Quantifying the bias in place emotion extracted from photos on social networking sites: A case study on a university campus

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ABSTRACT

Various fields have widely used place emotion extracted from social networking sites (SNS) information in recent years. However, the emotional information may contain biases as users are a particular subset of the whole population. This research studies whether there are significant differences between place emotion extracted from SNS and the place *in-situ* (a campus of Wuhan University). Two datasets from different sources, Weibo (a platform similar to twitter) and *in-situ* cameras, are collected over the same time periods in the same geographical range. By utilizing online cognitive services on the photos collected, the diversity of people with a recognizable face in terms of age, gender, and emotions are determined. The results suggest that there are significant differences in place emotion extracted from Weibo and *in-situ*. Furthermore, the pattern of differences varies among diverse demographic groups. This paper quantitatively contrasts place emotion extracted from SNS and the place *in-situ*, which can help researchers achieve a more profound understanding of human behavior differences between online and offline place emotion. This research also provides a theoretical basis to calibrate the emotion metrics obtained from SNS facial expressions on future place emotion studies.

1. Introduction

Emotion, which is innately generated from human neural systems (Izard, 2013; Wierzbicka, 1986), is a fundamental component of human beings (Brave & Nass, 2002). Prior works discovered how visual, temporal, and social contexts trigger emotional fluctuation (Chakraverty, Sharma, & Bhalla, 2015; Golder & Macy, 2011; Singh, Atrey, & Hegde, 2017). In fact, place plays a key part in daily life as it affects how people perceive and experience the surrounding environment (Goodchild, 2011; Goodchild, 2015; Tuan, 1977; Winter & Freksa, 2012). Therefore, place is also a fundamental contextual trigger for memories and emotions of individuals (Hasan, Zhan, & Ukkusuri, 2013; Kabachnik, 2012; Scheider & Janowicz, 2014). Several works have been able to depict and calculate the interaction between human and places. However, most share a common limitation as they take an objective view to infer people's feelings in places by using metrics such as traffic accessibility (Hamersma et al., 2014), atmospheric pollution (Smyth, Mishra, & Qian, 2008), and floor-area ratio (Zhang, 2003). Place emotion, proposed by Kang et al. (2019) with a focus on a special case of the general affective computing in geography, provides a theoretical basis to obtain subjective perceptions of people in places. Understanding the spatial pattern of human emotions is a glaring issue in a wide range of fields such as urban planning (Svoray et al., 2018), economics (Kang et al., 2017a), and public health (Zheng, 2019).

Traditionally in social sciences, most research measured human emotions by self-reported questionnaires and body sensor data (Mizna, Bachani, & Memon, 2013; Niedenthal et al., 2018; Silk et al., 2011; Watson, Clark, & Tellegen, 1988). For example, Silk et al. (2011) illustrated a case had children rate their current emotion using Positive and Negative Affect Schedule (PANAS). Mizna et al. (2013) utilized a machine called an "emotional mouse" to obtain subjects' physiological data and emotional states. However, these approaches are either fraught with multiple social and cognitive biases (Robinson & Clore, 2002) or require controlled in-lab settings (Saha et al., 2014).

In recent years, online social networking sites (SNS), such as Facebook, Twitter, and Weibo, have grown tremendously and allow everyone to share their life moments to wide internet audiences (Dwyer, Hiltz, & Passerini, 2007). Since they bring new opportunities for scientists to understand socioeconomic environments, the studies overwhelmingly employ SNS posts to investigate human behavior (Liu

