DOI: 10.1111/tgis.12552

RESEARCH ARTICLE

Transactions in GIS WILEY

Extracting human emotions at different places based on facial expressions and spatial clustering analysis

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Abstract

The emergence of big data enables us to evaluate the various human emotions at places from a statistical perspective by applying affective computing. In this study a novel framework for extracting human emotions from large-scale georeferenced photos at different places is proposed. After the construction of places based on spatial clustering of user-generated footprints collected from social media websites, online cognitive services are utilized to extract human emotions from facial expressions using state-of-the-art computer vision techniques. Two happiness metrics are defined for measuring the human emotions at different places. To validate the feasibility of the framework, we take 80 tourist attractions around the world as an example and a happiness ranking list of places is generated based on human emotions calculated over 2 million faces detected from greater than 6 million photos. Different kinds of geographical contexts are taken into consideration to find out the relationship between human emotions and environmental factors. Results show that much of the emotional variation at different places can be explained by a few factors such as openness. The research offers insights into integrating human emotions to enrich the understanding of sense of place in geography and in place-based GIS.

1 | INTRODUCTION

Place, which plays a central role in daily life not only as a location reference but also reflecting the way humans perceive, experience and understand the environment, is a key issue in geography and GIScience (Tuan, 1977; Goodchild, 2011; Winter & Freksa, 2012; Scheider & Janowicz, 2014; Goodchild, 2015; McKenzie, Janowicz, Gao, Yang, & Hu, 2015; Gao et al., 2017a; Gao, Li, Li, Janowicz, & Zhang, 2017b; Blaschke et al., 2018; Zhang, Zhang, Liu, & Lin, 2018a; Purves, Winter, & Kuhn, 2019; Wu, Wang, Shi, Gao, & Liu, 2019). Agnew (2011) proposed three aspects of place: location, locale, and sense of place, which refers to the experiences of people and their perceptions and conceptualizations of place. And place has been comprehensively depicted as the context and affordance with various human activities, linking to memories and emotions of individuals (Jordan, Raubal, Gartrell, & Egenhofer, 1998; Kabachnik, 2012; Scheider & Janowicz, 2014; Merschdorf & Blaschke, 2018). Human emotions, which are innately stored in human neural systems (Wierzbicka, 1986; Izard, 2013), provide bridges linking the surrounding environments and human perceptions. On the one hand, emotions color human experiences (Tuan, 1977), and show how places are psychologically felt by people (Davidson & Milligan, 2004). One the other hand, emotions are proved to be connected to and affiliated with surrounding things, including living organisms (Wilson, 1984), natural environments (Capaldi, Dopko, & Zelenski, 2014), and cultural environments (Mesquita & Markus, 2004). Therefore, understanding human emotions in the environmental context is important for human behavior analysis toward the understanding of sense of place (Grossman, 1977; Rentfrow & Jokela, 2016; Smith & Bondi, 2016).

Early studies used questionnaires to investigate the emotions of people in different environmental contexts, which is costly in terms of human resources and lacks timeliness (Golder & Macy, 2011). The emergence of big data and the development of information and communications technology (ICT) and artificial intelligence (AI) provide advanced methodologies and opportunities to solve the aforementioned problems in social sensing (Liu et al., 2015; Ye, Huang, & Li, 2016; Janowicz, McKenzie, Hu, Zhu, & Gao, 2019; Zhang, Zhu, & Wu, 2019). Affective computing, as an interdisciplinary domain spanning computer science, psychology, and cognitive science, was proposed by Picard (1995) with a focus on investigating the interactions between computer sensors and human emotions. Everyday, large volumes of geotagged user-generated content (UGC) is uploaded to social networking websites such as Facebook and Twitter, photo-sharing sites such as Flickr and Instagram, as well as the video-sharing platform YouTube (O'Connor, 2008), which can reflect human perceptions of environments as sensors and their contributions to the volunteered geographic information (Goodchild, 2007). Affective memories are produced and archived in these technology-mediated platforms (Elwood & Mitchell, 2015). In such UGC, people express their emotions actively or passively, through tone of voice (Schuller, Vlasenko, Eyben, Rigoll, & Wendemuth, 2009), facial expressions (Ekman, 1993), body gestures, and written forms (Bollen, Mao, & Pepe, 2011). Also, state-of-the-art AI technologies make it possible to collect human emotions from massive data sources and have revolutionized research in cognitive science. Several existing studies have tried to connect geography and collective emotions from UGC using advanced technologies and have obtained promising results (Mitchell et al., 2013). However, there is still an absence of attention to the role of place as locale in human emotions (Smith & Bondi, 2016). In addition, most existing research has used natural language processing to extract human emotions from textual corpuses (Strapparava & Valitutti, 2004; Cambria, Havasi, & Hussain, 2012). Such methods may face challenges such as multicultural differences in language, which may not be suitable for global-scale research (see Sections 2 and 5). In comparison, the facial expression of emotions is said to be universal across countries and different periods, and can capture human emotions in real time, which may support a place-based emotion extraction framework on a global scale.

In this research, our goal is to investigate human emotions in places and explore potentially influential environmental factors. We term the study phenomenon *place emotion*, which is a special case of the general affective computing in geography, that is, to examine the human emotions at different places with different affordances (including the environment and human activities). The research questions are as follows. First, how do we extract and compute human emotion scores from georeferenced photos taken in different places? Second, what is the relationship between human emotions and environment factors in specific places? To answer these questions, a general framework utilizing UGC to compute human emotion scores at places based on facial expression recognition and spatial clustering techniques is proposed. However, since there are many types of places with a variety of environment factors, we only select one specific type of place (i.e. tourist attraction sites) as a case study to test the feasibility of our proposed workflow.

Tourist attractions, which attract “non-home” travelers for sightseeing, activities, and experiences (Leiper, 1990; Lew, 1987), are a popular type of place (Jones, Purves, Clough, & Joho, 2008) and are located across the world, making them suitable as a case study of global-scale research. In recent decades, with economic growth and developments in transportation, tourism has experienced continued growth and deepening diversification to become one of the fastest-growing economic sectors in the world (Ashley, De Brine, Lehr, & Wilde, 2007). For a tourist, the choice of places to visit in planning a trip is the first step (Bieger & Laesser, 2004; Sun, Huang, Peng, Chen, & Liu, 2019); the options are often numerous. When retrieving information about tourist sites, a fair and comprehensive ranking list of tourist attractions is often useful. However, existing ranking lists rely on the environment (Amelung, Nicholls, & Viner, 2007) and socioeconomic (Bojic, Belyi, Ratti, & Sobolevsky, 2016; Chon, 1991) aspects of the tourist sites. These factors indeed influence travel flows, but only in an objective manner. The perceptions and feelings of tourists are often ignored. A ranking list based on human emotions might provide different insights from human-oriented preferences. Additionally, happiness is one of the most common basic emotions (Ekman & Davidson, 1994; Eimer, Holmes, & McGlone, 2003; Izard, 2007). Therefore, a ranking list of the happiest tourist sites in the world could be created as an outcome of the affective computing at each site.

To this end, this study presents a novel framework to measure human emotions at places from facial expressions and to explore factors that influence the degree of happiness at different places. Tourist sites are taken as a specific type of place for experiment. The contributions of the study are threefold. First, we propose a novel approach for extracting and characterizing the average happiness score at each place using computer vision and spatial analysis techniques. Second, we explore the relationship between different kinds of environmental contexts and the degree of happiness extracted from human facial expressions. Third, we create a ranking list of the happiest tourist sites based on crowdsourcing human emotions rather than objective indices, and provide new insights into integrating human emotions to enrich the understanding of sense of place in geography and in place-based GIS.

The remainder of this article is organized as follows. In Section 2 we present a review of the literature on place emotion related studies. In Section 3 we set out a methodological framework and explain our computational procedures. In Section 4 we test the framework with a case study of human emotions at 80 tourist attractions around the world. We discuss the implications and comparison of our image-based method to the text-based studies in Section 5. Finally, in Section 6, we present our vision for future research and our conclusions.

2 | RELATED WORK

There are two categories of affective computing. One is about several instinctive basic emotions such as happiness, sadness, and anger (Ekman & Davidson, 1994). The other is concerned with detecting the polarity of sentiments like positive, neutral and negative expressions, which are organized feelings and mental attitude (Pang & Lee, 2008). Unless specifically clarified, in this article we use the general term “emotion" to represent both categories interchangeably. Both emotion and sentiment studies enable us to understand human perceptions of society and the environment (Zeng, Pantic, Roisman, & Huang, 2009). Exploration and understanding of human emotions and sentiments have attracted considerable interest from psychology (Ekman, 1993; Berman et al., 2012; Svoray, Dorman, Shahar, & Kloog, 2018), biology (Darwin & Prodger, 1998), computer science (Lisetti, 1998), geography (Davidson & Milligan, 2004; Mitchell, Frank, Harris, Dodds, & Danforth, 2013; Svoray et al., 2018; Hu, Deng, & Zhou, 2019), and public health (Zheng, Wang, Sun, Zhang, & Kahn, 2019), to name but a few.

Methods of collecting emotion data have evolved over time. Traditionally, scholars from the social sciences use questionnaires and self-reports to investigate the emotions of people in different environmental contexts (Niedenthal, Rychlowska, Wood, & Zhao, 2018). Several rankings of human's happiness have been published in recent years, including the *World Happiness Report* released by the United Nations Sustainable Development Solutions Network (http://worldhappiness.report), which ranks the happiness of countries' citizens by investigating socioeconomic indices. The Measuring National Well-being program of the UK Office of National Statistics aims to monitor and measure the well-being of citizens. Gross National Happiness is an index used by the government of Bhutan to measure aspects of living standards, health, and education. The Satisfaction With Life Scale measures the life satisfaction components of subjective well-being (http://www.midss.org/satisfaction-life-scale-swl). However, those methods are beset with challenges despite their widespread use in psychological science. For example, they tend to be costly in terms of human resources and to lack timeliness (Golder & Macy, 2011). Results relying on questionnaires may be subject to constraints of self-knowledge and the psychological influence of informed consent (Baumeister, Vohs, & Funder, 2007).

