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Effects of Air Quality and Weather Conditions on Chinese Tourists' Emotional Experience

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Abstract

Though the effects of air quality and weather conditions on tourism have been examined from different perspectives, their effects on tourists' emotional experience have not been investigated. Due to lack of effective measurements, tourists' real-time on-site emotional experience have not been duly examined. This study used tourists' geo-tagged check-in user-generated content (UGC) to extract the sentiments underlying tourists' real-time on-site emotional experience, and modelled the effects of air quality and weather conditions on tourists' emotional experience. The empirical results confirmed a negative and non-linear impact of air pollution, and an inverted-U effect of temperature on tourists' emotional experience. By developing a new and effective measure of tourists' emotional experience, this study provides hard evidence on the effects of air quality and weather conditions on tourists' emotional experience, and thus advances the knowledge of environmental psychology and tourist experience studies. Results have practical implications for sustainable destination development and tourist experience management.

Keywords: air quality; weather conditions; emotional experience; tourist sentiment

1. Introduction

Environmental quality is a prevailing factor in determining destination competitiveness and attractiveness, and in tourists' travel decision-making process (Deng, Li, & Ma, 2017; Peng & Xiao, 2018; Peng, Xiao, Wang, & Zhang, 2020). Air quality, as one of the important environmental concerns, has attracted increasing academic attention and its impact on tourism has become a widespread concern, especially in China (Deng et al., 2017). In China, 29% of 5,796 outdoor tourist attractions had severe air pollution issues in 2016, and this ratio may rise to 34% by 2030 (Sun, Mei, Li, & Shi, 2019). Current tourism studies show that air quality is significantly associated with tourist arrivals (Deng et al., 2017; Poudyal, Paudel, & Green, 2013; Xu, Huang, Hou, & Zhang, 2020; Zhou, Qu, Du, Yang, & Liu, 2018), tourist demand (Peng et al., 2020; Wang, Fang, & Law, 2018), destination image (Becken, Jin, Zhang, & Gao, 2017; Peng & Xiao, 2018), tourist health (Guindi, Flaherty, & Byrne, 2018; Vilcassim et al., 2019), tourist perception (Li, Pearce, Morrison, & Wu, 2016; Peng & Xiao, 2018; Zhang, Hou, Li, & Huang, 2020), tourist behavior (Law & Cheung, 2007; Zhang, Zhong, Xu, Wang, & Dang, 2015), and tourist experience (Peng & Xiao, 2018; Poudyal et al., 2013; Zajchowski, Brownlee, & Rose, 2019; Zhang, Yang, Zhang, & Zhang, 2020). In addition, weather is also an important environmental factor that affects tourist perception, experience, and behavior (McKercher, Shoval, Park, & Kahani, 2015; Wilkins, Stone, Weiskittel, & Gabe, 2018). According to environmental psychology studies, poor air quality may increase anxiety and depression (Marques & Lima, 2011; Peng et al., 2020), and weather conditions also affect human emotional state (Keller et al., 2005; Noelke et al., 2016). In tourism, though environmental quality, like air quality (Zhou et al., 2018) and weather conditions (Lin & Matzarakis, 2011) are deemed to be associated with tourists' perception and emotion, little empirical evidence can be found to support those effects on tourists' emotional experience, and little attention had been paid to tourists' real-time on-site emotional experience.

Tourists' emotional experience significantly affects tourist satisfaction (Hosany, Prayag, Veen, Huang, & Deesilatham, 2017; Ma, Scott, Gao, & Ding, 2017; Mason & Paggiaro, 2012), destination image (Prayag, Hosany, Muskat, & Del Chiappa, 2017) and tourist behavioral intention (Barnes, Mattsson, & Sørensen, 2016; Lee, 2016; Wang, Chen, Fan, & Lu, 2012). Existing studies have identified determinants of tourists' emotional experience, including tourist motivation (Yan, Zhang, Zhang, Lu, & Guo, 2016), service quality (Wang et al., 2012) and tourist personality (Faullant, Matzler, & Mooradian, 2011); however, little attention has been paid to the effect of environmental quality, such as air quality and weather conditions, on tourists' real-time on-site emotional experience, due to the difficulty of measuring real-time on-site emotional experience. Most studies used surveys with different scales (Barnes et al., 2016; Hosany & Gilbert, 2010) to evaluate tourists' emotional experience. Such self-reporting methods involve potential bias (Rylander, Propst, & Mcmurtry, 1995), and can only capture tourists' post-trip or remembered experience. As such, some researchers have called for physiological measures for capturing tourists' real-time emotional experience (Prayag et al., 2017). These could include, for instance, electrodermal activity technology (Kim & Fesenmaier, 2015; Shoval, Schvimer, & Tamir, 2018). Despite its effectiveness, the use of physiological measures is limited by devices, laboratory settings, and sample size (Kim & Fesenmaier, 2015; Shoval et al., 2018). Recently, online user-generated content (UGC) has provided an efficient way to capture tourists' emotional experience. The effectiveness of UGC in evaluating tourist satisfaction (Gitto & Mancuso, 2017), tourist attitude (Hao, Fu, Hsu, Li, & Chen, 2019), destination image (Gkritzali, 2017), and tourist experience (Rahmani, Gnoth, & Mather, 2019; Tussyadiah & Fesenmaier, 2008) has been acknowledged. Also, locational and temporal data are critical when trying to capture tourists' real-time on-site experience and feelings (Han & Back, 2007; Shoval et al., 2018). This rationale underlies the current study's use of sentiment scores calculated from geo-tagged check-in UGC to measure tourists' real-time on-site emotional experience.