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et al., 2015). For instance, Hu et al. (2015) utilized the geotagged photos in Flickr to infer and understand urban areas of interest (AOI). Meanwhile, the ever-increasing amount of text and photos posted by SNS users contains a wealth of information about the individuals' emotions (Chakraverty et al., 2015). They provide a unique source to collect numerous and large-scale individual-level subjective perceptions, which have been widely used in human behavior research. In the past decades, most related works are limited to text analysis of this resource by using natural language processing (NLP) (Bollen, Pepe, & Mao, 2009; De Choudhury, Gamon, & Counts, 2012). With the rapid development of both face and emotion recognition technology, several studies have used social media geotagged images to automatically infer users' emotions. These studies then applied to various fields as an attribute of places to understand human-environment interaction (Kang et al., 2017a; Singh et al., 2017; Svoray et al., 2018). For instance, Kang et al. (Kang et al., 2019) generated emotion maps of 80 tourist attractions around the world based on Flickr photos. However, it has been widely suggested that big data and whole data are not the same, and users do not represent "all people" since they are a very particular subset (Boyd & Crawford, 2012). Therefore, it is worthy to doubt the representativeness of place emotion extracted from SNS information. Moreover, since users may inadvertently conform to social pressures imposed by SNS or intentionally post tweets based on personal preference to build an adorable image (Pénard & Mayol, 2017; Sabatini & Sarracino, 2016), they would suppress or exaggerate their emotions to a certain extent. With a growing number of studies worldwide relying on SNS information to understand human behavior and perception in places, it has become important to provide a method to quantitatively answer this question.

For these reasons, one may wonder to what extent the SNS based place emotion extraction is biased towards the posts of SNS users. Our objective is to test whether place emotion extracted from SNS–Weibo in particular–allows for reliable quantification of place emotion. Specifically, we aim to quantitatively measure the extent to which the place emotion extracted from Weibo is misaligned with respect to what collected from the place *in-situ*.

This paper proposes a framework to quantify the emotional bias between human emotions collected from SNS and the place *in-situ*. We term the human emotions extracted from SNS users within a certain place as *Online Place Emotion*, and from the people of the place *in-situ* as *Offline Place Emotion*.

In this work we ask the following research questions:

- **Research question 1** (RQ1): Are there significant differences between *Online Place Emotion* and *Offline Place Emotion*?
- **Research question 2** (RQ2): If the answer to the research question 1 is positive, is there any pattern showing what emotion is suppressed and what emotion is exaggerated on SNS compared with their offline counterparts?
- **Research question 3** (RQ3): If the answer to the research question 2 is also positive, do demographic characteristics influence the pattern that has been observed?

The following two collections of datasets were utilized: images collected from Weibo and from *in-situ* cameras at the same time period (from May 16th, 2018 to May 30th) within the same geographical range of Wuhan University. By using computer vision APIs of online cognitive services, demographic and emotion information of each of the individuals in photos was captured and analyzed. The results not only reveal the differences of place emotion that was extracted using different data sources, but also prompt us to rethink some conclusions of place emotion measured by SNS information that have been reported in prior literature.

The remainder of this paper is organized as follows. Firstly, we review the related work. Secondly, we state and explain the methods we developed to quantitatively measure the bias between online and offline place emotion in the work and introduce the two datasets collected. Thirdly, we state our findings around the research questions. Finally, we interpret our results with a discussion, and elaborate on the main contributions of this work and current limitations.

2. Related work

Affective computing (Picard, 1997) has been an important subfield in both computer science and social science. Social science pays more attention to the relationship between emotions and life experiences. The notions of emotions, sentiment, affect, and well-being are nuanced, but these aspects are usually interrelated and frequently studied together (Munezero, 2014).

Surveys play an important role in measuring human emotions. Since the seminal works of Bradburn (1969), Andrew and Withey (1976), and Campbell, Converse, and Rodgers (1977), many studies on human emotions were conducted by surveys including interviews and questionnaires to measure human emotions. One common test is called Satisfaction With Life (SWL) which scores the extent to which a person feels that his/her life is worthwhile (Diener, Diener, & Diener, 1995; Diener, Inglehart, & Tay, 2013). Volkmer and Lermer (2019) utilized the German version of the WHO-Five well-being index (WHO-5) to assess participants' well-being and found more extensive mobile phone use (MPU) is associated with lower well-being, SWL, and mindfulness. However, prior research showed that people, in general, have 'blind spots' in their self-knowledge, and they may not always understand their emotions very accurately (Barrett et al., 1998; Robinson & Clore, 2002).