With the emergence of affective computing technologies, more efficient ways for detecting human emotions can be used. Numerous studies on affective computing have been conducted and enjoy great success, especially using natural language processing methods to extract emotions from texts and explain them from a geographic perspective. For example, Mitchell et al. (2013) estimated human happiness at the state level in the U. S. and explored the impact of socioeconomic attributes on human moods. Ballatore and Adams (2015) utilized a corpus of about 100,000 travel blogs to extract the emotional structure (including joy, anger, fear, sadness, etc.) of different place types. Bertrand, Bialik, Virdee, Gros, and Bar-Yam (2013) generated a sentiment map of New York City via extraction of emotions from tweet data. Zhen, Tang, and Chen (2018) calculated human emotion scores using Weibo tweet data and explored the spatial distribution of sentiments in Nanjing. Zhen et al. (2018) demonstrated that high levels of air pollution (e.g. PM 2.5) may contribute to the urban population's reported low level of happiness on social media based on analytics of over 210 million geotagged tweets on Weibo. Hu et al. (2019) presented a semantic-specific sentiment analysis on online neighborhood textual reviews for understanding the perceptions of people toward their living environments.

However, text-based measurements of emotions may encounter challenges. One problem is that texts are often recorded after events. This means that the emotions expressed are not in real time, but often after a period of transition. The buffering time period may be beneficial to the user who expresses emotions: during a calm-down period, the user may utilize more dispassionate linguistic expression to maintain a stable social identity (Coleman & Williams, 2013). Another challenge in extracting emotions from texts is the multilingual environment. Different languages may vary in vocabulary and syntax for expressing emotions. Furthermore, most emotion extraction models are based on the words or syntactic and semantic structures of sentences, which are unique in each language (Shaheen, El-Hajj, Hajj, & Elbassuoni, 2014). So far, no existing method has been able to standardize the emotional scores computed from all different language models. Therefore, affective computing based on texts has been limited to the analysis of materials in one language at a time. For multilingual problems, text-based affective computing may be beset with difficulties.

In comparison, image-based approaches (Zhang et al., 2018b), especially facial expression-based emotion extraction methods, have improved greatly in recent years because of the emergence of deep convolutional neural networks (Yu & Zhang, 2015), which even perform better than humans in face-recognition benchmark testing (Wang & Deng, 2018). Svoray et al. (2018) analyzed Flickr photos and found a positive relationship between human facial expressions of happiness and exposure to nature with urban density, green vegetation, and proximity to water bodies in the city of Boston. By extracting and identifying key points from facial images based on facial activities and muscles, machine learning models can learn the visual patterns of faces according to the emotional labels (Calvo & D'Mello, 2010). Therefore, the emotions of faces can be extracted. Each culture has its own verbal language, and emotion has its own language of facial expressions. The relationship between emotions and facial expressions has been extensively explored. Levenson, Ekman, and Friesen (1990) pointed out that subjective emotions have significant connections to facial activity, which provides the fundamental theories of affective computing based on facial expressions. Emotion recognition methods based on facial expressions have several advantages. First, facial expressions are both universal and culturally specific (Matsumoto, 1991). Though connections between emotions and cultures vary (Cohn, 2007), strong evidence has been provided that there is a pan-cultural element in facial expressions of emotion (Ekman & Keltner, 1970). People from ancient times to the present, from all over the world, and even our primate relatives have similar basic facial expressions, especially smiling and laughter (Preuschoft, 2000; Parr & Waller, 2006). This indicates that humans are universal when representing basic emotions and that facial expression-based emotion extraction methods are suitable for global-scale issues, especially for solving the multilingual problem. In fact, some existing researchers have explored the worldwide expression of emotions based on facial expressions in photos (Kang, Zeng, Zhang, Wang, & Fei, 2018), which shows the universal compatibility of such methods. In addition, facial expressions are produced spontaneously when emotions are elicited (Berenbaum & Rotter, 1992). By recording and analyzing facial expressions, researchers can identify emotions as they are formed. As advanced computer-vision based systems and algorithms are becoming more mature, facial expressions as well as facial muscle actions can be recognized and computed with quantitative scores (possibilities) of recognized emotions (Ding, Zhou, & Chellappa, 2017; Kim, Roh, Dong, & Lee, 2016; Zeng et al., 2009). As a result, research based on facial expression is spreading in affective computing. For instance, Kang, Wang, Wang, Angsuesser, and Fei (2017) examined the emotion expressed by users in Manhattan, NY, and compared human emotions with stock market movement to explore the relationship between the two. Abdullah, Murnane, Costa, and Choudhury (2015) used images from Twitter to calculate emotions from facial expressions and compared them with socioeconomic attributes. Singh, Atrey, and Hegde (2017) analyzed smiles and diversity via social media photos and pointed out people that smile more in diverse company.

In sum, considering that emotions can be recorded in real time and are universal in multilingual environments, facial expressions might be more suitable for place-based emotion extraction on a global scale, as places are located around the world with affording different groups of people and various kinds of activities. To the best of our knowledge, our research is one of the first studies to utilize state-of-the-art facial expression recognition techniques and large-scale georeferenced photos to explore human emotions at different places on a global scale.

3 | METHODOLOGY

3.1 | Framework

As shown in Figure 1, there are four steps in the framework of extracting and measuring human emotions at different places. First, large-scale georeferenced crowdsourcing photos in social media are collected and positioned on the data server. Several geographical and environmental attributes (e.g. the proximity to water bodies, openness, landscape type) of each place are also retrieved and recorded. Second, the footprints of "places" in our study are generated using the area of interest extraction approach based on the spatial density of photos (Li & Goodchild, 2012; Hu et al., 2015). Then, with state-of-the-art cognitive recognition methods based on computer vision technologies (e.g. object detection and localization), human emotions are extracted and measured via facial expressions detected in the social media photos. In order to examine whether results of affective computing are robust and solid, we also implemented sensitivity tests to check the concordance of results with varying algorithm parameter settings.

After the calculation of human emotions at different places, it is necessary to explore what environmental factors influence the expression of human emotions. Correlation analysis and multilinear regression models are utilized to explore the relationship between human emotions and environmental factors.

3.2 | Data preparation

There are two data sets used in this research. One is the places as well as their geographic attributes for exploring the relationship between human emotions and environments. The other is georeferenced social media photos for affective computing, which are collected from the Flickr website based on place name coordinate information.

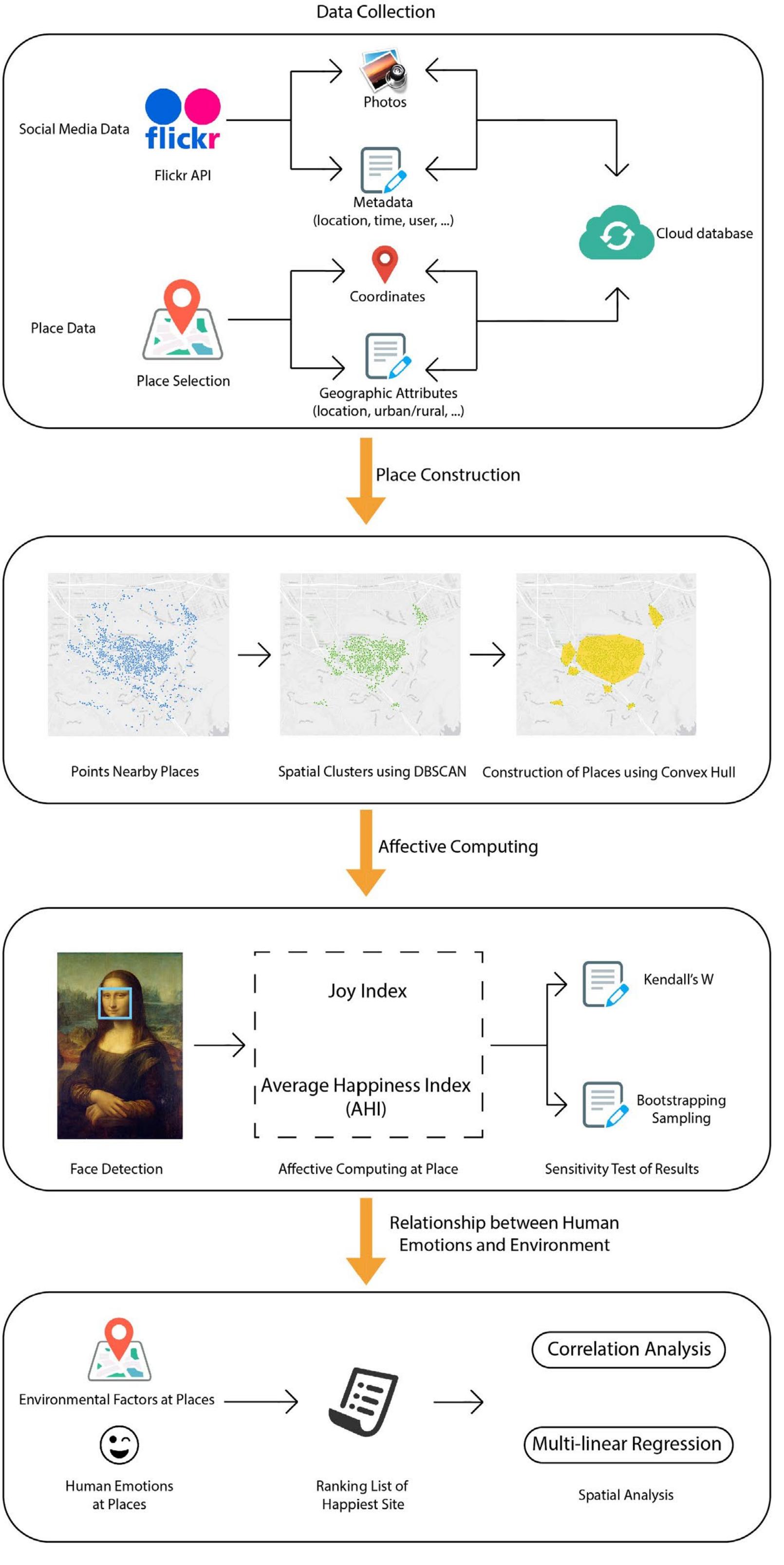


FIGURE 1 Workflow of this research

In many geographic information systems and digital gazetteers, places are often represented as points of interest, although places have footprints that vary by type (e.g. points, lines, or polygons) (Goodchild & Hill, 2008). Based on the place names, the coordinates of those place centers are harvested from the Google Maps Places API (https://developers.google.com/places/web-service/intro). A list of geographic attributes and environment factors are recorded at each place (see Section 4.1 for more details).

Photos taken at different places are obtained from the Yahoo Flickr platform. Flickr is a publicly available social media platform where users can upload and share their photos, and it is one of the most commonly cited websites in the era of Web 2.0 (Cox, 2008). Options for geotagging photos are also provided in the website as more and more GPS chips are embedded in smart phones and cameras. Time and geographical information are recorded automatically when saving photos from location-aware devices. In addition, users can drag their photos onto a map and input their locations for geotagging upon uploading. Therefore, each photo can be positioned on the map. For most photos, the locations can be labeled correctly and any uncertainty in the data (e.g. incorrect location of photo) can be removed by construction of the place introduced in Section 3.3.