Studies on environmental psychology have demonstrated the effects of air quality and weather conditions on human emotions (Marques & Lima, 2011; Noelke et al., 2016; Peng et al., 2020). Tourism is highly environment-dependent (Wang & Chen, 2020) and experience-based (Laing, Wheeler, Reeves, & Frost, 2014); thus it is particularly important to understand the effects of environmental quality on tourists' emotional experience. However, the effects of both air quality and weather conditions on tourists' emotional experience have not been empirically examined in tourism settings, and existing tourism studies have mostly failed to effectively capture tourists' real-time on-site emotional experience. Nowadays, the sentiment analytic techniques and big data sources have provided an opportunity to better capture tourists' emotional experience. Therefore, this study aimed to measure tourists' real-time on-site emotional experience, and examined the effects of air quality and weather conditions on tourists' emotional experience grounded on both environmental psychology and tourism literatures. Specifically, this study developed an effective measure to capture tourists' real-time on-site emotional experience based on geo-tagged check-in Weibo data and sentiment analytic technique, and proposed empirical models to test the impact of air quality and weather conditions on tourists' emotional experience. Empirical results demonstrated a significant negative and non-linear effect of air pollution on tourists' emotional experience and identified the important impacts of weather conditions including temperature and cloudiness.

This study makes several contributions to current literature. First, this study provides hard evidence of the significant and non-linear effects of air quality on tourists' emotional experience, identifying an important environmental factor influencing tourists' emotional experience, and thus extending the studies on tourists' emotional experience. Second, this study offers a methodological contribution by adding an objective and effective real-time measure of tourists' emotional experience and demonstrating the usefulness of sentiment analytics and online UGC data in monitoring tourists' emotional experience. Finally, this study examines the impact of both air quality and weather conditions on tourists' emotional experience, providing deep insights into the impact of environment on tourism, and advancing the applications of environmental psychology theories in tourism settings. Managerially, the findings indicate that destinations should pay more attention on environmental quality, including air quality and weather conditions. Also, this study offers a new and effective method for destinations to evaluate and monitor tourists' emotional experience.

2. Literature Review

2.1 The impact of air quality on tourism

Impact of environmental factors (including air quality and weather conditions) on human perception and behavior is a focused topic in environmental studies (Keller et al., 2005; Marques & Lima, 2011) and have received much attention in tourism studies. Tourism is highly environment-dependent (Wang & Chen, 2020), and a destination's attractiveness and competitiveness can be largely impacted by the environment (Mihalic, 2000; Peng et al., 2020). In particular, air quality affects tourists' physical comfort and tourist experience (Wang et al., 2018), and determines destination competitiveness (Mihalic, 2000), thus prompting recent research into its impact on tourism.

Some researchers modeled the impact of air quality based on objective data, and found a negative relationship between air pollution and tourist arrivals (Deng et al., 2017; Poudyal et al., 2013; Xu et al., 2020; Zhou et al., 2018), tourism sales revenue (Yoon, 2019), and tourism economy (Anaman & Looi, 2000). Other researchers considered the impact dialectically. For instance, Peng et al. (2020) surveyed Beijing residents and found that poor air quality in tourist attractions can stimulate local travel demand. Wang et al. (2018) found that poor air quality has a pushing effect on local tourism demand. In this sense, researchers argued that air pollution can aid in the development of tourism economy.

Studies that explored the impact of air quality on destinations focused on destination images and the visibility of tourist attractions. Poor air quality increases tourists' concerns, and may damage the destination image (Becken et al., 2017; Peng & Xiao, 2018). Also, poor air quality often corresponds to poor visibility, and may negatively affect tourists' enjoyment of the sceneries and attractions in the destination (Poudyal et al., 2013).

Researchers are also concerned about the impact of air quality on tourists. Although travel-related exposure to air pollution is not long-term, it is still a threat to tourists' health (Guindi et al., 2018; Vilcassim et al., 2019). The health risks associated with air pollution increase tourists' concerns, and many researchers have investigated tourists' perceptions of air pollution using surveys or interviews. They found that tourists' air pollution concerns can increase tourists' risk perception (Becken et al., 2017; Li et al., 2016; Peng & Xiao, 2018) and social suspicion (Zhang et al., 2020), decrease tourist satisfaction (Li et al., 2016; Peng & Xiao, 2018), and affect tourists' behavioral intentions (Becken et al., 2017; Li et al., 2016; Zhang et al., 2015). Air quality may also alter tourists' travel plan (Zhang et al., 2015) and affect tourists' destination choice (Law & Cheung, 2007).