In order to make computers 'see' and 'feel' the human emotions, existing literature has focused on human-computer interaction (HCI) (Picard, 1997) and applied sensing technology to identify users' physical, emotional and informational state. For instance, Saha et al. (2014) classified five emotions including anger, fear, happiness, sadness, and relaxation from gestures by Zhang (2012). Furthermore, it is more common to recognize human emotions by physiological signals (Jerritta et al., 2011) collected from stationary and wearable sensors (Choi, Ahmed, & Gutierrezosuna, 2011; Ollander et al., 2016; Setz et al., 2009). Burleson (2006) developed a learning companion that depended on a sensor framework (incorporating a mouse, posture chair, video camera, and skin conductance bracelet) to recognize and respond to people's emotions. In addition, emotions in real-world driving (Healey & Picard, 2005) and school learning (Arroyo et al., 2009; Woolf et al., 2009) settings were collected and analyzed. Nevertheless, this approach to collect human emotions is costly in terms of time, money, and labor and therefore is typically administered with limited samples available over small durations of time (Wijsman et al., 2011).

Since the idea of "Citizens as Sensors" was put forward by Goodchild (2007) in his classic paper which suggested general individuals can be compared to environmental sensors, plentiful studies have explored urban development patterns by implying individual-level big geospatial data, called "social sensing" (Liu et al., 2015). Moreover, with the popularity of SNS, much research has utilized information extracted from SNS to measure human emotions. Primary literature focused on generating sentiment lexicons and analyzing users' text content. For example, Bandhakavi et al. (2016) proposed two different methods to develop sentiment lexicons from a corpus of emotion-labeled tweets and comparatively evaluated the quality of the proposed lexicons. Chakraverty et al. (2015) also performed a novel emotion analysis lexicon that was compiled by integrating information from multiple fields and analyzed the predominant emotions carried by tweets originating from three different cities.

In recent years, several studies have used computational algorithms to automatically infer emotions in images because of the emergence of deep convolutional neural networks (Yu, 2015) and universality of facial expression in multilingual environment (Ekman, 1992). Recent efforts like that of Kang et al. (2017a) employed Mircosoft Cognitive
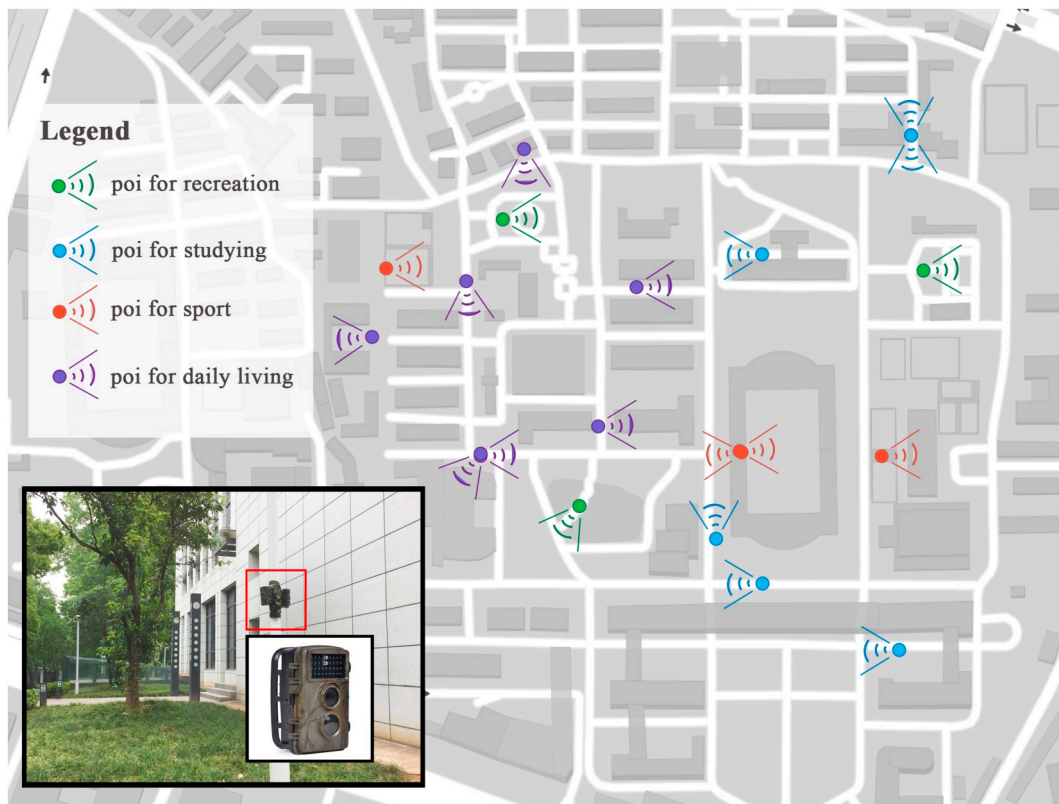
Fig. 1. Spatial distribution of cameras and actual shooting scene in the field of view of the cameras.