Flickr's API (https://www.flickr.com/services/api/) allows developers and researchers to collect a large amount of data from the platform. Public geotagged photos, with information including user ID, photo ID, latitude, longitude, tag text, time-stamp and so on, are retrieved and recorded within a certain distance of the center point at specific places. The center point coordinates of places are retrieved from the Google Place API. Each photo is saved with its original resolution while keeping a link pointing to its original URL. All the information is stored in a database for data manipulation.

3.3 | Construction of Places

As place is a product of human conceptualization that is derived from the human experience of describing a specific space (Tuan, 1977; Couclelis, 1992; Curry, 1996; Merschdorf & Blaschke, 2018), a major challenge for modeling places in GIS is the vague boundaries (Burrough & Frank, 1996; Montello, Friedman, & Phillips, 2014; Gao et al., 2017a). The boundary is often generated from the density estimation and spatial clustering of georeferenced photos (Feick & Robertson, 2015; Hu et al., 2015). In this research, places are constructed by the following steps based on user generated photo footprints: (1) utilizing density-based spatial clustering for application with noise (DBSCAN) to extract the hotspot zones of human activities; and (2) using the convex hull to find out the minimum bounding geometry based on a set of points remaining after spatial clustering.

DBSCAN, which is a point-based spatial clustering algorithm (Ester, Kriegel, Sander, & Xu, 1996), is used to identify clusters of geotagged photos. Compared with the k-means clustering algorithm, DBSCAN can find arbitrarily shaped clusters, and it does not require the predefined number of clusters in advance. In addition, it is relatively stable and robust to noise. Some geotagged photos are manually uploaded by users without specific criteria and may generate noise; for example, a user may drag photos to incorrect locations. By applying the DBSCAN algorithm, those noiseye data can be removed and the core areas of each place, in other words, the hotspots where users are most likely to stay and to take photos, will remain.

The DBSCAN algorithm requires two parameters, namely ε and *minPts*. The first, the search radius, representing the maximum distance from the search neighborhood to the center point, is denoted by ε. The second, denoted *minPts*, indicates the minimum number of points a cluster should have. Different values of the two parameters will influence the results, and proper values according to the characteristics of places should be selected. As suggested by several previous researchers (Hu et al., 2015; Mai, Janowicz, Hu, & Gao, 2018; Liu, Huang, & Gao, 2019), a value between 40 and 300 m for ε is suggested in clustering human activities. As the number of photos and users may vary in different places, it is not appropriate to use an universal absolute number for *minPts*. Therefore, a percentage of the number of photos at a certain place is used. Consequently, a combination of different parameter settings should be tested to find out the best parameter combination.

After the spatial clustering of photo locations, the next step is to derive the core areas of places from the clustered points. The convex hull is a high-quality geometric approximation method used for efficiently clustering geographical features (Graham, 1972; Barber, Dobkin, & Huhdanpaa, 1996; Liu et al., 2019; Yu et al., 2014). A convex hull is the minimum bounding polygon containing a set of points. It has been utilized in a number of studies to find the minimum bounding shape of the clustered points (Liu et al., 2019).

Figure 2 shows the process of construction of places that are represented as polygons generated from the aforementioned steps.

3.4 | Measurement of human emotion

One main research question in this work is how to extract basic human emotions and to quantify the degree of happiness expressed by users at different places. State-of-the-art computer vision and cognitive recognition technologies make it possible to extract and quantify human emotions from facial expressions. In this study we propose two indices, namely the "joy index" and the "average happiness index," to measure the degree of "happiness atmosphere" at each place.

3.4.1 | Affective computing

We used the Face++ Emotion API (https://www.faceplusplus.com/emotion-recognition/) to detect human faces in photos and to extract human emotions based on their facial expressions. The Face++ platform is a mature commercial cloud computing enabled AI technology provider with a large number of customers and developers using its products, and is said to perform well in several facial recognition-related competitions (https://www.faceplusplus.com/blog/article/coco-mapillary-eccv-2018/), which proves the reliability of the system, and hence its selection for extracting emotions from human faces. A set of computer vision-based services are provided for human facial recognition and analysis. The attributes of all faces in a photo are extracted, including the face position and extent, human emotion, age, ethnicity, gender, and even beauty. The Face++ API produces two measurements for evaluating the emotion of human faces. One is the *smile*, which describes the smile intensity (Whitehill, Littlewort, Fasel, Bartlett, & Movellan, 2009) and includes two elements, the *smile value* and *smile threshold*. The smile value is a numeric score (from 0 to 100) to indicate the degree of smiling, while the smile threshold is provided by the cloud AI system to judge whether the detected face is smiling or not. Generally, if the smile value is greater than the smile threshold, the face is judged to be smiling. Therefore, based on the smile attribute, each face in the photo is classified as either smiling or not smiling. The other measurement is *emotion structure*, which is a vector of scores (from 0 to 100) to describe seven basic emotional fields: anger, disgust, fear, happiness, neutral, sadness, and surprise. All scores of any one face sum to 100. The higher the score is, the more confidence an emotion represents. Hence, the emotion field could illustrate the intensity of a particular emotion from different dimensions.

It is worth noting that not all emotion fields are used in this study. Happiness is often recognized as one of the most common basic emotions (Izard, 2007). Although some arguments exist (Frank & Ekman, 1993), smile can represent happiness in general. In addition, as happiness is the clearest emotional domain compared with all other dimensions of emotion (Wilhelm, Hildebrandt, Manske, Schacht, & Sommer, 2014), we only use the happiness value from the emotion structure. Figure 3 shows the happiness scores extracted from different human faces in photos. Notice that the actual human faces rather than those on paintings will be detected and analyzed in the experiments.

3.4.2 | Emotional indices for places

Two place-based human emotion measurement indices are proposed to evaluate the degree of happiness at different places in this study: the "joy index" based on the smiling score and the "average happiness index" based on the happiness score.

The joy index is calculated with consideration of the normalized difference between the number of smiling faces and the number of non-smiling faces using geotagged photos within the spatial footprint of each place as follows:

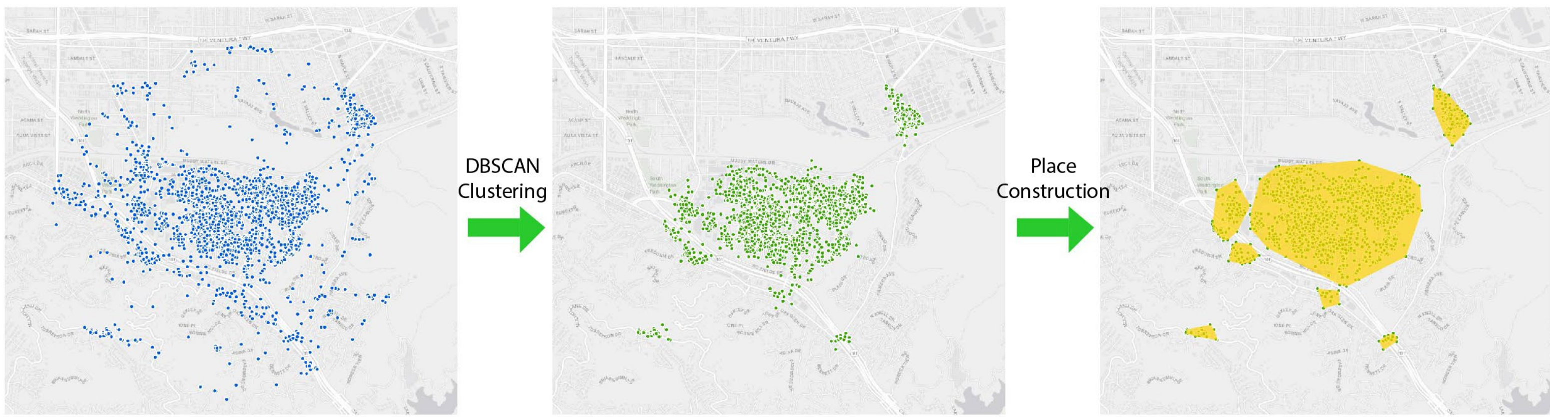


FIGURE 2 Construction of a place based on spatial clustering and the convex-hull approach

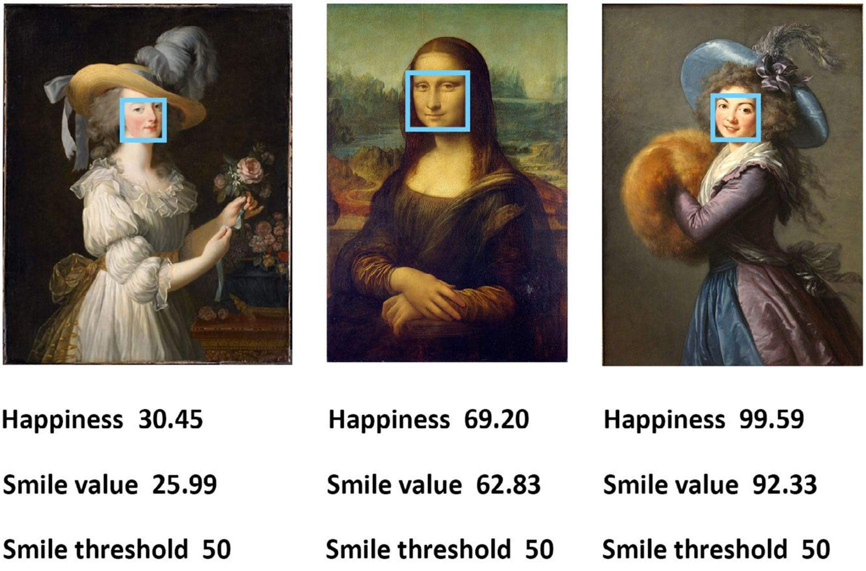


FIGURE 3 Emotional indices calculated for faces (Source: Face++)

$$J_i = \frac{C_s - C_{ns}}{C_s + C_{ns}} \tag{1}$$

where J_i is the joy index calculated at place i, C_s is the number of smiling faces in the photos within this place, and C_{ns} is the number of non-smiling faces. This index ranges between −1 and 1, a symmetric closed interval. A positive value means that more people are smiling at a place, which indicates positive emotion conditions, while a negative value means that more people do not have smiling faces, which may indicate a serious atmosphere at that place.

In comparison, the "average happiness index (AHI)" calculates the average of happiness values for all detected faces in those geotagged photos at a place:

$$AHI_i = \frac{1}{n} \sum_{j=1}^{n} H_j(i) \tag{2}$$

where $H_j(i)$ is the happiness value of human face j at place i. The AHI indicates the average degree of happiness for people at each place.