In addition, psychological impacts of environmental factors may be larger than physical impacts. Emerging evidence can be found in environmental psychology literature. For example, poor air quality may cause negative feelings, such as anxiety and depression (Marques & Lima, 2011; Peng et al., 2020). Many tourism researchers also argue that air quality may impact tourist perception, tourist experience and enjoyment (Peng & Xiao, 2018; Poudyal et al., 2013; Zajchowski et al., 2019; Zhang et al., 2020) and ignite unfavorable emotions for tourists during travelling (Zhou et al., 2018). Also, tourists reported reduced positive sentiments due to poor air quality (Zhang et al., 2020). Therefore, it is reasonable to believe that air quality may affect tourists' emotional experience. However, no empirical evidence has been found to support this statement in tourism studies.

Weather is also an important environmental factor that affects human emotional state (Keller et al., 2005). Weather conditions, such as temperature, wind, and precipitation, significantly affect human emotions (Kööts, Realo, & Allik, 2011) and life satisfaction (Kämpfer & Mutz, 2013). For example, higher temperature may increase negative feelings like stress and tiredness and reduce positive feelings like joy (Noelke et al., 2016). In tourism, the effects of weather conditions on tourism demand (Chen, Lin, Li, & Liu, 2017; Falk, 2014; Goh, 2012), tourism expenditure (Wilkins et al., 2018), tourist arrivals (Becken, 2013; Hewer, Scott, & Fenech, 2016), thermal comfort (Lin & Matzarakis, 2011), and tourist behavior (McKercher et al.,

2015) have been well documented. For example, Chen et al. (2017) found that number of rainy days and uncertainty of the temperature decreased the number of tourists, confirming the significance of weather on tourist activities. However, most studies mainly focused on the effect of weather at a macro level, and several studies on tourists were limited to tourist behavior (McKercher et al., 2015) and tourist comfort (Lin & Matzarakis, 2011). Also, little empirical evidence was provided to suggest the effects of weather conditions on tourists' real-time on-site emotional experience. Furthermore, very few studies have investigated the effect of both air quality and weather conditions on tourists' experience. Thus, this study aims to empirically examine the effects of environmental quality (both air quality and weather) on tourists' emotional experience based on both environmental psychology and tourism literatures.

2.2 Tourists' emotional experience

Emotion is a core component of tourist experience (Mcintosh & Siggs, 2005), and has been regarded as more seminal than cognition (Rahmani et al., 2019). Thus, many researchers have made great efforts to explore the role of tourists' emotional responses (Hosany, 2012). Some of these studies recognized the effect of tourists' emotional experience on tourist satisfaction (Faullant et al., 2011; Han & Back, 2007; Hosany et al., 2017; Hosany & Gilbert, 2010; Ma et al., 2017; Mason & Paggiaro, 2012; Prayag et al., 2017; Prayag, Hosany, & Odeh, 2013), and found that tourists' emotion or emotional experience is a significant determinant of tourist satisfaction. Researchers also found that tourists' emotional experience acts as an important antecedent to destination image (Prayag et al., 2017), place attachment (Hosany et al., 2017), tourist cognition (Lee, 2016) and behavioral intentions (Barnes et al., 2016; Lee, 2016; Wang et al., 2012).

In addition to the consequences of tourists' emotional experience, the antecedents of tourists' emotional experience have been studied by several researchers. In this line of research, the effects of tourist motivation (Yan et al., 2016), tourist cognitive appraisal (Hosany, 2012), service quality (Wang et al., 2012) and tourist personality traits (Faullant et al., 2011) on tourists' emotional experience have been investigated. Wang et al. (2012) used questionnaires to investigate tourists, and found that service quality including resource conditions, recreational activities and related personnel significantly improve tourists' emotional experience. Nevertheless, the effect of environmental quality on tourists' emotional experience has received little attention. Researchers have mostly considered that air quality may affect tourist experience (Peng & Xiao, 2018; Poudyal et al., 2013; Zajchowski et al., 2019; Zhang et al., 2020) and tourists' emotion (Zhou et al., 2018). Further to this, weather is also believed to affect people's thermal comfort (Lin & Matzarakis, 2011), and tourist experience (McKercher et al., 2015; Wilkins et al., 2018). But the effects of air quality and weather conditions on tourists' emotional experience have not been empirically investigated.

A critical issue with the above-mentioned studies is the use of self-reporting methods to capture tourists' emotional experience, which may not effectively measure tourists' real-time on-site emotional experience. Specifically, most studies surveyed tourists shortly after their visits (Hosany et al., 2017; Lee, 2016; Prayag et al., 2017) or recorded their previous experience resorting to memory recalls (Han & Back, 2007; Hosany, 2012). As tourist memories may fade or change over time (Barnes et al., 2016), using memory recall may lead to inaccurate measurements of actual experience (Prayag et al., 2017). Researchers have called for better measurements of tourists' emotional experience in real time after recognizing the limitation of measuring tourists' emotional experience through post-trip self-reporting based on memory recall (Han & Back, 2007; Hosany & Gilbert, 2010; Prayag et al., 2017). However, measuring tourists' emotional experience is challenging and complex (Li, Scott, & Walters, 2015; Rahmani et al., 2019), not to mention measuring tourists' real-time on-site emotional experience.