Services, the Emotion API to detect emotions in photos from Flicker, and created a sensitivity map to show areas where human emotions are easily affected by the stock market changes. Singh et al. (2017) used Face + + API to measure smiles in photos from Twitter and Instagram, and found that people tend to smile more when they are not alone. A large body of valuable findings regarding subjective well-being and urban planning have been reported, since emotion data derived from SNS information became prevalent in the research community in recent years (Abdullah et al., 2015; Bandhakavi et al., 2016; Chakraverty et al., 2015; Singh et al., 2017). Some existing studies have explored place emotion extracted from SNS and found some interesting results. For example, Abdullah et al. (2015) extracted emotion from geo-located tweets of areas of the United States. Kang et al. (2018) investigated the worldwide expression of emotions by utilizing Flickr geo-tagged photos to create a ranked list of happier countries.

The analyses above rest upon the assumption that SNS datasets are representative of human emotions in real world. It is worth noting that prior literature has confirmed the bias of user-generated content (UGC) from SNS users, a specific small group (Cha et al., 2007; Chang et al., 2014; Dai et al., 2012; Rost et al., 2013). For instance, Rost et al. (2013) showed that the number of check-ins of Foursquare at a venue (*e.g.*, an airport) and its actual visitors (*e.g.*, airport passengers) can differ by orders of magnitude. Stephens (2013) explored the large gender divide in contributions to OpenStreetMap (OSM) and examined its effects on OSM's content. Similarly, another study suggested that OSM has significant geographic bias and the bias in terms of precision varies with culture (Quattrone, Capra, & Meo, 2015). However, few studies exist in the domain of bias in place emotion which make it unclear whether the bias of UGC will influence the accuracy of place emotion measurement. Therefore, are we optimistic about the usefulness of place emotion in SNS and the validity of our conclusions? The representativeness of place emotion in SNS need to be carefully examined. In this paper, we propose a method to quantify different forms of emotional bias in online and offline place emotion. We then apply this method to the case of

Weibo in one campus of Wuhan University to measure how biased the emotional information is towards the photos of a distinct subset of total population—SNS users.

3. Methods

This section includes the following subsections: data collection, face recognition, and emotion indices. The data collection section explains how and where the dataset was collected and what have been done to wash the data. The face recognition section illustrates how human facial information (including emotion, gender, and age) were computed quantitatively. The emotion indices section describes four indices that were used to measure the place emotion in a confined spatial-temporal range.

3.1. Data collection

Two datasets were collected. One is from an online platform like Twitter known as Weibo.com (*online dataset*) and the other one is from photos taken by road cameras *in-situ* (*offline dataset*).

Online dataset: in this paper, we chose to apply our method to Weibo since this is the biggest microblogging platform in China which is also popular in our study area. Tens of millions of users created personal accounts and share life moments with photos and text with their followers (Data Center of Sina Micro-blog, 2018). The Weibo data was sampled *via* web crawler from 00:00 am May 16th, 2018 to 23:59 pm May 30th, 2018 for all photos with geotags and taken in the spatial range of one campus of Wuhan University, China. It should be noted that as restrained by Weibo's user privacy terms, the exact geo-location of each microblog is not available in Weibo data. Therefore, we can only search and obtain data within certain place of area such as a campus of Wuhan University. This sample consisted of microblog information, including images, if any. After two weeks of continuous collection, this dataset consisted of 5780 microblogs. All images were

extracted from the dataset which resulted in a sample of 31,824 unique images in 4819 unique microblogs.