3.5 | Sensitivity tests

3.5.1 | Test for place construction

During the construction of place described in Section 3.3, a set of combinations of parameters ε and *minPts* are used. Although the shape of place boundaries may vary with different parameters, the derived place emotion results should have a similar distribution and trend if the proposed approach is stable. In order to check this, human emotion scores are calculated at each place with different parameter settings. Then Kendall's coefficient of concordance (W) is utilized to measure the agreement among those different human emotion detection results.

In order to do so, a ranking of places based on the proposed emotional index score is created for each pair of ε and *minPts*. We assume there are m combinations of parameters for n places. We sum the ranks $r_{i,j}$ in all m scenarios to get a a total rank R_i for place i:

$$R_i = \sum_{j=1}^{m} r_{i,j} \tag{3}$$

Then we calculate the average value R of the total ranks across all places:

$$\bar{R} = \frac{1}{n} \sum_{i=1}^{n} R_i \tag{4}$$

and find the sum of squared deviations:

$$S = \sum_{i=1}^{n} (R_i - \bar{R})^2 \tag{5}$$

Finally, Kendall's W is given by:

$$W = \frac{12S}{m^2(n^3 - n)} \tag{6}$$

In general, if the test statistic W is 1, it means all judges with different parameter settings have ranked places in the same order. If $W = 0$, it means that there is no agreement among all judges and the ranks are random. If the results show that the emotion score rankings are similar with different parameters in place construction, then the influence of shape during the place construction process is limited. It would also show that the emotion scores calculated at each place are consistent.

3.5.2 | Test for affective computing

As the number of photos varied at different places, it is necessary to know whether the data collected are sufficient for human emotion calculation. To test the reliability and stability of the facial expression based on emotion recognition results, a bootstrapping strategy was applied to assess the robustness of the emotional indices calculated in Section 3.4.

Bootstrapping is a resampling approach proposed by Efron (1992). It is often used to approximate the distribution of the test samples. By doing this, a confidence interval can be derived for the range of emotion scores at each place. The procedure is described as follows:

1. Assume that n faces are collected at place i as a sample set D'. Perform random sampling with replacement n times to form a new sample set of the same size as D. Note that more than one face may exist in D.
2. Then the emotion index e of the new sample set D is calculated.
3. Repeat the two steps above N times to generate $D_1, D_2, \ldots, D_N$ to obtain emotion results $e_1, e_2, \ldots, e_N$.
4. Rank the affective computing results and calculate the average value of the emotion indices as the final output for place i. Discard the lowest 2.5% and the highest 2.5% of results. The remaining results show the 95% confidence interval of emotion indices calculated at place i.

The results of bootstrapping show the confidence intervals of the possible emotion scores at each place, which help evaluate the stability of the emotion calculation results. Although it is impossible to know the true confidence interval as photos are collected in bias anyway, the derived results are more asymptotical to be the truth (DiCiccio & Efron, 1996). Further analyses are conducted based on the emotion results after the bootstrapping process.

3.6 | Influence of Environmental Factors

As suggested by environmental psychology studies (Capaldi et al., 2014; Svoray et al., 2018), human emotions can be affected by the surrounding environment. Therefore, exploring the potentially influential geographical and environmental factors and their importance is of great significance for understanding human emotions at different places. To do so, Pearson's correlation analysis (Benesty, Chen, Huang, & Cohen, 2009) and multiple linear regression (MLR) were employed in this study.

As mentioned in Section 3.2, a group of social and physical geographic attributes are collected when retrieving the information for each place. We denote those factors at each place by $a_1, a_2, \dots, a_n$. Note that since the aim of this article is to propose a general computational framework for extracting place emotions, and the environmental factors may vary in different types of places, we do not define a complete set of factors in this research, and further research is needed to draw up a complete list of variables related to a specific type of place. As a case study, with reference to several existing works and our geographical knowledge, we choose several environmental factors in this work as described in Section 4.1.

Pearson's correlation coefficient ρ is employed to explore the positive and negative impacts and the strength of linear relationship between an environmental factor and the emotion score at each place. As correlation analysis is only suitable for numeric values, for categorical variables (e.g. continents), the correlation coefficient between the emotion and each category is calculated by converting categorical variables to dummy variables (0, 1).

For each influential factor a, correlation analysis was performed with a combination of one emotion index e via:

$$\rho_{e,a} = \frac{E[(e-\mu_e)(a-\mu_a)]}{\rho_e \rho_a} \tag{7}$$

where Pearson's correlation coefficient $\rho_{e,a}$ is calculated with the expected covariance value E of the two variables e and a with their mean values μ_e and μ_a, and the standard deviations ρ_e and ρ_a. A positive value shows that the factor has positive impact on the emotion index e and vice versa.

MLR uses all geographical and environmental variables $(a_1, a_2, \dots, a_n)$ to predict the emotion index value E_i at each place i as:

$$E_i = f(a_1 + a_2 + \ldots + a_n) + \gamma \tag{8}$$

where γ is an unobserved error term. The impact of each attribute could be measured using the coefficient of each independent variable. R^2 is calculated as a goodness-of-fit statistic to determine how well the MLR model fits the observed place emotion data.

4 | EXPERIMENTS AND RESULTS

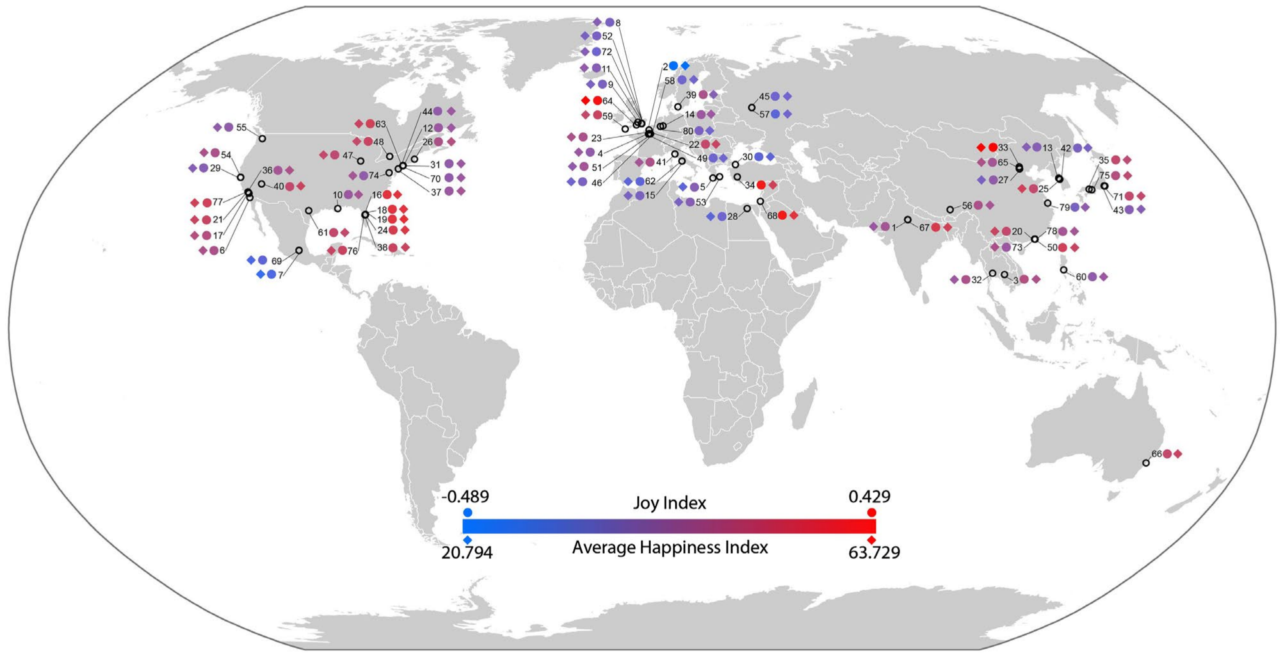
As the experience of travel and tourism is deeply connected to place (Wearing, Stevenson, & Young, 2009), we take tourist attractions as a case study place type to examine the feasibility of our place emotion sensing framework.

4.1 | Input data sets

The tourist sites selected in this study are located around the world. The sites selected had to have a large annual number of visitors, be comprehensive in terms of cultural representativeness, and diverse in terms of site types. In addition, in order to get reliable emotion detection results, the sites had to have a large number of photos taken and uploaded by tourists. To find them, several official resources (https://whc.unesco.org/en/map) and open statistics were checked (see https://www.lovehomeswap.com/blog/latest-news/the-50-most-visited-tourist-attractions-in-theworld and https://www/travelandleisure.com/slideshows/worlds-most-visited-tourist-attractions). The attractions selected are listed in Figure 4. In total, there are 80 sites, including 24 sites located in Asia, 25 in Europe, 29 in North America, and 1 each in Africa and in Oceania. A total of 22 countries are represented. The spatial distribution of all of these tourist sites can be seen in Figure 4.

A group of geographical attributes and environmental factors were searched for and recorded, to the best of our knowledge, which might influence the tourists' degree of happiness at each site. As human emotions are complex and influenced by multiple individual and environment variables, we only selected a small group of variables according to some existing studies from environmental psychology (White et al., 2010; Capaldi et al., 2014; Svoray et al., 2018). Other socioeconomic and environmental factors as well as individual differences may be added in future work to explore. The selected variables are as follows.