2.3 Measuring tourists' emotional experience

Given the importance of emotional experience in tourism, the measurement of tourists' emotional experience is a critically important but equally challenging and complex task (Li et al., 2015; Rahmani et al., 2019). As mentioned earlier, most studies measured tourists' emotional experience based on self-report (Barnes et al., 2016; Hosany, 2012). In these studies, commonly used scales include Watson, Clark, and Tellegen's (1988) Positive Affect and Negative Affect Scales (PANAS) (Faullant et al., 2011), Hosany and Gilbert's (2010) Destination Emotion Scale (DES) (Hosany, Prayag, Deesilatham, Caušević, & Odeh, 2015; Prayag et al., 2013), Richins's (1997) Consumption Emotion Set (CES) (Han & Back, 2007), and other adapted or self-developed scales (Barnes et al., 2016; Lee, 2016; Ma et al., 2017).

These self-report methods with post-visitation measures often measure tourists' remembered experience, which is temporally unstable (Barnes et al., 2016). This prompted the use of experience sampling methods (ESM) to measure tourists' real-time experience (Shoval et al., 2018), by surveying tourists while they are in the middle of their experience. ESM eliminates recall biases, but cognitive bias, interviewer bias, and other known problems induced by self-report methods are still inevitable. The limitations of this self-report method have been reported in many studies on tourists' emotional experience (Hosany et al., 2015; Kim & Fesenmaier, 2015; Rahmani et al., 2019; Shoval et al., 2018).

Some researchers have stressed the need for physiological measurements because self-report methods with post-visitation measures cannot effectively capture tourists' real-time experience (Prayag et al., 2017). Therefore, objective physiological measures, such as electrodermal activity (EDA), were used to capture tourists' emotional experience. Kim and Fesenmaier (2015) combined EDA data with interviews to measure tourists' emotion in real-time and natural settings. Following this study, Shoval et al. (2018) took a step further by combining EDA, GPS, survey and real-time survey data to measure tourists' emotional experience. The limitations of these physiological measures are obvious. Since they require special devices or equipment, these studies are mainly conducted in laboratories (Kim & Fesenmaier, 2015).

To overcome those shortcomings, new and effective measures of tourists' emotional experience are needed. Recently, the fast development of online user-generated content (UGC) provides a promising alternative. Online UGC data often reflect tourist experience or emotions (Becken, Alaei, & Ying, 2019). Furthermore, tourists' online expressed sentiments have been proven effectively affected tourists' satisfaction (Gitto & Mancuso, 2017), tourists' attitude (Hao et al., 2019), and destination image (Gkritzali, 2017). The effectiveness of using UGC data to evaluate tourists' experience (Tussyadiah & Fesenmaier, 2008) and emotional experience (Rahmani et al., 2019) has also been demonstrated.

Geo-tagged check-in data are records of users presenting at a location and contains both tourist locational data and temporal information. Thus, geo-tagged check-in UGC data can effectively capture tourists' real-time emotional experience at the destination.

3. Methods

3.1 Data

We calculated tourists' sentiments using their geo-tagged check-in UGC to measure real-time on-site tourists' emotional experience. The data were collected from Sina Weibo, the most popular microblogging platform in China, using web crawler technology. When users are near a certain location, they can post a geo-tagged check-in Weibo message with text or images, which contains the users' location information. All check-in Weibo posts of a location will be listed in the check-in homepage of that location.

Geo-tagged check-in Weibo data were collected from the check-in pages of China's AAAAA tourist attractions for the following reasons. First, China is suffering from increasing and concerning levels of air pollution (Becken et al., 2017). In China, air pollution and its impact on tourism have become a widespread concern (Deng et al., 2017; Peng & Xiao, 2018). Second, the uneven spatial distribution of air quality in China across provinces and cities makes it easier to capture the impacts of air quality on different destinations. Third, the AAAAA tourist attraction certification is a quality accreditation system implementation by the Chinese government, in which an AAAAA tourist attraction represents the highest level of tourist attractions in China; an AAAAA tourist attraction is generally large in its scale and attracts large volumes of tourists. A total of 201,653 geo-tagged check-in Weibo posts between August 14th, 2015 and October 14th, 2019 were collected from 233 AAAAA tourist attractions in China.

The limitations of the data must be acknowledged. First, due to the limitation of Sina Weibo's application programming interface (API), only Weibo posts listed in the last 150 pages of each check-in homepage can be collected. However, since we successfully collected more than 200,000 Weibo posts, we believe that the volume is acceptable to conduct big data analysis. Second, our data may suffer from self-selection bias (Goh, 2012; Hughes, Swaminathan, & Brooks, 2019; Li & Xie, 2019; Meire, Hewett, Ballings, Kumar, & Poel, 2019). We will address this issue in the robustness check section.

3.2 Dependent variable

The sentiment analytic technology in natural language processing provides a new way to calculate online expressed sentiment (Zheng, Wang, Sun, Zhang, & Kahn, 2019), and thus can be used to measure tourists' emotional experience. In this study, we carried out a sentiment analysis of extracted tourists' online expressed sentiments. Before the sentiment analysis, we cleaned our Weibo posts data in the following steps: (1) Weibo posts that seemed to be advertisements were excluded by identifying keywords (e.g., "promotion", "discount") and manual checking; (2) Weibo posts that have too few words (less than 15 Chinese characters) were excluded, as those short posts cannot effectively reveal the emotional reactions of tourists.

