Mid-Autumn Festival, and National Day); δ_t reflects month-specific effects (for 73 months); and ω_t reflects day-of-the-week effects (for 7 days of the week). Lastly, $\varepsilon_{i(k)jt}$ represents the normal error term. This model was estimated using the full Gauss–Seidel algorithm to account for high-dimensional fixed effects. The algorithm generates identical estimation results to least square estimators with dummy variables capturing the fixed effects (Guimaraes & Portugal, 2010). We estimated the standard error of estimates using the clustered standard error based on attractions.

Our proposed fixed-effects model offers several notable advantages over alternative models. First, the five fixed effects we incorporated can alleviate plausible omitted variable biases (Greene, 2007). In this model, origin-country–specific effects capture all determinants of the tourist experience that apply to visitors from the same country/territory, such as national cultural dimensions (Huang & Crotts, 2019). Likewise, attraction-specific effects reflect attraction-specific determinants of the tourist experience, such as attraction type, amenities, and location. After controlling for various confounding factors embedded in fixed effects, we could effectively unveil the genuine impact of pollution on tourists' experiences. Different from a hierarchical linear model that treats origin-country–specific, attraction-specific, and time-specific effects as random, our fixed-effects model placed fewer restrictions on the independence between error terms and specific effects and was therefore anticipated to generate more reliable and robust estimation results (Greene, 2007).

In addition to the variable of interest, *lnpm25*, we specified the following control variables using $\mathbf{X}_{it}$:

- *mobile*: a dummy variable indicating whether a given TripAdvisor review was posted via a mobile device. In our case, *mobile* = 1 if the review was posted via a mobile device and *mobile* = 0 otherwise. Scholars have confirmed that mobile reviews are associated with lower TripAdvisor ratings (Huang, Burtch, Hong, & Polman, 2016).
- *expertise*: the log of a tourist's TripAdvisor contributions, taken as a proxy of the traveler's expertise. Experienced travelers have been shown to be more discerning and to assign lower TripAdvisor ratings compared with inexperienced travelers (Park et al., 2019).
- *temp*: the daily average temperature (in °C) of the destination hosting a given attraction. Temperature greatly affects visitors' destination experiences (Zhang et al., 2020b). Both extremely high and low temperatures can hinder the tourist experience (Yan et al., 2019);

thus, a quadratic term of *temp*, *temp_square*, was incorporated into our model as well.

- *sunny*: an indicator of a sunny day in the destination (*sunny* = 1 for sunny days and 0 otherwise). Weather-related factors have been shown to influence tourists' destination experiences (Yang & Chen, 2020).
- *rainy*: an indicator of a rainy day in the destination (*rainy* = 1 for rainy days and 0 otherwise).
- *snowy*: an indicator of a snowy day in the destination (*snowy* = 1 for snowy days and 0 otherwise).
- *cloudy*: an indicator of a cloudy day in the destination (*cloudy* = 1 for cloudy days and 0 otherwise).

Several moderating variables were considered in $Z_{i(k)jt}$ to assess factors moderating the effect of *lnpm25* to test H1a, H1b, H1c, H1d, H1e, H1f. The following moderating variables were considered:

- *expertise*: the log of a tourist's TripAdvisor contributions. The estimated coefficient of the interaction term between *lnpm25* and *expertise* can be used to test H1a
- *t*: the year of travel (*t* = *year*–2012). The interaction term between *lnpm25* and *t* reflected the time-varying effect of the PM2.5 concentration on tourists' experiences, and the estimated coefficient of this term can be used to test H1b.
- *outdoor*: an indicator of outdoor activities by TripAdvisor attraction type (*outdoor* = 1 for experiences in attractions associated with outdoor activities and 0 otherwise). The interaction term between *lnpm25* and *outdoor* indicated whether tourists' outdoor activities were more affected by the PM2.5 concentration than others (McKercher et al., 2015), and the estimated coefficient of this term can be used to test H1c.
- *lnmas*: the log of the "masculinity versus femininity" dimension score based on Hofstede's cultural framework. A larger score indicates a more masculine society (Hofstede, 2011). The coefficient of its interaction term with *lnpm25* can be used to test H1d.
- *lnidv*: the log of the "individualism versus collectivism" dimension score based on Hofstede's framework. A larger score indicates a more individualistic society (Hofstede, 2011). The coefficient of its interaction term with *lnpm25* can be used to test H1e.
- H1f
- *pm25_clean_home*: a variable indicating the level of air cleanliness in a tourist's country of origin. In our study, *pm25_clean_home* = 1 if the home country has no population living in places where mean annual concentrations of PM2.5 exceed 35 μg per cubic meter; *pm25_clean_home* = 0 otherwise. These data were obtained from the World Bank World Development Indicators database. The coefficient of its interaction term with *lnpm25* can be used to test H1f.

Table 1
Descriptive statistics of model variables.