1. The coordinates of the site location, which are found using the Google Maps Places API.
2. The continent where the site is located.
3. The country where the site is located.
4. The existence of water bodies. As suggested by several related studies from psychology, landscape containing water bodies can influence human activities and consequently affect mood (White et al., 2010). A water body is deemed to exist if it is actually located within the tourist site, or if it is near the tourist site and can be seen from it; otherwise a water body is deemed not to exist.
5. The distance to the nearest water body. If the water body exists within the site, the distance is 0.
6. Whether the main part of the site is in an open or closed space. Parks, squares, lakes, etc., which are open to the air, are defined as open spaces, while sites such as museums, stations, and cathedrals, whose main contents are indoors, are considered as closed spaces. Most previous studies have proved that activities in an outdoor environment have a positive effect on happiness (Thompson Coon et al., 2011).
7. The green vegetation coverage of each place. Several studies have suggested that green space could reduce pressure and have a positive impact on mental health (Maas et al., 2009; Thompson et al., 2012). In order to measure the green space and its impact on the human emotions, the Normalized Difference Vegetation Index (NDVI), which is widely used in remote sensing of vegetation (Goward, Markham, Dye, Dulaney, & Yang, 1991), was harvested from NASA Earth Observations (https://neo.sci.gsfc.nasa.gov/view.php?datasetId=MOD_NDVI-M). The NDVI product in June 2017 was downloaded and values were spatially joined to each site.
8. Whether the place is located in an urban or rural environment. Similar to open or closed spaces, urban areas which have higher building density than rural areas which have a more natural environment, have great influence on human emotions (Wooller, Rogerson, Barton, Micklewright, & Gladwell, 2018).
9. The type of tourist site. Different types of tourist sites may have different types of visitors and mobility patterns, and may be associated with different mental conditions (Leiper, 1990). Based on the site type defined by the Google Maps Places API as well as several tourism-related studies (Lew, 1987), there are six types of tourist attractions defined in this research: *natural* (e.g. waterfalls, where places are characterized by limited human intervention); *amusement* (e.g. the Disneyland theme parks, where tourists visit places to enjoy games and other fun activities); *religious* (e.g. cathedrals, where people visit mostly for religion-related activities); *museum* (e.g. the Metropolitan Museum of Art, where historical, scientific, and artistic objects are kept); *palace* (e.g. the Forbidden City, where old cities and castles are located); and *other cultural categories* (e.g. the Grand Bazaar,



1	Agra Fort, India	17	Disney California Adventure, USA	33	Great Wall, China	49	Notre Dame Cathedral, France	65	Summer Palace, China
2	Amiens Cathedral, France	18	Disney Holly Wood Studios, USA	34	Hierapolis Pamukkale, Turkey	50	Ocean Park,Hong Kong	66	Sydney Opera House, Australia
3	Angkor Wat, Cambodia	19	Disney Worlds Magic Kingdom, USA	35	Himeji Castle, Japan	51	Palace of Versailles, France	67	Taj Mahal, India
4	Arc De Triomphe, France	20	Disneyland Hong Kong, Hong Kong	36	Hollywood Walk of Fame, USA	52	Palace of Westminster, UK	68	The Old City of Jerusalem
5	Archaeological Site of Olympia, Greece	21	Disneyland Park, USA	37	Independence Hall, USA	53	Parthenon, Greece	69	The Zocalo Plaza, Mexico
6	Balboa Park, USA	22	Disneyland Park, France	38	Islands of Adventure,USA	54	Pier 39, USA	70	Times Square, USA
7	Basilica of Our Lady of Guadalupe, Mexico	23	Eiffel Tower, France	39	Kronborg Castle, Denmark	55	Pike Place Market, USA	71	Tokyo Disneyland, Japan
8	Big Ben, UK	24	Epcot, USA	40	Las Vegas Strip, USA	56	Potala Palace, China	72	Tower of London, UK
9	Blenheim Palace, UK	25	Everland, Gyeonggi-Do, South Korea	41	Leaning Tower of Pisa, Italy	57	Red Square, Russia	73	Tsim Sha Tsui, Hong Kong
10	Bourbon Street, USA	26	Faneuil Hall Marketplace, USA	42	Lotte World, South Korea	58	Sacre Coeur Basilica, France	74	Union Station, USA
11	British Museum, UK	27	Forbidden City, China	43	Meiji Jingu Shrine, Japan	59	Saint Michaels Mount, UK	75	Universal Studios, Japan
12	Central Park, USA	28	Giza Pyramid Complex, Egypt	44	Metropolitan Museum of Art, USA	60	San Agustin Church, Philippines	76	Universal Studios, Florida, USA
13	Changdeokgung Palace Complex, South Korea	29	Golden Gate Park, USA	45	Moscow Kremlin, Russia	61	San Antonio River Walk, USA	77	Universal Studios,Hollywood, USA
14	Cologne Cathedral, Germany	30	Grand Bazaar, Turkey	46	Musee Du Louvre, France	62	St. Peters Basilica, Vatican City, Italy	78	Victoria Peak, Hong Kong
15	Colosseum In Rome, Italy	31	Grand Central Terminal, New York City, USA	47	Navy Pier, USA	63	Statue of Liberty, USA	79	Zhuo Zheng Yuan, China
16	Disney Animal Kingdom, USA	32	Grand Palace, Bangkok, Thailand	48	Niagara Falls, Canada	64	Stone Henge, UK	80	Aachen Cathedral, Germany

FIGURE 4 The spatial distribution of all tourist sites and their associated happiness indices

where places have cultural and historical value, but do not belong to other categories). Note that the six types are selected only based on the attributes of the 80 tourist attractions. More types of tourist attractions can be defined in other data sets.

After the selection of tourist attractions, all photos taken between January 2012 and June 2017, within a distance of 1 km from the center of each attraction site, were downloaded from the Flickr website. The search radius is larger than the spatial footprint of a place in most cases to ensure the number of photos harvested is sufficient. In total, 6,199,615 photos were collected.

4.2 | Construction of place and affective computing

Following the steps in Sections 3.3 and 3.4, each tourist site was constructed by the user-generated footprints with DBSCAN spatial clustering and the convex-hull minimum bounding geometry algorithms, and the place emotions were calculated. In total, 2,416,191 faces were detected and evaluated, so that the ratio of the number of faces to the number of photos collected is 38.97%, while the proportion of pictures with faces is about 20%. For each site, two emotional indices, namely the joy index and the average happiness index, were calculated from the faces remaining within each site. However, since different DBSCAN parameter settings in the place construction process might impact the generated sites, a set of combinations of parameters were tested. In the experiment, we iteratively chose the ε as 50, 100, 200, and 300 m, and *minPts* as 0.5, 1, and 2% according to the recommendations of previous studies (Hu et al., 2015; Gao et al., 2017b). In sum, 12 combinations of parameter settings were tested individually and applied in Kendall's concordance test.

For each pair of parameters, a ranking of sites was returned based on each emotional index. Kendall's *W* was found to be 0.99 for 12 rankings based on the normalized joy index, 0.99 for all rankings based on the AHI, and 0.98 for 24 ranking lists including both indices. The results illustrate that all pairs of parameters result in a very similar ranking order of the happiest places, which means that the proposed method is stable and the selected DBSCAN parameters have limited impact on the overall place emotion ranking. The happiness indices calculated at each place are almost invariant in all of the different experiments. We therefore chose just one parameter setting, ε = 100 m and *minPts* = 1%, for further analyses.

As for the exploration analysis, four famous tourist attractions of interest—the Great Wall, Amiens Cathedral, Disneyworld Magic Kingdom, and Universal Studios Hollywood—were selected as individual examples to demonstrate the specific place emotion distributions (Figure 5). The spatial distributions of photos with and without smiling faces in the respective sites are shown on the left, while the most frequent word tags shared by the Flickr users across those sites are shown on the right. The places constructed are multi-part polygons, and photos taken outside the polygons are removed in order to reduce data noise. Red points show smiling faces, while blue points indicate non-smiling faces. According to the figure, the Great Wall, Disneyworld Magic Kingdom, and Universal Studios Hollywood have more smiling tourists, while tourists at Amiens Cathedral have fewer smiling faces as people in the religious site may be less inclined to smile.

The semantics of the photos was also explored. The word cloud visualization shows the top 100 tags on social media photos at each place. In addition to the country, department (in France) and city names, a list of tourist site names including Mutianyu, Great Wall, Cathedrale, DisneyWorld, Universal Studios are identified from those geotags, which indicate that those photos could represent the place information although not all the words and topics are necessarily indicative of a specific place (Adams & Janowicz, 2012; Adams & McKenzie, 2013). These examples show that the computational framework for emotion extraction based on facial expressions at places is generally effective.

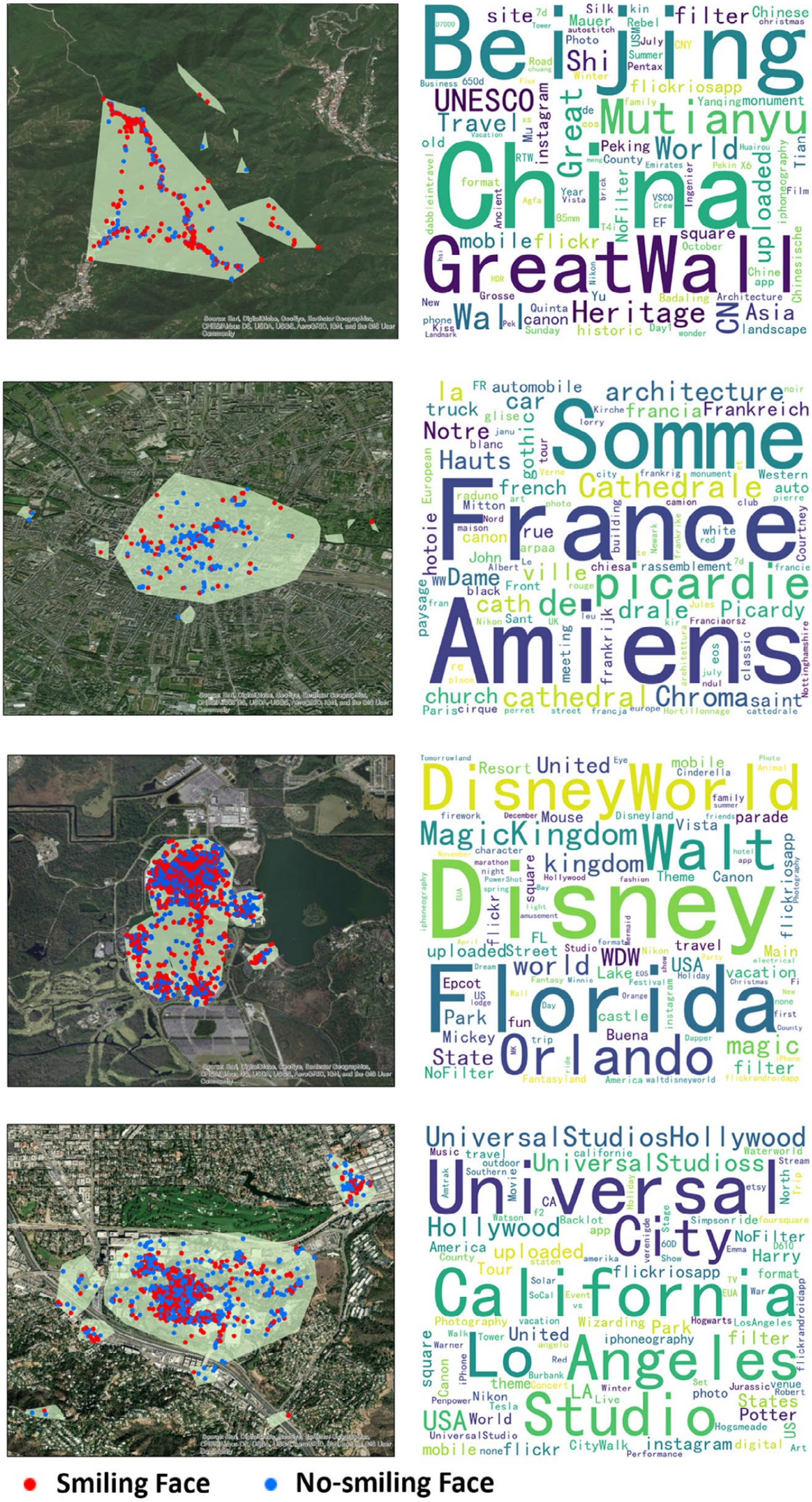


FIGURE 5 The spatial distribution of Flickr photos with smiling faces and without smiling faces and their most frequent word tags across four sample tourist sites: the Great Wall, Amiens Cathedral, Disneyworld Magic Kingdom Park, and Universal Studios Hollywood