Sentiment analysis was conducted using the API of Tencent sentiment analysis service from Tencent natural language processing platform[1]. Tencent sentiment analysis technique is based on trillions of Chinese corpus data and different deep neural network models and has been successfully applied on many Tencent products. The Tencent sentiment analysis technique uses machine learning method to extract text sentiment. First, text data were preprocessed to segment sentences into Chinese words, and non-Chinese characters (e.g., numbers, English characters, punctuations) were then excluded. Second, words were tokenized and labeled. Third, the Tencent sentiment analysis was performed using the predefined Long Short-Term Memory (LSTM) and Bidirectional Encoder Representations from Transformers (BERT) models based on Tencent's large Chinese corpus. Finally, the possibility of sentiment classification was generated as the output. The sentiment scores extracted by Tencent sentiment analysis range from 0 to 1, with 0 representing an extremely

[1] https://nlp.qq.com/help.cgi?topic=api#sentiment

negative sentiment and 1 representing an extremely positive sentiment. Following Zheng et al. (2019), we rescaled the range of sentiment scores from 0 to 100 by multiplying 100. In order to measure the emotional experience in one tourist attraction, the user-level Weibo posts were collapsed into attraction/day-level, thus an overall index for a tourist attraction on a given day was measured as the mean sentiment of all check-in Weibo posts in this tourist attraction on the day. Eventually, a total of 43,506 observations (overall emotional experience of a tourist attraction on a day) were included in our analysis.

3.3 Air quality variables

The air quality data were collected from the China National Environmental Monitoring Centre (CNEMC). The CNEMC website reports real-time hourly air quality information on 1,633 monitoring stations. We collected the air quality records from the nearest monitoring station to each tourist attraction, by calculating the distance between the tourist attraction and the monitoring station based on latitude and longitude data. Finally, the real-time air quality records were collected and collapsed to the attraction/day-level. Since Air Quality Index (AQI) is a synthesized and widely used index that measures air quality levels, our first measure of air quality is *AQI*, which synthesizes information on the PM2.5, PM10, SO_2, O_3, NO_2 and CO.

Furthermore, as an AQI of 100 is set in China as the threshold of "blue sky", we developed a dummy variable named *POLLUTED* to measure whether the air is polluted or not, with 1 representing "polluted air" ($100<AQI \leq 500$) and 0 representing "clean air" ($0 \leq AQI \leq 100$).

The Ministry of Environment ranks air quality into six levels based on AQI: excellent ($0 \leqslant AQI \leqslant 50$), good ($50<AQI \leqslant 100$), lightly polluted ($100<AQI \leqslant 150$), moderately polluted ($150<AQI \leqslant 200$), heavily polluted ($200<AQI \leqslant 300$) and severely polluted ($300<AQI \leqslant 500$). As previous studies have observed, tourists may react to air quality according to the air quality standards established by the government (Yoon, 2019). We therefore used the government air quality levels (*LEVEL*) as an alternative measure for air quality. We designed six dummy variables (*EXCELLENT, GOOD, LIGHTLY, MODERATELY, HEAVILY, SEVERELY*) to record

the six levels.

3.4 Weather variables

It is accepted that weather conditions may affect tourist perceptions, experience and behavior (McKercher et al., 2015; Wilkins et al., 2018). Thus, we include weather conditions as independent variables in our model. A number of studies have shown that temperature (Falk, 2014; Hewer et al., 2016; Wilkins et al., 2018), precipitation (Falk, 2014; Hewer et al., 2016), wind (Becken, 2013; Goh, 2012) and cloudiness (Lin & Matzarakis, 2011) affect tourist perception and tourism activity. Thus, daily average temperature (*TEMPERATURE*), wind level (*WIND*), precipitation (*RAIN*) and cloudiness (*CLOUD*) in the tourist attraction were considered.

Temperature has been found to have an inverted U relationship with tourism demand (Falk, 2014), tourist arrivals (Hewer et al., 2016), and social media expressed sentiment (Zheng et al., 2019); hence we created a quadratic term for temperature (*TEMPERATURE_2*) to reflect this non-linear relationship in the model. Weather data of each destination were collected from a widely used Chinese weather query website[2].

3.5 Control variables

Control variables in our model include tourist attraction dummies and time variables. The tourist attraction dummy variables were used to control for the effects of tourist attraction. Tourist experience may differ across different tourist attractions, and tourist attractions' heterogeneity is observed. Also, some studies have controlled for the tourist attraction or city effects when investigating tourist perception or behaviors (Wang et al., 2018). Thus, the tourist attraction dummies (*ATTRACTION*) was used, with 1 representing that the observation is from the attraction and 0 otherwise.

Second, considering seasonality and annual or monthly variation of tourism (Becken, 2013; Hewer et al., 2016), we designed two dummy variables, *YEAR* and

[2] https://tianqi.911cha.com/guoneijingdian.html

MONTH, to reflect the effect of seasonality.