Variables	Obs	Mean	Std. Dev.
rating	94,823	4.265	0.882
lnpm25	94,823	3.405	0.737
mobile	94,823	0.382	0.486
expertise	94,823	3.434	1.507
temp	94,823	20.662	8.605
sunny	94,823	0.150	0.357
rainy	94,823	0.335	0.472
snowy	94,823	0.006	0.076
cloudy	94,823	0.466	0.499
t	94,823	4.394	1.513
outdoor	94,823	0.134	0.341
lnmas	92,496	3.995	0.358
lnidv	92,496	4.148	0.553
pm25_clean_home	94,823	0.576	0.494

3.3. Data description

Table 1 presents the descriptive statistics of variables in our econometric analysis. The dependent variable *rating* had a mean value of 4.265 out of 5, and 48.87% of foreign tourists reported a score of 5 out of 5, indicating a high level of satisfaction on Chinese attractions. The mean of *lnpm25*, the major variable of interest, was 3.405. As indicated by the mean value of the dummy variable, *mobile*, 38.2% of reviews were posted via mobile devices. In terms of weather-related variables, the average temperature (*temp*) was 20.662 °C. Furthermore, 15.0% of reviews reported experiences on sunny days (*sunny*), 33.5% on rainy days (*rainy*), 0.6% on snowy days (*snowy*), and 46.6% on cloudy days (*cloudy*). The mean value of *t* was 4.394, corresponding to mid-2016. Regarding attraction types, 13.4% of reviews were for outdoor activities (*outdoor*). The mean value of *pm25_level0* was 0.576, revealing that 57.6% of foreign tourists came from countries with no population exposed to an annual PM2.5 concentration greater than 35 μg per cubic meter. Lastly, variance inflation factor (VIF) scores were used to identify potential multicollinearity in the model. All VIF scores were well below the suggested cutoff value of 10, indicating the absence of severe multicollinearity issue in our study (Dormann et al., 2013). The results of VIF scores are available upon request.

4. Empirical results

Table 2 presents the estimation results for our fixed-effects models without interaction terms. We introduced each control variable successively. Model 1 contained the key variable of interest, *lnpm25*, alone; its coefficient was estimated to be negative and statistically significant after controlling for four fixed effects. In Model 2, the negative estimated coefficient of *lnpm25* remained significant upon integrating two traveler-specific control variables (*mobile* and *expertise*). Additional weather-related variables were incorporated into Model 3; the estimated coefficient of *lnpm25* was negative and statistically significant. The

Table 2
Estimation results of fixed-effects models without interaction terms.

	Model 1	Model 2	Model 3
lnpm25	−0.00877*	−0.00911*	−0.00864*
	(0.005)	(0.005)	(0.005)
mobile		−0.0522***	−0.0524***
		(0.007)	(0.007)
expertise		−0.00581	−0.00579
		(0.004)	(0.004)
temp			0.00155
			(0.001)
temp_square			−0.0000443
			(0.000)
sunny			−0.0169*
			(0.010)
rainy			−0.0232***
			(0.008)
snowy			−0.0268
			(0.035)
cloudy			−0.0299***
			(0.008)
constant	4.296***	4.337***	4.350***
	(0.016)	(0.018)	(0.025)
Attraction-specific effects	Yes	Yes	Yes
Month-specific effects	Yes	Yes	Yes
Holiday-specific effects	Yes	Yes	Yes
Day-of-week-specific effects	Yes	Yes	Yes
Country-of-origin-specific effects	Yes	Yes	Yes
N	94447	94447	94447
N (attractions)	2324	2324	2324
R-sq	0.187	0.187	0.187
adj. R-sq	0.164	0.165	0.165

(Notes: *** indicates significance at the 0.01 level; ** indicates significance at the 0.05 level. Attraction-based clustered standard errors are presented in parentheses.).

estimated coefficient of *lnpm25* was consistently negative and significant in Models 1 to 3, lending support to H1. Models 2 and 3 returned negative and significant coefficients of *mobile*, suggesting that travelers who posted reviews via mobile devices were more likely to score their travel experiences lower on TripAdvisor. Among the selected weather-related variables, *sunny*, *rainy* and *cloudy* were estimated to be statistically significant.

Table 3 displays the estimation results for models incorporating various moderators. Model 4 included the interaction term between *lnpm25* and *expertise*; this interaction was statistically significant and negative. Accordingly, past travel experience moderated the air pollution–tourist experience relationship, such that experienced tourists were more affected by air pollution when visiting China. Therefore, H1a was supported by the empirical result. Fig. 3 depicts the estimated coefficient of *lnpm25* and its 95% confidence interval along with different contribution scores of TripAdvisor users. The coefficient becomes negative and statistically significant for TripAdvisor users with a contribution score higher than 38 in the sample. Model 5 involved the interaction between *lnpm25* and *t*, which was found to be positive and insignificant. As a result, H1b was not accepted. To clarify the time-changing effect of PM2.5 concentration, we re-estimated the model with year-specific coefficients for *lnpm2.5*. Fig. 4 depicts the estimated coefficient and its 95% confidence interval. As illustrated in the graph, the coefficient was negative and statistically significant in 2013 and 2014, the beginning of the research period. The negative coefficient was not statistically significant thereafter. Model 6 incorporated the interaction term *lnpm25* * *outdoor*, which was estimated to be statistically significant and negative. Attraction type hence appeared to moderate the impact of air pollution on the tourist experience, lending support to H1c. This effect was significantly higher for outdoor activities.

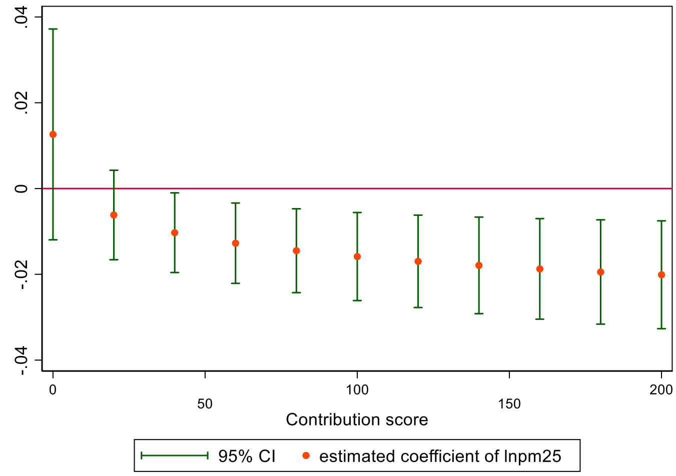

Fig. 3. Effects of PM2.5 concentration over different levels of expertise.