4.3 | The world ranking list of happiest tourist attractions

Figure 4 shows the spatial distribution of tourist sites as well as their emotional indices. The circles represent the joy index while diamonds represent the AHI of each site. A deeper red color shows more happiness at a site while a deeper blue indicates less happiness. For each site on the map, its associated name can be found via the index. Based on the emotional indices, two ranking lists of tourist attractions were generated in Figures 6 (joy index) and 7 (AHI). Based on the bootstrapping strategy, the 95% confidence interval of the emotional indices at each site is shown by the blue bars, and the circles at the center of the lines indicate the average values of the emotion indices. For the joy index, a positive value represents more smiling faces, indicating a happy atmosphere, while a negative value indicates that happiness cannot be deduced clearly from facial expressions at a site. The average joy index across all sites is slightly negative at about −0.115, while the average of all AHI values is about 38.04. Correlation analysis shows that Pearson's correlation coefficient between the two rankings is 0.97, which means that the two rankings are very similar. Interestingly, the official slogan for Disneyland is "The Happiest Place On Earth." However, according to the ranking lists from user-generated crowdsourcing data, the top site that has the highest happiness indices in the world is the Great Wall, China based on the two measurements (joy index 0.429, AHI 63.72). But several amusement parks, such as the Disneyland parks, Everland in South Korea, and Ocean Park in Hong Kong, do have high rankings, as might be expected. Meanwhile at the bottom of the ranking list is the Amiens Cathedral, scoring −0.489 on the joy index and 20.79 on the AHI. It is worth noting that low happiness scores do not necessarily mean that people at sites (e.g. religious places) are not as happy as people in other types of places, but it could mean that people are less inclined to smile at those sites. However, since only tourist sites are chosen in our case study, most smiling faces are enjoyment smiles and seem to be associated with positive emotion and happiness at the top-ranked sites.

4.4 | Relationships between human emotions and environmental factors

Each tourist site listed in Figure 4 was assigned a set of attributes, namely, the continent, open or closed space, urban or rural area, attraction type, vegetation coverage, existence of a water body, and the distance to the nearest water body. Figure 8 and Tables 1 and 2 show the results of correlation analysis and multiple linear regression on the emotion indices and those attributes.

The results of the correlation analysis show that amusement parks have significant positive impact (joy index 0.41, AHI 0.46) on tourists' smiles and happiness, in accordance with our common knowledge. As tourists often go to amusement parks to relax and enjoy themselves, they may be happier there than when visiting other places. Natural landscapes (joy index 0.27, AHI 0.28), open spaces (joy index 0.25, AHI 0.28), the existence of water bodies (joy index 0.21, AHI 0.25), North America (joy index 0.19, AHI 0.23), rural areas (joy index 0.31, AHI 0.22), and vegetation coverage by NDVI (joy index 0.18, AHI 0.20) all have positive impact. Except for the continent variable, the coefficients of the aforementioned variables hint that, to some degree, places with more open environment can increase the degree of happiness of tourists, with more enjoyment smiles. In contrast, compared with sites on other continents, people visiting sites in Europe (sites selected in our case study only) may not explicitly express as much happiness by smiling as when visiting other continents. What is more, religious sites (joy index −0.31, AHI −0.34), closed spaces (joy index −0.25, AHI −0.28), non-existence of water bodies (joy index −0.21, AHI −0.26), palaces (joy index −0.16, AHI −0.23) and urban areas (joy index −0.31, AHI −0.22) have negative impact on the average happiness score of tourists.

The MLR results (Tables 1 and 2) paint a similar picture to the correlation analysis. The impact of Europe on the happiness conditions is negative, and is statistically significant in the regression model. Sites with water bodies have a positive impact on human happiness, but are not significant in our samples. Conversely, for sites located in urban areas, the emotional indices are negative, and this result is significant. Natural landscape has a positive impact on the happiness indices, but this is not statistically significant. The goodness of fit R^2 is about 0.57 and statistically significant with p-value less than 0.001 for both indices, showing that the variation of human emotions at different places can be explained by those geographical and environmental factors to a certain degree.

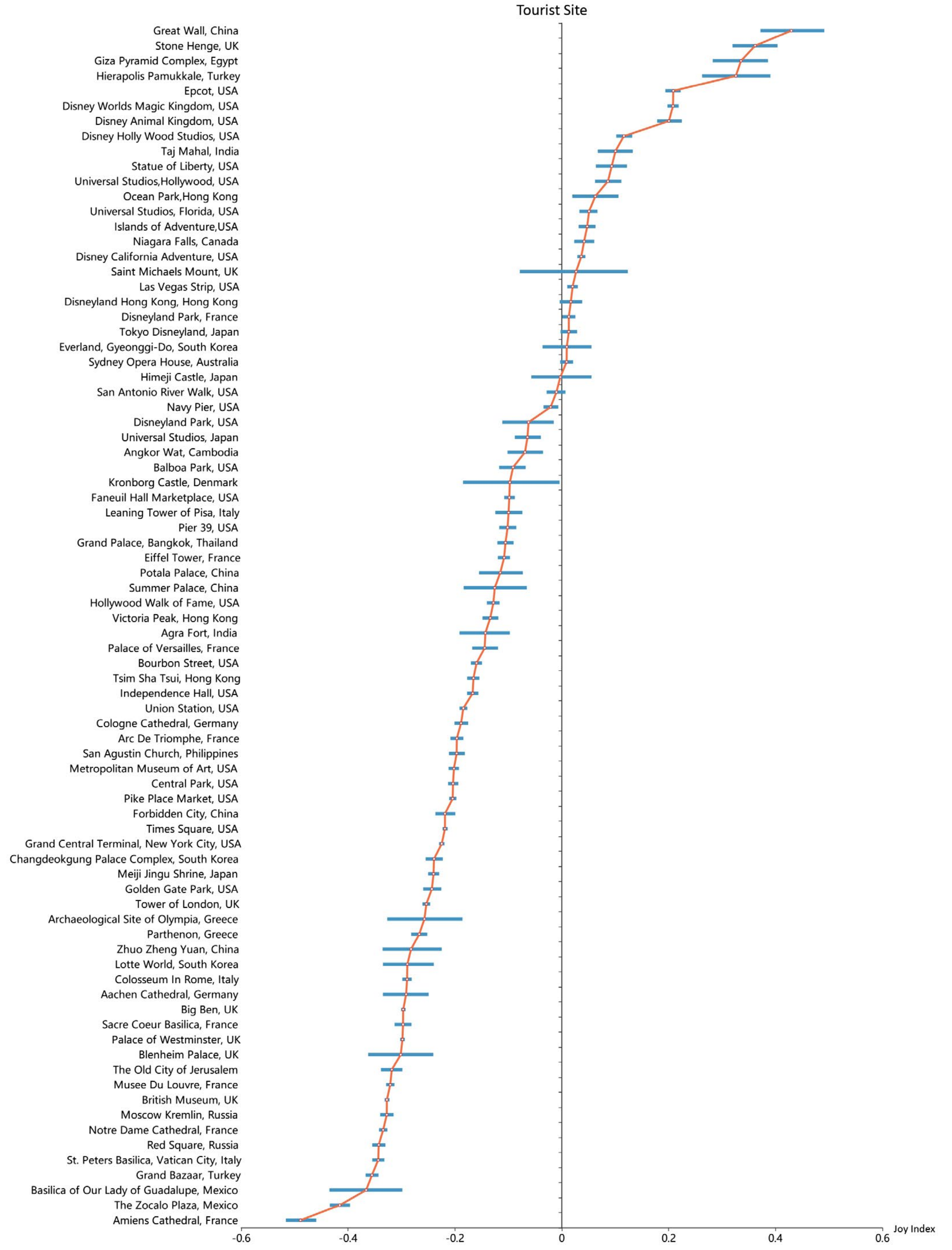


FIGURE 6 The ranking list of tourist sites based on the joy index. The 95% confidence interval of the emotional index at each site is shown by the blue bars, and the circles indicate the average values of the emotion index (note: figure is zoomable)