Further, the effects of weekends and holidays should be considered (Hewer et al., 2016), as people are more likely to have more time to travel in these times. On the other hand, people may be happier and express more positive sentiment on social media on weekends and public holidays (Zheng et al., 2019). A dummy variable named *HOLIDAY* was used to show how tourists' sentiments change during the weekends and holidays. All variables used in this study are listed in Table 1.

<Insert Table 1 about here>

4. Results

4.1 Base model

We first looked into the relationship between air quality and tourists' emotional experience. First, the data were sorted by AQI and divided into 500 groups based on the AQI, each group representing a 0.2% AQI range. As shown in Figure 1, the mean value of mean sentiment index for each group is represented by a dot, and fitted by the downwards sloping line with a 95% confidence interval. Figure 1 shows the negative correlation between AQI and tourists' emotional experience. Second, we plotted the mean sentiment index across different air quality levels. The line chart in Figure 2 also shows a significant decrease of mean sentiment index in higher polluted air quality levels. Figure 2 also shows a negative correlation between air pollution and tourists' emotional experience. We took AQI as the independent variable and the mean sentiment index as the dependent variable and proposed a base ordinary least squares (OLS) model without any control variables:

$$MEAN_{i,t} = \beta_0 + \beta_1 AQI_{i,t} + \varepsilon_{i,t} \tag{1}$$

In this model, $MEAN_{i,t}$ indicates the mean sentiment index of tourist attraction i on date t, β_0 is the intercept term, $AQI_{i,}$ indicates the AQI of tourist attraction i on date t, and $\varepsilon_{i,t}$ is the random error term.

The result of the base model shows that the *AQI* has a significant and negative effect on the mean sentiment index ($\beta_1 = -0.0256$, $p < 0.01$). Given that the dependent variable may be affected by other factors, for example, weather conditions, we must specify our main model considering weather conditions as well as tourist attraction effects and time effects.

<Insert Figure 1 about here>

<Insert Figure 2 about here>

4.2 Model specification

To specify the effects of air quality and weather on tourists' emotional experience, we controlled for tourist attraction and time effects. The following models were proposed:

$$MEAN_{i,t} = \beta_0 + \beta_1 AQI_{i,t} + \beta_2 TEMPERATURE_{i,t} + \beta_3 TEMPERATURE\_2_{i,t} + \beta_4 RAIN_{i,t} + \beta_5 WIND_{i,t} + \beta_6 CLOUD_{i,t} + \beta_7 HOLIDAY_{i,t} + \Pi YEAR + \Lambda MONTH + \Omega ATTRACTION + \varepsilon_{i,t} \quad (1a)$$

$$MEAN_{i,t} = \beta_0 + \beta_1 POLLUTED_{i,t} + \beta_2 TEMPERATURE_{i,t} + \beta_3 TEMPERATURE\_2_{i,t} + \beta_4 RAIN_{i,t} + \beta_5 WIND_{i,t} + \beta_6 CLOUD_{i,t} + \beta_7 HOLIDAY_{i,t} + \Pi YEAR + \Lambda MONTH + \Omega ATTRACTION + \varepsilon_{i,t} \quad (1b)$$

$$MEAN_{i,t} = \beta_0 + \gamma LEVEL_{i,t} + \beta_2 TEMPERATURE_{i,t} + \beta_3 TEMPERATURE\_2_{i,t} + \beta_4 RAIN_{i,t} + \beta_5 WIND_{i,t} + \beta_6 CLOUD_{i,t} + \beta_7 HOLIDAY_{i,t} + \Pi YEAR + \Lambda MONTH + \Omega ATTRACTION + \varepsilon_{i,t} \quad (1c)$$

In the above models, *i* and *t* represent tourist attractions and date respectively; *MEAN* is the dependent variable; *AQI*, *POLLUTED*, *LEVEL* are air quality variables; *TEMPERATURE*, *TEMPERATURE_2*, *RAIN*, *WIND*, and *CLOUD* are weather variables; *HOLIDAY*, *YEAR*, *MONTH*, and *ATTRACTION* are control variables. β_0 is the intercept term, β is the estimated coefficient for each variable, and $\varepsilon_{i,t}$ is the random error term.

4.3 Effects of air quality and weather conditions on tourists' emotional experience

Considering that the air quality measure and weather variables may correlate with each other, multicollinearity check were conducted. Results suggest that the multicollinearity should not be a problem in all the three models, with the variance inflation factor (VIF) ranging from 1.01 to 4.55, less than the legitimate cutoff value in the range of 5 to 10 (Stine, 1995).

The results of our full models (Equations1a-1c) are presented in Table 2. After considering the control variables, the AQI still shows a negative and significant relationship with the mean sentiment index. In Model 1a, the coefficient (β_1 = −0.0150, $p< 0.01$) indicates that a one standard deviation increase in AQI would result in a 0.0150 standard deviation decrease in the mean sentiment index.

Then, we estimated the effects of the dummy variable *POLLUTED*. Results in Model 1b show that the mean sentiment expressed in the polluted days (AQI > 100), was significantly smaller than that in the unpolluted condition (AQI ≤ 100), indicating that tourists presented more negative sentiment on polluted days (β_1 = -1.2372, $p< 0.05$).