Table 3 also lists the estimation results of models with origin-country–specific moderators. Models 7–8 included the interaction term

Table 3
Estimation results of fixed-effects models with interaction terms.

	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
lnpm25	0.0126	−0.0299**	−0.00695	−0.0910**	−0.0696**	0.000639
	(0.013)	(0.014)	(0.005)	(0.042)	(0.030)	(0.007)
*lnpm25 * expertise*	−0.00617**					
	(0.003)					
*lnpm25 * t*		0.00496				
		(0.003)				
*lnpm25 * outdoor*			−0.0191*			
			(0.014)			
*lnpm25 * lnmas*				0.0203*		
				(0.010)		
*lnpm25 * lnidv*					0.0144**	
					(0.007)	
*lnpm25 * pm25_clean_home*						−0.0160*
						(0.008)
mobile	0.0152	−0.00577	−0.00580	−0.00582	−0.00582	−0.00580
	(0.011)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
expertise	−0.0525***	−0.0523***	−0.0524***	−0.0540***	−0.0539***	−0.0523***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
temp	0.00150	0.00158	0.00167	0.00147	0.00142	0.00151
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
temp_square	−0.0000439	−0.0000464	−0.0000470	−0.0000403	−0.0000398	−0.0000434
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
sunny	−0.0167	−0.0164	−0.0172*	−0.0178*	−0.0180*	−0.0168*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
rainy	−0.0230***	−0.0230***	−0.0235***	−0.0223***	−0.0223***	−0.0232***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
snowy	−0.0264	−0.0266	−0.0269	−0.0248	−0.0248	−0.0267
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
cloudy	−0.0298***	−0.0294***	−0.0301***	−0.0295***	−0.0296***	−0.0300***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
constant	4.279***	4.349***	4.349***	4.354***	4.355***	4.351***
	(0.048)	(0.025)	(0.026)	(0.026)	(0.026)	(0.025)
Attraction-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Holiday-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-of-origin-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
N	94447	94447	94447	92108	92108	94447
N (attractions)	2324	2324	2324	2301	2301	2324
R-sq	0.188	0.187	0.187	0.187	0.187	0.187
adj. R-sq	0.165	0.165	0.165	0.165	0.165	0.165

(Notes: *** indicates significance at the 0.01 level; ** indicates significance at the 0.05 level. Attraction-based clustered standard errors are presented in parentheses.).

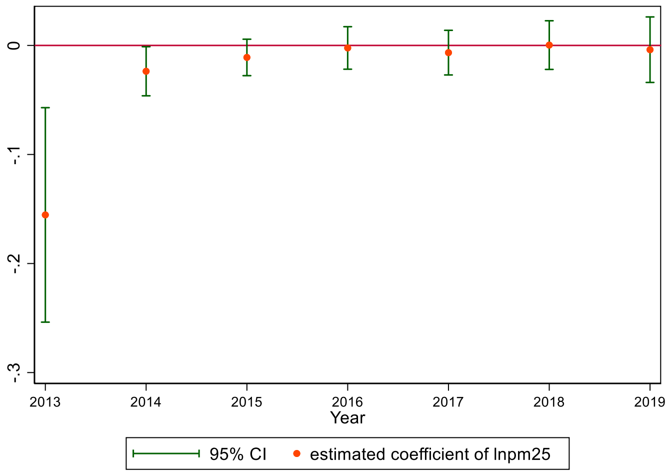

Fig. 4. Year-specific effects of PM2.5 concentration on tourists' experiences.

between *lnpm25* and the score on each one of Hofstede's cultural dimensions highlighted in H1d, H1e,The interactions with *lnmas* and *lnidv* were estimated to be positive and significant, and H1d, H1e were accepted. The impact of air pollution was, therefore, smaller for foreign tourists coming from countries with higher scores on masculinity and individualism . In Fig. 5, we found that the estimated coefficient of *lnpm25* was no longer statistically significant in countries with high "Masculinity versus Femininity" and "Individualism versus Collectivism" cultural scores. In Model 9, the interaction term between *lnpm25* and *pm25_clean_home* partially captured the effect of relative air pollution. The negative and significant coefficient of the interaction term supports H1f, suggesting that the negative impact of air pollution was substantially larger in origin countries with low air pollution.

As other air pollutants are also likely to influence tourists' experiences, we further estimated our model using the log of daily air pollutant concentration for the following six pollutants: PM2.5 (*lnpm25*), PM10 (*lnpm10*), SO_2 (*lnso2*), CO (*lnco*), NO_2 (*lnno2*), and O_3 (*lno3*). In addition, we estimated the effect of all air pollutants using *lnAQI*, representing the log of the concentration of these air pollutants. Estimation results are provided in Table 4. Among these estimates, only PM2.5 (*lnpm25*) in Model 3 and PM10 (*lnpm10*) in Model 10 were estimated to be significant. Based on the magnitude of each coefficient, the negative impact of PM10 was more detrimental to the foreign tourist experience than PM2.5. A moderator analysis taking the PM10 concentration as the major variable of interest came to the same conclusion regarding the significance of different moderators shown in Table 3.