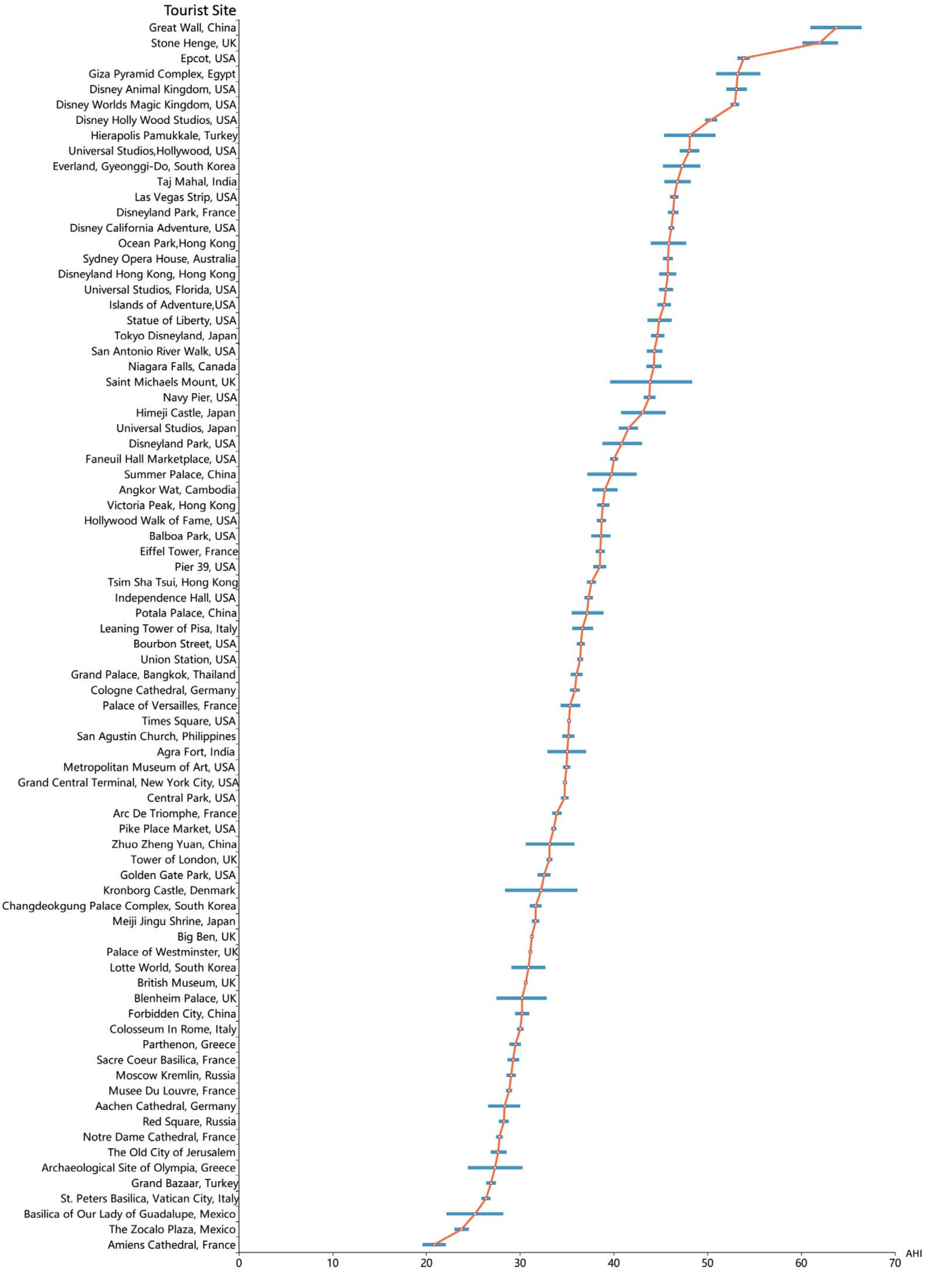


FIGURE 7 The ranking list of tourist sites based on the average happiness index. The 95% confidence interval of the emotional index at each site is shown by the blue bars, and the circles indicate the average values of the emotion index (note: figure is zoomable)

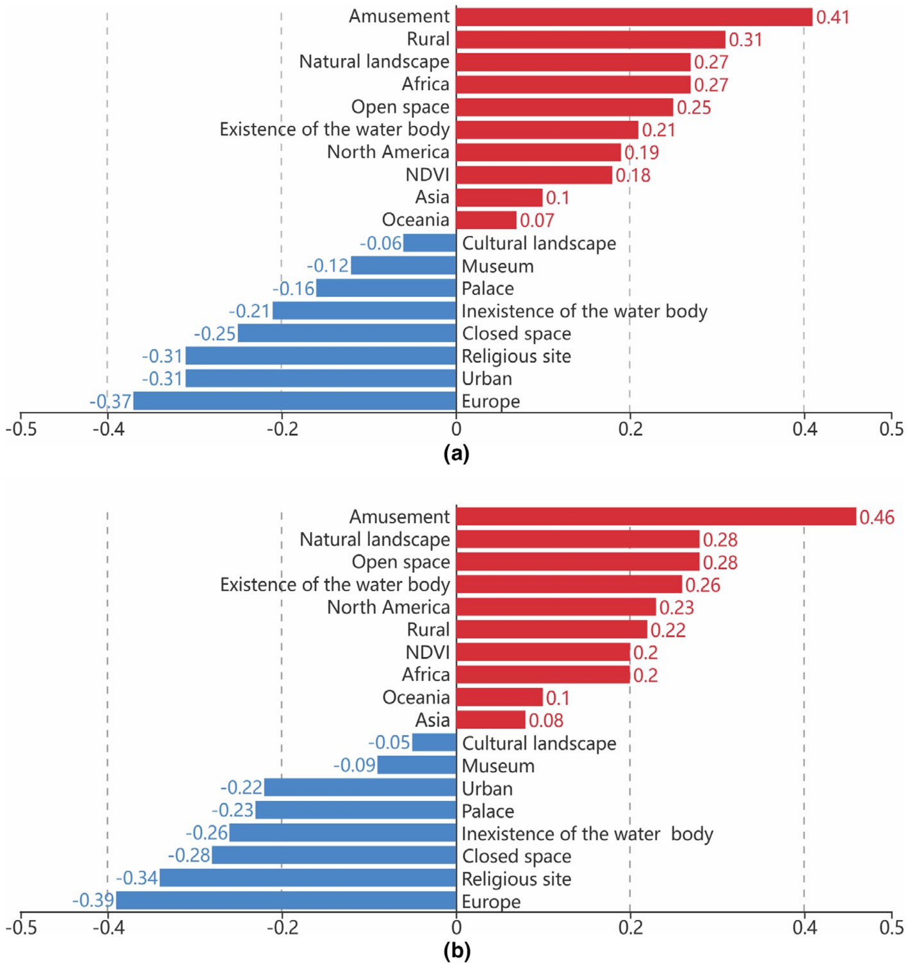


FIGURE 8 Pearson's correlation coefficients for the geographical and environmental attributes of the human emotions: (a) joy index; and (b) average happiness index

In addition, as the type of tourist site has an impact on human emotions in the statistical analyses, we further explore a specific type of tourist attraction, amusement parks, to illustrate the results. As shown in Table 3, there are 17 amusement parks in this study and they generally have higher AHI (average 45.72) and joy index scores (average 0.52) compared with other types of tourist site. Most amusement parks are located in open spaces in urban areas, as well as containing water bodies (e.g. lakes) inside them. The average NDVI value at amusement parks is about 0.52, which is similar to the value of all sites (about 0.54) and not type-biased. A more specific exploration could be conducted in future to investigate more factors that may affect human emotions at amusement parks.

5 | DISCUSSION

5.1 | Human-environment perspective of results

Scholars from environmental psychology have proved that the surrounding environment has impacts on human emotions. The results of the present study demonstrate a similar conclusion from a big-data-driven perspective.

TABLE 1 Coefficients of multilinear regression based on the joy index and the geographical and environmental factors

Attribute	Regression coefficient
Constant	0.486**
Continent	
Asia	−0.396*
Europe	−0.458**
North America	−0.353*
Oceania	−0.235
Africa	N/A
Open/closed space	
Open space	−0.0044
Closed space	N/A
Urban/rural	
Urban	−0.1458*
Rural	N/A
Type	
Cultural landscape	−0.1923**
Museum	−0.254*
Natural landscape	0.002
Palace	−0.203*
Religious site	−0.319*
Amusement park	N/A
Water body	
Existence of water body	0.021
Non-existence of water body	N/A
Distance to nearest water body	0.0004
NDVI	0.0004

$R^2 = 0.51^{**}$. $^{*}p < 0.05$, $^{**}p < 0.001$.

By combining the results of correlation analysis and multilinear regression, amusement parks are shown to be the places that most positively affect individuals' happiness expressions. Environments such as open spaces, places where there is a body of water, places where the green vegetation is denser, and rural areas all seem to have positive impacts on the degree of human happiness. Therefore, it can be concluded that people who stay in such areas may tend to feel happier. Our findings are consistent with several existing theories in psychology (Kaplan, 1995), that exposure to nature has a positive impact on human mood (Bowler, Buyung-Ali, Knight, & Pullin, 2010), which also supports the theoretical foundation of the framework and proves the validity of this study to some extent.

However, some limitations should be pointed out. As expressions of human emotions are quite complex and are influenced by multiple variables, both internally and externally, the results from this study may not be guaranteed for individuals (Junot, Paquet, & Martin-Krumm, 2017) nor for all tourist attractions around the world. And some cultural environments, religious sites and museums may suppress people's positive emotional expressions. It is worth noting that such suppression does not mean that people are not happy at those places, just that their

TABLE 2 Coefficients of multilinear regression based on the average happiness index and the geographical and environmental factors

Attributes	Regression Coefficient
Constant	60.649**
Continent	
Asia	−13.805*
Europe	−16.647*
North America	−12.196
Oceania	−5.058
Africa	N/A
Open/closed space	
Open space	−0.015
Closed space	N/A
Urban/rural	
Urban	−5.083*
Rural	N/A
Type	
Cultural landscape	−9.264**
Museum	−10.645*
Natural landscape	0.81
Palace	−10.889**
Religious site	−15.547**
Amusement park	N/A
Water body	
Existence of water body	0.7484
Non-existence of water body	N/A
Distance to nearest water body	0.0172
NDVI	0.018

$R^2 = 0.57^{**}$. $^{*}p < 0.05$, $^{**}p < 0.001$.

expression of happiness is more muted. In addition, although the semantics of geotags shows that most photos are related to the places, tourists' emotions may not be directly relevant to the views of surrounding environments but could be affected by the activities they are engaged in or the events they are participating in at that place. A deeper exploration should be conducted to find other factors impacting human emotion expressions.

5.2 | Uncertainty in the data

Social media data are uploaded by volunteers based on their experiences and opinions, producing "ambient geographic information" (Degrossi, Porto de Albuquerque, dos Santos Rocha, & Zipf, 2018). As user-generated photos are used in this study, the uncertainty in and quality of the data should be tested (Goodchild & Li, 2012). Three types of data uncertainty are addressed: the vagueness of place, the different numbers of faces, and the different groups of people.

As the size and boundaries of a place might be vague, it is not appropriate to use a fixed distance for data analysis. Place boundaries are constructed based on the density distribution of photos. Georeferenced photos

TABLE 3 List of amusement parks with their average happiness index (AHI) and joy index scores

Tourist site	AHI	Joy index
Epcot, USA	53.86	.60
Disney Animal Kingdom, USA	53.07	.60
Disney World Magic Kingdom, USA	52.91	.60
Disney Hollywood Studios, USA	50.37	.56
Universal Studios, Hollywood, USA	48.05	.54
Everland, Gyeonggi-Do, South Korea	47.34	.50
Disneyland Park, France	46.34	.51
Disney California Adventure, USA	46.14	.52
Ocean Park, Hong Kong	45.89	.53
Disneyland Hong Kong, Hong Kong	45.76	.51
Universal Studios, Florida, USA	45.55	.53
Islands of Adventure, USA	45.34	.52
Tokyo Disneyland, Japan	44.68	.51
Universal Studios, Japan	41.57	.47
Disneyland Park, USA	40.86	.47
Balboa Park, USA	38.60	.45
Lotte World, South Korea	30.95	.35

outside the place boundary are removed to minimize error in the results. In addition, by using the DBSCAN algorithm, which is not sensitive to noise, for place construction, the vagueness of the results is decreased. Besides, a combination of parameter settings as well as Kendall's *W* are tested to ensure data consistency. Therefore, the uncertainty in the results is minimized.