Finally, we analyzed the effect of air quality levels. The results from Model 1c show a non-linear and negative relationship between air pollution and tourists' emotional experience, which indicates that tourists' emotional experience decreased monotonically and non-linearly with the increase in air quality levels. Specifically, tourists' emotional experience was significantly and negatively affected by air pollution when the air pollution levels are *MODERATELY* (β_1 = -2.6443, $p< 0.05$), *HEAVILY* (β_1 = -4.1465, $p< 0.01$) and *SEVERELY* polluted (β_1 = -7.2830, $p< 0.05$).

Subsequently, we examined the effects of weather conditions on tourists' emotional experience. First, temperature shows an inverted U effect on tourists' emotional experience in the three full models, with a positive coefficient of *TEMPERATURE* and a negative coefficient of the quadratic term (*TEMPERATURE_2*). Second, cloudiness (*CLOUD)* shows negative and significant effects in the three full models. Finally, *WIND* and *RAIN* have non-significant effects on tourists' emotional experience.

In terms of the control variables, *HOLIDAY* has no significant effect on tourists' emotional experience. Further, tourists' emotional experience varies across years (*YEAR*), showing an upward trend in the year effective from 2016 to 2018 and some drop in 2019. There is no significant month effect (*MONTH*) on tourists' emotional experience. Finally, tourists' emotional experience varies greatly in different tourist attractions, indicating that tourists' emotional experience was significantly affected by tourist attractions.

<Insert Table 2 about here>

5. Robustness Tests

5.1 The robustness of air quality measure

PM2.5 is one of the main components of air pollution and the primary pollutant in many areas, and it is a suitable proxy of air quality. In our data, AQI and PM2.5 show a high and significant correlation (coefficient = 0.9415, $p< 0.01$). Therefore, we used PM2.5 to test the robustness of our air quality measure. As shown in Table 3 (column 1), PM2.5 had a negative and significant effect on the mean sentiment index ($\beta_1 = -0.0151$, $p< 0.05$). For the weather variables, temperature shows a significant inverted U effect, and cloudiness (*CLOUD*) has a negative and significant effect, confirming the results of our main model.

5.2 The robustness of the dependent variable

In our models, we used the mean sentiment index as the dependent variable. To test the robustness of our results, we collapsed the sentiments into attractions/day level based on the median value of the sentiment, and took the median sentiment index as the dependent variable. Similarly, we estimated the effects of three measures (*AQI*, *POLLUTED* and *LEVEL*) on the median sentiment index. As shown in Table 3 (columns 2-4), after replacing our dependent variable with the median sentiment index, the variable of air pollution still negatively and significantly affects the sentiment index. Temperature still shows an inverted U effect on tourists' emotional experience; cloudiness (*CLOUD*) shows negative and significant effects on the median sentiment index, while *WIND* and *RAIN* have non-significant effects.

<Insert Table 3 about here>

5.3 Selection bias

Our data may suffer from self-selection bias since we were dealing with an online population (Hughes et al., 2019; Li & Xie, 2019; Meire et al., 2019). Thus, we used a Propensity Score Matching (PSM) method to alleviate the endogeneity and selective bias concern. In this regard, we mainly considered the relationship between air quality and tourists' emotional experience. The propensity score is the predicted probability that the observed unit (a certain attraction in a certain day) receives a treatment condition (a polluted day) on the value of covariates. When the propensity scores are close enough, the treatment is considered random, and the selection bias can be considered eliminated.

A logit model was specified to predict the probability of an attraction on a polluted day. The dummy variable (*POLLUTED*) was used as the dependent variable, and the predictor variables include attraction variables, time variables and weather variables. We used the latitude (*LATITUDE*) and longitude (*LONGITUDE*) to capture the location of attractions. Other variables are the same as those in the main model. Results indicate that those variables are good predictors to the probability of an attraction in a polluted day. Thus, those variables were used in the matching step. A 1:1 nearest-neighbor matching algorithm was used. The matched results contain a total of 7,590 observations, with 3,975 in the polluted condition and 3,795 in the unpolluted condition.

After matching, the control group (unpolluted condition) and treatment group (polluted condition) do not have significantly different covariates (see Table 4). Also, the mean sentiment index was significantly different between the control group and the treatment group. Specifically, the mean sentiment index in the polluted condition (mean = 75.50) was significantly smaller than the mean sentiment index in the unpolluted condition (mean = 77.77, $p < 0.01$), again confirming the robustness of our results.

<Insert Table 4 about here>

6. Conclusions and Discussion

Environmental psychology studies have demonstrated the effects of air quality (Marques & Lima, 2011; Peng et al., 2020) and weather conditions (Noelke et al., 2016) on human emotional states. In tourism, the significant role of air quality (Peng & Xiao, 2018; Poudyal et al., 2013; Zajchowski et al., 2019; Zhang et al., 2020) and weather (McKercher et al., 2015; Wilkins et al., 2018) on tourist experience has been noticed, but their effects on tourists' emotional experience have not been empirically investigated. Also, studies on tourists' emotional experience paid limited attention on tourists' real-time on-site emotional experience, due to the lack of efficient and effective measures. To fill these gaps, this study developed an innovative measure, and empirically modelled the impact of air quality and weather conditions on tourists' real-time on-site emotional experience.