We next conducted a robustness check using alternative models—ordered logit models and hierarchical linear models—to re-estimate Models 3. The ordered logit model treats the dependent variable as an ordinal measure and estimates the coefficients based on the discrete choice modeling framework (Greene, 2007). Due to the high degree of within-attraction variation in our dataset, a five-way fixed-effects ordered logit model exhibited convergence issues during estimation (Baetschmann, Ballantyne, Staub, & Winkelmann, 2020). Instead, we used a model with four-way fixed effects. In the hierarchical linear model, we specified the random effects instead of fixed effects on attraction-specific effects (Hox, Moerbeek, & van de Schoot, 2010); Models 16–17 in Table 5 present these estimation results. The models provided findings similar to those for Models 3, and the estimated coefficient of *lnpm25* was statistically significant and negative for foreign tourists. Our robustness checks confirm the robustness of empirical results from the five-way fixed-effects model.

5. Discussion

The study represents a pioneering effort to investigate the impact of air pollution on tourists' experiences at different destinations covering a long period, thus guaranteeing sufficient variation in air pollution levels. Unlike domestic tourists, foreign tourists were less familiar with the destination environment within the country and less capable of handling air pollution due to limited access to the various resources needed to combat such pollution. Therefore, they are particularly vulnerable to air pollution. Moreover, our results unveiled a time-varying impact of air pollution; the effect declined over our research period. This pattern emerged because as a growing number of foreign tourists become aware of the presence of air pollution in many Chinese tourism destinations (e.g., based on coverage from traditional media and social media outlets) (Chen et al., 2020), they will become better prepared to protect themselves while traveling, leading to a declining impact of air pollution over time. Media coverage can also shape tourists' expectations about their travel experiences in a potentially polluted environment overseas. Therefore, according to the expectation–disconfirmation theory (Oliver, 1997), they are likely to post a higher rating with the same level of air pollution than before.

Our study also highlighted intercultural differences in air pollution sensitivity among foreign tourists. Findings enhance our understanding of cross-cultural tourist behavior. The results specifically showed that national cultural traits moderate the effect of air pollution: we observed a larger effect for tourists from more feminine national cultures. A possible explanation is that feminine cultures emphasize needs of other members in the society and quality of life, leading to a high level of environmental sensitivity (Park, Russell, & Lee, 2007). We also identified a larger effect of air pollution among tourists from more collectivist cultures, which advocates for a commitment to future well-being and environmental actions (Praveen et al., 2012). Accordingly, tourists from these cultures are more pollution-sensitive. Lastly, our results indicated a more sizable impact for tourists from countries without significant air pollution; that is, foreign tourists appeared to evaluate air pollution

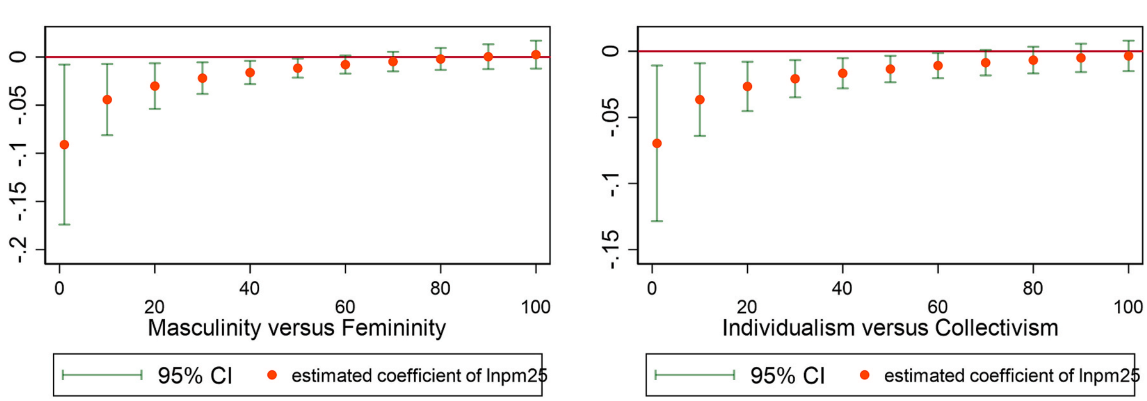

Fig. 5. Effects of PM2.5 concentration over different national cultural scores.

Table 4
Estimation results of models for different pollutants.

	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
lnpm10	−0.0113*					
	(0.006)					
lnso2		0.00657				
		(0.009)				
lnco			0.0111			
			(0.024)			
lnno2				0.00615		
				(0.009)		
lno3					−0.00475	
					(0.006)	
lnAQI						−0.0104
						(0.007)
mobile	−0.0524***	−0.0523***	−0.0523***	−0.0523***	−0.0523***	−0.0524***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
expertise	−0.00580	−0.00581*	−0.00582*	−0.00582*	−0.00581*	−0.00580
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
temp	0.00152	0.00153	0.00138	0.00125	0.00154	0.00147
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
temp_square	−0.0000422	−0.0000469	−0.0000438	−0.0000401	−0.0000436	−0.0000403
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
sunny	−0.0158	−0.0192*	−0.0179*	−0.0188*	−0.0164	−0.0160
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
rainy	−0.0238***	−0.0217***	−0.0223***	−0.0222***	−0.0228***	−0.0233***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
snowy	−0.0264	−0.0267	−0.0261	−0.0258	−0.0257	−0.0261
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
cloudy	−0.0296***	−0.0309***	−0.0304***	−0.0307***	−0.0298***	−0.0297***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
constant	4.365***	4.307***	4.317***	4.305***	4.342***	4.364***
	(0.030)	(0.032)	(0.027)	(0.035)	(0.032)	(0.033)
Attraction-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Holiday-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-of-origin-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
N	94447	94447	92108	92108	92108	94447
N (attractions)	2324	2324	2301	2301	2301	2324
R-sq	0.187	0.187	0.187	0.187	0.187	0.187
adj. R-sq	0.165	0.165	0.165	0.165	0.165	0.165

(Notes: *** indicates significance at the 0.01 level; ** indicates significance at the 0.05 level. Attraction-based clustered standard errors are presented in parentheses.).

using their home countries' air quality as a benchmark.