Since the number of faces varied across different tourist sites, a key issue is to examine whether the number of photos collected at one site is sufficient to extract human emotions and whether the emotional condition calculated is stable. Using the bootstrapping strategy, a 95% confidence interval of emotion scores at each site is generated. The variability is derived by subtracting the lower bound from the upper bound of the confidence interval. To explore the relationship between the uncertainty of the emotion indices and the number of faces analyzed at each site, linear regression was employed. Figure 9 illustrates that the relation between the variability of emotional indices at each site and the number of faces identified from photos taken at each site fits into a power model very well (with goodness-of-fit coefficient 0.99). In general, the more faces detected at a site, the more stable is the emotion measurement calculated. For most sites, the variability of the 95% confidence interval for the joy index is less than 0.05 and for the AHI is less than 3, and has limited influence on the ranking lists. Therefore, the results of the emotional conditions at each site are reliable and can be trusted.

In addition, as different groups of people with various cultural backgrounds and being locals or visitors may express different degrees of excitement, enjoyment, and emotions at the same place, the results might be influenced by the proportion of various types of tourists. For instance, in order to distinguish between tourists and local people, we follow the criterion used in previous studies to define tourists: if the period of one user who takes multiple photos at one place is longer than 1 month, then the user was labeled as local, otherwise as a visitor (García-Palomares, Gutiérrez, & Mínguez, 2015). Results show that for most tourist attractions (more than 90%), the majority of Flickr photos (more than 80%) are uploaded by tourists. The average difference of the AHI scores between tourists and locals in those tourist sites is just 3, showing that such influence is minimal and it has limited effect on the ranking list.

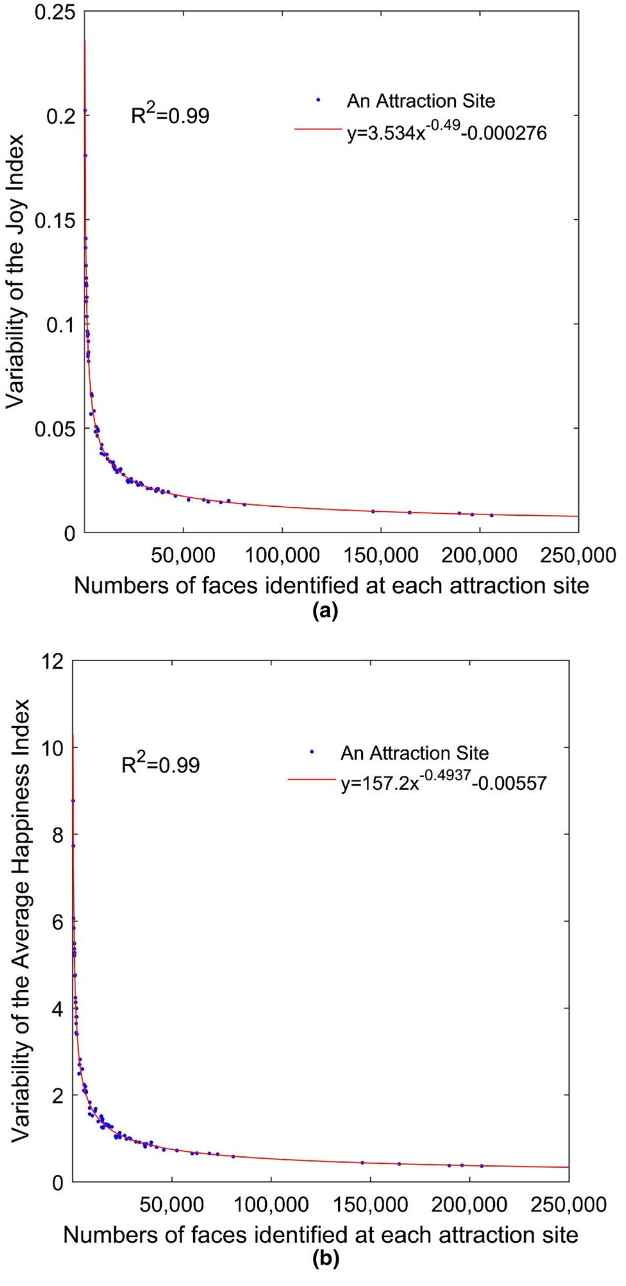


FIGURE 9 Relation between the variability of emotional indices at each site and the number of faces identified from photos based on (a) the joy index; and (b) the average happiness index

Although we tried our best to reduce uncertainty, some limitations still exist. Data bias commonly exists in volunteered geographic information (Senaratne, Mobasheri, Ali, Capineri, & Haklay, 2017). As suggested previously (Gao et al., 2017b; Jolivet & Olteanu-Raimond, 2017), one data bias issue of volunteered geographic information is that the contributions of volunteers often follow a power-law or exponential-law frequency distribution with a long tail, which indicates that most photos are posted by only a small proportion of users and a large number of users contribute only few (Goodchild & Li, 2012). In this study, a large number of faces detected might belong to a small group of users and the information provided by social media users may not always comply with quality

TABLE 4 Spearman's correlation coefficients between the text-based method and the facial-expression-based method

Emotion index	Correlation coefficient	*p*-value
Joy index	0.28	0.0472
Average happiness index	0.30	0.0314

standards. However, the results of emotions based on facial expressions do reflect active users' experiences, opinions, interests, and feelings at those places, and can provide new insights for place-based information research (Blaschke et al., 2018).

5.3 | Comparison between text-based and facial-expression-based methods

Though emotion detection methods based on facial expressions are becoming more mature, and have begun to be implemented in research, a key issue is whether the methodology is reliable. We conducted a comparison between our methodology and a text-based framework, with specific reference to the research of Mitchell et al. (2013). In this study, scholars followed the method of Dodds, Harris, Kloumann, Bliss, and Danforth (2011), where a daily happiness score was calculated from Twitter with state-of-the-art natural language processing technologies, summarizing a range of human emotions in the U.S. from a state level, and examining the connections to the socioeconomic attributes. In comparison, the YFCC100 data set containing the most photos in Flickr was used (Thomee et al., 2015). We also evaluated emotions using our framework of all photos in each state in the U.S. Since Mitchell's research was conducted in 2011, we only retrieved photos taken in the same year within the U.S. to ensure consistency with regard to time period. Both the joy index and average happiness index were used to calculate the happiness scores for each state for the photo data. The results of our metrics and the results of Mitchell's research across 50 states were subjected to Spearman's correlation analysis (Fieller, Hartley, & Pearson, 1957), which compares the rank of each value in the data series. As shown in Table 4, results in the two studies have positive correlation (joy index 0.28, AHI 0.30), which shows some degrees of similarity between the two technologies.

It should be noted that the focus of our research is not to compare or even contrast the existing text-based emotion extraction technologies with facial expression approaches. Different research methods have their own strengths and weaknesses. As already mentioned, text-based approaches cannot record real-time emotions and might not be suitable for global-scale research due to the multilingual environment. But they typically have larger volumes of data and rich semantics (Hu et al., 2019). Combining the two approaches for affective computing could help improve the holistic understanding of human emotions from different aspects and enrich the understanding of such an innate neural program (Abdullah et al., 2015).

Our approach also has some limitations. First, as already mentioned, the results might be biased toward certain groups of people (visitors versus local citizens, and different ethnicities or culture backgrounds) and affected by the diversity of faces in the trained data sets. Second, people's emotions may not be directly relevant to the views of surrounding environments. Moreover, people may not always express emotions explicitly by either facial expressions or texts. Further exploration should be conducted in order to show the collective connections between human emotions and facial expressions on technology-mediated platforms (Elwood & Mitchell, 2015).

6 | CONCLUSIONS AND FUTURE WORK

In this research, in order to understand the interaction between human emotions and the environment, a data-driven framework to measure human emotions at different places using large-scale user-generated photos from social media is proposed. We utilize state-of-the-art social computing tools to detect and measure human happiness from facial expressions in photos. Tourist attractions, as a specific type of place, are exemplified for deriving place-based human emotion indices. A tourist site ranking list is created not from the statistics of tourist flow, but from the degree of happiness expressed and shared by millions of tourists, which also shows that our framework is suitable for global-scale issues. In addition, we explore the impacts of several geographical and environmental factors on human emotions. Results are consistent with common sense and with existing studies from psychology, that is, people visiting open spaces and with opportunities to explore nature express more happiness. Overall, this research advances our knowledge of human emotions at different tourist attractions. Our study connects crowdsourced human emotions to the geographic attributes of environment using advanced artificial intelligence techniques and spatial analytics, and provides a new paradigm for research in geography and in GIScience. The proposed framework and the findings could also lead to practical guidance for environmental psychology, human geography, tourism management and urban planning.

In the future, several potential directions will be pursued to explain related research questions. One direction is about data fusion. As only Flickr photos are employed in the experiment, this study can be further improved with diverse data sources such as surveys. A data-synthesis-driven method might provide varied perspectives on human emotions. And the mix of text- and facial-expression-based emotion extraction methods may enhance confidence of the final output. Another direction is to explore fundamental factors impacting human emotions. As we propose the framework for *place emotion* research, we will focus more on spatial analysis of emotion patterns. Human emotions at different scales will be compared to revisit the scale effect in geography. And different groups of people, as suggested by existing studies (Niedenthal et al., 2018; Kang et al., 2018), will be explored to try to obtain deeper insights into factors that influence human emotions. Moreover, different place types as well as spatial units on different scales, including points of interest, census blocks, neighborhoods, and communities will be combined to examine the geographic patterns and socioeconomic linkages of human emotions. One specific line of research taking a limited number of places but with more environmental factors to be examined can be conducted to enrich the understanding of place-based emotions.

ACKNOWLEDGMENTS

The authors would like to thank Wanjuan Bie, Shan Lu, and Dan'nan Shen at Wuhan University, for their contributions on figures. We thank Timothy Prestby at UW-Madison for his help with language edits of earlier versions of this article. We also thank Jialin Wang, Zimo Zhang, Wenyuan Kong and Zijun Xu in the Place & Emotion Group, Urban Playground Lab, Wuhan University, for helpful discussions. The funding support for this research is provided by the Office of Vice Chancellor for Research and Graduate Education at the University of Wisconsin-Madison with funding from the Wisconsin Alumni Research Foundation, and the Fund for National College Students Innovations Special Project of China (Grant No. 201810486033), Dr. Yu Liu is partially supported by the National Natural Science Foundation of China (41625003).

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How to cite this article: Kang Y, Jia Q, Gao S et al. Extracting human emotions at different places based on facial expressions and spatial clustering analysis. *Transactions in GIS*. 2019;00:1–31. https://doi.org/10.1111/tgis.12552