Using the sentiment scores of tourists' geo-tagged check-in UGC data, this study confirmed the significantly negative impact of air pollution on tourists' emotional experience. This finding is consistent with other empirical studies that show the negative effect of air pollution on tourist perceptions (Li et al., 2016; Peng & Xiao, 2018; Zhang et al., 2020). Furthermore, our results provide empirical evidence to support previous arguments that air quality may affect tourist experience (Peng & Xiao, 2018; Poudyal et al., 2013; Zajchowski et al., 2019; Zhang et al., 2020). A non-linear relationship was observed between air quality and tourists' real-time on-site emotional experience. Air quality has a significant impact on tourists' experience only when air pollution exceeds the moderately polluted level. This finding echoes other studies (Wang & Chen, 2020; Yoon, 2019), which indicate that slight air pollution seems to be acceptable to tourists, and tourists begin to realize the impact of air pollution only when the air quality level becomes worse than moderately polluted. More importantly, this study found that weather variables play significant roles in affecting tourists' emotional experience. It was found that temperature has an inverted U-shaped effect on tourists' emotional experience, which is in line with the findings of other relevant studies (Falk, 2014; Hewer et al., 2016; Zheng et al., 2019). Limited studies noticed the effects of cloudiness on tourism (Lin & Matzarakis, 2011). Our study found that cloudiness is a significant but largely overlooked weather factor for tourists' emotional experience. However, our findings show little empirical evidence that precipitation and wind affect tourists' emotional experience.

By investigating the impact of air quality and weather on tourists' emotional experience, this study contributes to the literature in three ways. First, this study provides hard evidence on the impact of air quality on tourists' emotional experience, extending the studies on environmental psychology and tourist experience. Though the impacts of air quality on tourism have been investigated in many aspects (Xu et al., 2020; Zhou et al., 2018), and the negative effects of air pollution on tourist experience have been noticed (Peng & Xiao, 2018), the relationship of air quality and tourists' emotional experience remains yet to be empirically verified. This study modelled this relationship and provided empirical evidence to support previous arguments that air quality (Peng & Xiao, 2018; Poudyal et al., 2013; Zajchowski et al., 2019; Zhang et al., 2020) may affect tourists' emotional experience, and found the non-linear effects of air quality on tourists' emotional experience,

Second, this study provides a methodological contribution by adding an objective and effective real-time measure of tourists' emotional experience. Previous methods either used the self-reporting approach (Barnes et al., 2016; Hosany, 2012) or applied physiological measures (Kim & Fesenmaier, 2015; Shoval et al., 2018) to evaluate tourists' emotional experience. Such approaches, however, cannot capture real-time responses (Barnes et al., 2016; Hosany & Gilbert, 2010; Prayag et al., 2013) and are not cost-efficient (Kim & Fesenmaier, 2015; Shoval et al., 2018). The emergence of sentiment analytic techniques and social media data provides a new opportunity to explore tourists' emotional experience. Thus, this study used the sentiment scores generated from tourists' geo-tagged check-in UGC data to measure tourists' real-time on-site emotional experience, providing an innovative method in measuring tourists' emotional experience and demonstrating the usefulness of sentiment analytics and online UGC data in monitoring tourists' emotional experience.

Finally, this study provides deep insights into the relationship between weather conditions, air quality and tourists' emotional experience grounded on environmental psychology literature. Weather is also an important environmental factor affecting tourism activities (Chen et al., 2017; Wilkins et al., 2018). This study explored the effects of several weather conditions and observed an inverted-U effect of temperature on tourists' emotional experience, and thus expanded our understanding of how weather conditions affect tourist experience. Also, by examining the effects of both air quality and weather conditions on tourists' emotional experience, this study provides deep insights into the impact of environment on tourism and advances the applications of environmental psychology in tourism settings.

This study has important implications for destinations. First, since poor air quality will undermine tourists' emotional experience, destination management should involve measures to improve the air quality in the destination. The interaction between tourism activity and air quality has been observed (Becken et al., 2017). Thus, some concrete actions, such as putting limits on the number of tourists, can be employed to improve the air quality in the destination. Second, destinations can report real-time air quality and weather information on social media to better prepare tourists to make flexible travel plans. Finally, the combination of tourists' online UGC data and natural language processing can be used to monitor tourists' sentiment and word-of-mouth, and thus offering a new approach for destination experience management.

Several limitations of this study should be acknowledged. First, the use of check-in data from Weibo is a limitation. Although Weibo is one of the most commonly used social media platforms in China, and deemed to be appropriate for this study, data from other social media platforms may be supplemented. Also, we did not consider international tourists, who may have different emotional responses compared to Chinese tourists. Thus, the exploration of international tourists' emotional experience in a western setting is encouraged in future studies. Finally, the attraction-level sentiment index was used in this study to capture tourists' overall emotional experience. As such, the individual characteristics of tourists' emotional experience are not considered. Researchers should include individual characteristics of tourists in future studies considering that different market segments may perceive air quality differently (Becken et al., 2017).

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