Among different air pollutants, only PM2.5 and PM10 were found to significantly compromise the tourist experience, with a larger impact from PM10. This result supports Li and Liu's (2013) discovery that PM10 plays a prime role in one's overall evaluation of environmental air quality. From a medical perspective, exposure to harmful particulate matter through extreme air pollution greatly affects the respiratory system; consequent symptoms include cough, chest tightness, and headache (Gehring et al., 2013). Epidemiological studies have pointed out that high concentrations of PM air pollution are associated with conditions such as chronic obstructive pulmonary disease, cerebrovascular disease, ischemic heart disease, and acute lower respiratory illness (Matus et al., 2012).

This study also provides practical implications for national and local tourism administration units and destination marketing organizations. First, Chinese destinations, especially those facing problems attributable to air pollution, can strategically target potential international markets whose tourists are less vulnerable to air pollution. For example, our moderator analysis pointed to several relevant origin-country features. Second, destinations—especially those susceptible to air pollution—should develop an air pollution alert system for incoming tourists. Notifications via text messages, emails, and social media channels can help tourists arrange their itineraries around air pollution and thus improve the overall tourist experience. Third, destinations' online tourism planning/recommendation systems should include air quality indicators when helping visitors arrange their activities. According to our results, travel experiences at some attractions are more resilient to air pollution than others. Fourth, cost-benefit analyses of pollution reduction efforts should factor in tourism-related benefits. The documented adverse effects of a PM2.5 concentration on tourists' experiences challenge traditional notions of economic and welfare losses from air pollution that have focused exclusively on local residents (Nam, Selin, Reilly, & Paltsev, 2010). Tourists, as victims of air pollution, should also be considered as important stakeholders in the model of welfare loss calibration. The erosion of a destination's reputation due to poor experiences should be incorporated into long-term economic losses as well. Last but not least, we calibrated the effects of different air pollutants on foreign tourists' experience. A tourist air quality index (TAQI) can be developed based on these estimates to monitor air pollution for incoming foreign tourists.

6. Conclusion

This study examined the impact of air pollution, measured by the PM2.5 concentration, on tourist attraction ratings on TripAdvisor. Using nationwide review data in mainland China from foreign tourists, we found that the impact of air pollution was negative and significant for foreign tourists. Also, several moderators of the air pollution–tourist experience relationship were identified. For example, the effect was much larger for more experienced travelers, in earlier years, and at attractions offering outdoor activities. We also observed some country-of-origin–specific factors, such as national cultural traits and average air pollution level. Tourists were more vulnerable to air pollution when coming from countries with more feminine and collectivist cultures and

Table 5
Estimation results of models for robustness checks.

	Model 16	Model 17
	Ordered logit model	Hierarchical linear model
lnpm25	−0.0919*	−0.00784*
	(0.050)	(0.005)
mobile	−0.139***	−0.0547***
	(0.020)	(0.006)
expertise	−0.122***	−0.00690***
	(0.022)	(0.002)
temp	0.00297	0.00220*
	(0.008)	(0.001)
temp_square	0.000195	−0.0000683**
	(0.000)	(0.000)
sunny	−0.0973**	-0.0156
	(0.046)	(0.010)
rainy	−0.0523**	−0.0228***
	(0.021)	(0.008)
snowy	−0.0439	−0.0275
	(0.082)	(0.037)
cloudy	−0.0419**	−0.0293***
	(0.020)	(0.008)
cut off 1	−7.041***	
	(0.794)	
cut off 2	−5.985***	
	(0.791)	
cut off 3	−4.366***	
	(0.790)	
cut off 4	−2.689***	
	(0.797)	
constant		4.711***
		(0.214)
Attraction-specific effects	No	Yes†
Month-specific effects	Yes	Yes
Holiday-specific effects	Yes	Yes
Day-of-week-specific effects	Yes	Yes
Country-of-origin-specific effects	Yes	Yes
N	94447	94447
N (attractions)	2324	2324
AIC	211576.2	230601.4
BIC	214025.3	233041.0

(Notes: *** indicates significance at the 0.01 level; ** indicates significance at the 0.05 level. † indicates specification of random effects in the model. Attraction-based clustered standard errors are presented in parentheses.).

countries with lower air pollution.

Several limitations temper the generalizability of our findings. First, because TripAdvisor is a popular platform among Western tourists, our sample included small subsets from several major origin countries in China's inbound tourism market (e.g., South Korea and Japan; see Fig. 2). Second, due to data limitations, we could not control for additional individual-level data points, such as visitors' sociodemographics or health conditions. These characteristics are nevertheless likely to influence individuals' vulnerability to air pollution. Third, the use of national-culture scores to represent tourists' cultural values could be problematic in light of countries' inherent cultural heterogeneity. Fourth, we did not fully leverage the textual information embedded in TripAdvisor reviews, which may provide further insight into tourists' experiences amid air pollution. Therefore, future studies should fully consider the textual and photographic details in TripAdvisor reviews to investigate the relationship between air pollution and the tourist experience more thoroughly. We also recommend that scholars integrate multiple data sources, such as online surveys, online reviews, and social media posts, to cross-validate relevant findings.

Credit author statement

Dr. Yang Yang: Conceptualization, Methodology, Visualization, Writing - review & editing. Dr. Xiaowei Zhang: Conceptualization, Data curation, Formal analysis, Writing - original draft. Dr. Yu Fu: Data curation, Formal analysis.

Impact statement

This study provides practical implications for foreign tourism administration units and destination marketing organizations. First, Chinese destinations, especially those facing problems attributable to air pollution, can strategically target potential source markets whose tourists are less vulnerable to air pollution. Second, destinations susceptible to air pollution should develop an air pollution alert system for incoming tourists. Third, destinations' online tourism planning/recommendation systems should include air quality indicators when helping visitors arrange their activities. According to our results, travel experiences at some attractions are more resilient to air pollution than others. Fourth, cost-benefit analyses of pollution reduction efforts should factor in tourism-related benefits. The documented adverse effects of a PM2.5 concentration on tourists' experiences challenges traditional notions of economic and welfare losses from air pollution that have focused exclusively on local residents. Tourists, as victims of air pollution, should also be considered as important stakeholders in the model of welfare loss calibration.

Declaration of competing interest

None.

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None.

References

Abdurahman, A. Z. A., Ali, J. K., Khedif, L. Y. B., Bohari, Z., Ahmad, J. A., & Kibat, S. A. (2016). Ecotourism product attributes and tourist attractions: UiTM undergraduate studies. *Procedia-Social and Behavioral Sciences, 224*, 360–367.

Anaman, K. A., & Looi, C. N. (2000). Economic impact of haze-related air pollution on the tourism industry in Brunei Darussalam. *Economic Analysis and Policy, 30*, 133–144.

Astell-Burt, T., Maynard, M. J., Lenguerrand, E., Whitrow, M. J., Molaodi, O. R., & Harding, S. (2013). Effect of air pollution and racism on ethnic differences in respiratory health among adolescents living in an urban environment. *Health & Place, 23*, 171–178.

Baetschmann, G., Ballantyne, A., Staub, K. E., & Winkelmann, R. (2020). feologit: A new command for fitting fixed-effects ordered logit models. *STATA Journal, 20*, 253–275.

Becken, S. (2013). Measuring the effect of weather on tourism: A destination-and activity-based analysis. *Journal of Travel Research, 52*, 156–167.

Becken, S., Jin, X., Zhang, C., & Gao, J. (2017). Urban air pollution in China: Destination image and risk perceptions. *Journal of Sustainable Tourism, 25*, 130–147.

Böhm, G., & Pfister, H.-R. (2011). Tourism in the face of environmental risks: Sunbathing under the ozone hole, and strolling through polluted air. *Scandinavian Journal of Hospitality and Tourism, 11*, 250–267.

Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of Consumer Research, 12*, 1–16.

Bullinger, M. (1989). Psychological effects of air pollution on healthy residents—a time-series approach. *Journal of Environmental Psychology, 9*, 103–118.

Chen, Z., Chen, D., Wen, W., Zhuang, Y., Kwan, M.-P., Chen, B., et al. (2019). Evaluating the "2+ 26" regional strategy for air quality improvement during two air pollution alerts in beijing: Variations in PM 2.5 concentrations, source apportionment, and the relative contribution of local emission and regional transport. *Atmospheric Chemistry and Physics, 19*, 6879–6891.

Chen, Z., Li, R., Chen, D., Zhuang, Y., Gao, B., Yang, L., et al. (2020). Understanding the causal influence of major meteorological factors on ground ozone concentrations across China. *Journal of Cleaner Production, 242*, 118498.

Chi, C. G.-Q., & Qu, H. (2008). Examining the structural relationships of destination image, tourist satisfaction and destination loyalty: An integrated approach. *Tourism Management, 29*, 624–636.

Choi, Y., Yoon, H., & Kim, D. (2019). Where do people spend their leisure time on dusty days? Application of spatiotemporal behavioral responses to particulate matter pollution. *The Annals of Regional Science, 63*, 317–339.

Danaher, P. J., & Arweiler, N. (1996). Customer satisfaction in the tourist industry: A case study of visitors to New Zealand. *Journal of Travel Research, 35*, 89–93.

Deng, T., Li, X., & Ma, M. (2017). Evaluating impact of air pollution on China's inbound tourism industry: A spatial econometric approach. *Asia Pacific Journal of Tourism Research, 22*, 771–780.

Denstadli, J. M., Jacobsen, J. K. S., & Lohmann, M. (2011). Tourist perceptions of summer weather in Scandinavia. *Annals of Tourism Research, 38*, 920–940.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., et al. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography, 36*, 27–46.
Eusébio, C., Carneiro, M. J., Madaleno, M., Robaina, M., Rodrigues, V., Russo, M., et al. (2020). The impact of air quality on tourism: A systematic literature review. *Journal of Tourism Futures*.
Evans, G. W., & Jacobs, S. V. (1981). Air pollution and human behavior. *Journal of Social Issues, 37*, 95–125.
Fonken, L. K., Xu, X., Weil, Z. M., Chen, G., Sun, Q., Rajagopalan, S., et al. (2011). Air pollution impairs cognition, provokes depressive-like behaviors and alters hippocampal cytokine expression and morphology. *Molecular Psychiatry, 16*, 987.
Gascon, M., Triguero-Mas, M., Martínez, D., Dadvand, P., Forns, J., Plasència, A., et al. (2015). Mental health benefits of long-term exposure to residential green and blue spaces: A systematic review. *International Journal of Environmental Research and Public Health, 12*, 4354–4379.
Gehring, U., Gruzieva, O., Agius, R. M., Beelen, R., Custovic, A., Cyrys, J., et al. (2013). Air pollution exposure and lung function in children: The ESCAPE project. *Environmental Health Perspectives, 121*, 1357–1364.
Gerdt, S.-O., Wagner, E., & Schewe, G. (2019). The relationship between sustainability and customer satisfaction in hospitality: An explorative investigation using eWOM as a data source. *Tourism Management, 74*, 155–172.
Greene, W. H. (2007). *Econometric analysis* (6th ed.). Upper Saddle River, NJ: Prentice Hall.
Guimaraes, P., & Portugal, P. (2010). A simple feasible procedure to fit models with high-dimensional fixed effects. *STATA Journal, 10*, 628–649.
Hofstede, G. (2011). Dimensionalizing cultures: The Hofstede model in context. *Online readings in psychology and culture, 2*, 2307-0919.
Hofstede, G. (1980). *Culture's Consequences*. Beverly Hills, CA: Sage.
Hox, J. J., Moerbeek, M., & van de Schoot, R. (2010). *Multilevel analysis: Techniques and applications* (2nd ed.). New York: Routledge.
Huang, N., Burtch, G., Hong, Y., & Polman, E. (2016). Effects of multiple psychological distances on construal and consumer evaluation: A field study of online reviews. *Journal of Consumer Psychology, 26*, 474–482.
Huang, S. S., & Crotts, J. (2019). Relationships between hofstede's cultural dimensions and tourist satisfaction: A cross-country cross-sample examination. *Tourism Management, 72*, 232–241.
Hu, X., & Yang, Y. (2020). Do lower costs necessarily induce higher value ratings? An analysis of online hotel reviews. *Current Issues in Tourism*, 1–17.
Kim, C., Jung, S. H., Kang, D. R., Kim, H. C., Moon, K. T., Hur, N. W., et al. (2010). Ambient particulate matter as a risk factor for suicide. *American Journal of Psychiatry, 167*, 1100–1107.
Kozak, M., & Rimmington, M. (2000). Tourist satisfaction with Mallorca, Spain, as an off-season holiday destination. *Journal of Travel Research, 38*, 260–269.
Kwok, L., Xie, K. L., & Richards, T. (2017). Thematic framework of online review research. *International Journal of Contemporary Hospitality Management, 29*, 307–354.
Law, R., & Cheung, C. (2007). Air quality in Hong Kong: A study of the perception of international visitors. *Journal of Sustainable Tourism, 15*, 390–401.
Li, A., & Liu, J. (2013). Efficient environmental air quality evaluation scheme based on the fuzzy mathematics method. In *Informatics and management science III* (pp. 645–651). Springer.
Lu, J. G., Lee, J. J., Gino, F., & Galinsky, A. D. (2018). Polluted morality: Air pollution predicts criminal activity and unethical behavior. *Psychological Science, 29*, 340–355.
Mace, B. L., Bell, P. A., & Loomis, R. J. (2004). Visibility and natural quiet in national parks and wilderness areas: Psychological considerations. *Environment and Behavior, 36*, 5–31.
Mage, D., Ozolins, G., Peterson, P., Webster, A., Orthofer, R., Vandeweerd, V., et al. (1996). Urban air pollution in megacities of the world. *Atmospheric Environment, 30*, 681–686.
Matus, K., Nam, K.-M., Selin, N. E., Lamsal, L. N., Reilly, J. M., & Paltsev, S. (2012). Health damages from air pollution in China. *Global Environmental Change, 22*, 55–66.
Mawby, R. I. (2000). Tourists' perceptions of security: The risk—fear paradox. *Tourism Economics, 6*, 109–121.
McKercher, B., Shoval, N., Park, E., & Kahani, A. (2015). The [limited] impact of weather on tourist behavior in an urban destination. *Journal of Travel Research, 54*, 442–455.
Nam, K.-M., Selin, N. E., Reilly, J. M., & Paltsev, S. (2010). Measuring welfare loss caused by air pollution in Europe: A CGE analysis. *Energy Policy, 38*, 5059–5071.
Nawijn, J., & Peeters, P. M. (2010). Travelling 'green': Is tourists' happiness at stake? *Current Issues in Tourism, 13*, 381–392.
Oliver, R. L. (1997). *Satisfaction: A behavioral perspective on the consumer*. Irwin-McGraw-Hill.
Park, H., Russell, C., & Lee, J. (2007). National culture and environmental sustainability: A cross-national analysis. *Journal of Economics and Finance, 31*, 104–121.
Park, S., Yang, Y., & Wang, M. (2019). Travel distance and hotel service satisfaction: An inverted U-shaped relationship. *International Journal of Hospitality Management, 76*, 261–270.
Peng, J., & Xiao, H. (2018). How does smog influence domestic tourism in China? A case study of beijing. *Asia Pacific Journal of Tourism Research, 23*, 1115–1128.
Poudyal, N. C., Paudel, B., & Green, G. T. (2013). Estimating the impact of impaired visibility on the demand for visits to national parks. *Tourism Economics, 19*, 433–452.
Power, M. C., Kioumourtzoglou, M.-A., Hart, J. E., Okereke, O. I., Laden, F., & Weisskopf, M. G. (2015). The relation between past exposure to fine particulate air pollution and prevalent anxiety: Observational cohort study. *British Medical Journal, 350*, h1111.
Praveen, P. K., Addae, H. M., & Cullen, J. B. (2012). Propensity to support sustainability initiatives: A cross-national model. *Journal of Business Ethics, 105*, 403–413.
Ruan, W., Kang, S., & Song, H. (2020). Applying protection motivation theory to understand international tourists' behavioural intentions under the threat of air pollution: A case of beijing, China. *Current Issues in Tourism*, 1–15.
Sass, V., Kravitz-Wirtz, N., Karceski, S. M., Hajat, A., Crowder, K., & Takeuchi, D. (2017). The effects of air pollution on individual psychological distress. *Health & Place, 48*, 72–79.
Sato, R., Gui, P., Ito, K., Kohzuki, M., & Ebihara, S. (2016). Effect of short-term exposure to high particulate levels on cough reflex sensitivity in healthy tourists: A pilot study. *The Open Respiratory Medicine Journal, 10*, 96.
Schiffman, S. S., & Williams, C. M. (2005). Science of odor as a potential health issue. *Journal of Environmental Quality, 34*, 129–138.
Spreng, R. A., MacKenzie, S. B., & Olshavsky, R. W. (1996). A reexamination of the determinants of consumer satisfaction. *Journal of Marketing, 60*, 15–32.
Sun, X., Yang, W., Sun, T., & Wang, Y. P. (2019). Negative emotion under haze: An investigation based on the microblog and weather records of Tianjin, China. *International Journal of Environmental Research and Public Health, 16*, 86.
Torres, E. N., Fu, X., & Lehto, X. (2014). Examining key drivers of customer delight in a hotel experience: A cross-cultural perspective. *International Journal of Hospitality Management, 36*, 255–262.
Wang, L.-J., & Chen, M.-H. (2020). Nonlinear impact of air quality on tourist arrivals: New proposal and evidence. *Journal of Travel Research, 60*, 434–445.
Wang, L., Zhou, X., Lu, M., & Cui, Z. (2020). Impacts of haze weather on tourist arrivals and destination preference: Analysis based on Baidu Index of 73 scenic spots in Beijing, China. *Journal of Cleaner Production, 273*, 122887.
Williams, A. M., & Baláž, V. (2015). Tourism risk and uncertainty: Theoretical reflections. *Journal of Travel Research, 54*, 271–287.
World Health Organization. (2014). 7 million premature deaths annually linked to air pollution. from http://www.who.int/mediacentre/news/releases/2014/air-pollution/en/.
Xu, D., Huang, Z., Hou, G., & Zhang, C. (2019). The spatial spillover effects of haze pollution on inbound tourism: Evidence from mid-eastern China. *Tourism Geographies*, 1–22.
Xu, X., & Reed, M. (2019). Perceived pollution and inbound tourism for Shanghai: A panel VAR approach. *Current Issues in Tourism, 22*, 601–614.
Yan, L., Duarte, F., Wang, D., Zheng, S., & Ratti, C. (2019). Exploring the effect of air pollution on social activity in China using geotagged social media check-in data. *Cities, 91*, 116–125.
Yang, Y., & Chen, G. (2020). In search of fresher air: The influence of relative air quality on vacationers' perceptions of destinations' restorative qualities. *International Journal of Tourism Research*.
Yang, J., Qu, S., Liu, M., Liu, X., Gao, Q., He, W., et al. (2021). Gray cityscape caused by particulate matter pollution hampers human stress recovery. *Journal of Cleaner Production, 279*, 123215.
Yang, Y., & Wong, K. K. F. (2013). Spatial distribution of tourist flows to China's cities. *Tourism Geographies, 15*, 338–363.
Žabkar, V., Brenčič, M. M., & Dmitrović, T. (2010). Modelling perceived quality, visitor satisfaction and behavioural intentions at the destination level. *Tourism Management, 31*, 537–546.
Zhang, K., Hou, Y., Li, G., & Huang, Y. (2020a). Tourists and air pollution: How and why air pollution magnifies tourists' suspicion of service providers. *Journal of Travel Research, 59*, 661–673.
Zhang, X., Yang, Y., Zhang, Y., & Zhang, Z. (2020b). Designing tourist experiences amidst air pollution: A spatial analytical approach using social media. *Annals of Tourism Research, 84*, 102999.
Zhang, X., Zhang, X., & Chen, X. (2017). Happiness in the air: How does a dirty sky affect mental health and subjective well-being? *Journal of Environmental Economics and Management, 85*, 81–94.
Zhang, Z., Zhang, Z., & Yang, Y. (2016). The power of expert identity: How website-recognized expert reviews influence travelers' online rating behavior. *Tourism Management, 55*, 15–24.
Zhang, A., Zhong, L., Xu, Y., Wang, H., & Dang, L. (2015). Tourists' perception of haze pollution and the potential impacts on travel: Reshaping the features of tourism seasonality in Beijing, China. *Sustainability, 7*, 2397–2414.
Zheng, S., Wang, J., Sun, C., Zhang, X., & Kahn, M. E. (2019). Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nature Human Behaviour, 3*, 237.
Zhou, X., Santana Jiménez, Y., Pérez Rodríguez, J. V., & Hernández, J. M. (2019). Air pollution and tourism demand: A case study of beijing, China. *International Journal of Tourism Research, 21*, 747–757.
Zijlema, W. L., Wolf, K., Emeny, R., Ladwig, K. H., Peters, A., Kongsgård, H., et al. (2016). The association of air pollution and depressed mood in 70,928 individuals from four European cohorts. *International Journal of Hygiene and Environmental Health, 219*, 212–219.

Yang Yang, PhD, is an associate professor at the Department of Tourism and Hospitality Management, Temple University. Email: yangy@temple.edu. His research interests include tourism and hospitality analytics.

Xiaowei Zhang, PhD, is an assistant professor at the School of Economics and Management, Beijing Jiaotong University. Email: zhxiaowei@bjtu.edu.cn. His research interests include AI system design, social media, and big data analytics in tourism.

Yu Fu, PhD, is an assistant professor at the School of Information Resource Management, Renmin University of China. E-mail: yu.fu@ruc.edu.cn. His research focuses on computational tourism science, information system, and text mining.