Offline dataset: the offline dataset contains photos taken at certain locations with a fixed time interval. The offline shooting data was collected by 20 Forsafe H901 hunting cameras in the same campus during the same time periods as the online dataset. The cameras were set to work at local time of 6:00 am to 19:00 pm to keep good imaging quality and take photos by a constant interval of 60 s. Fig. 1 depicts the spatial distribution of our cameras and actual shooting scene in the field of view (FOV) of the cameras. In the campus, the locations of camera placements are densely and evenly distributed. After two weeks of collecting, this dataset consisted of 69,676 unique images.

Since we are interested only in studying the human emotions from photos with facial expression, the Face++ Cognitive Services' API for facial recognition were utilized to delete photos without human faces. As a result, 11,164 unique faces and 18,315 unique faces were identified as online dataset and offline dataset respectively.

3.2. Face recognition

With state-of-the-art face detection and recognition technology (Weihong et al., 2008), we can perform batch image analysis. The online and offline datasets are submitted to the Face++ Cognitive Services (https://www.faceplusplus.com.cn/) to obtain information of each face in two datasets. The output gives the estimated emotion-related score, age, and gender of each of the individuals in the images.

The emotion-related score consists of seven-dimensional emotion confidence (EC) including sadness, neutral, disgust, anger, fear, surprise, and happiness. These scores are numbers between 0 and 100 which represent the confidence of each emotion, and the sum of the seven emotion confidences is 100.

The Face++ API outputs have been validated for high accuracy in facial detection in previous studies by Wang, Li, & Luo (2016), Singh et al. (2017) and Bakhshi, Shamma, and Gilbert (2014). Therefore, it is considered trustworthy in this study to estimate emotion confidence (EC), age, and gender from the datasets we have used.

RQ3 questions to what extent the demographic characteristics impact results. To investigate this, this study is indicative of two diversity coefficients which are age and gender. Concerning the factor of age and referring to the work of Yarlagadda, Murthy, and Krishna Prasad (2015), two datasets are both divided into three groups: teen (age <20); adult (age 20–50); old (age >50). Then, considering the factor of gender, the three groups are furtherly subdivided into six groups: teen female, adult female, old female, teen male, adult male, and old male.

The online and offline datasets included 11,164 and 18,315 faces with a mean age of 29.36 and 39.90 respectively. Within the online dataset, females are overrepresented (66.27%). But within the offline dataset, most faces (64.35%) were detected as male. The majority of the online dataset (91.76%) and the offline dataset (81.05%) were adults. The composition of datasets is summarized in Table 1.

Immediately after the emotion-related scores were calculated, all raw photos were deleted forever. Since the data used for our research was collected from the public SNS and the public spaces on real-world streets, our methodology respects people's privacy and does not violate any security guidelines.

Table 1
Profile of faces.

Measure	Items	Online dataset (%)	Offline dataset (%)
Gender	Female	66.27	35.65
	Male	33.73	64.35
Age	Teen	3.04	2.20
	Adult	91.76	81.05
	Old	5.20	16.75

3.3. Emotion indices

To measure human emotions in a specific region from a statistical view, four emotion indices are defined in this study which include EPI, EII, EEI, and ESI respectively. It should be noted that we do not discuss the "neutral" emotion because neutral is a special emotional state, and six emotions (sadness, disgust, anger, fear, surprise, and happiness) excluding "neutral" are named "basic emotions" by Ekman (1992).

Emotion Probability Index (EPI): this index calculates the probability of any basic emotion revealed by people in the datasets. For a confined geographical area A, during the period of t, the EPI is:

$$EPI_{At} = 100 - \frac{1}{n} \sum_{i=1}^{n} EC_{neutral}(i) \tag{1}$$

where n is the number of all faces in area A, and $EC_{neutral}$ is emotion confidence (EC) of neutral.

Emotion Intensity Index (EII): as for an individual-level scale, since the sum of the EC of all seven emotions is 100, the emotion with the highest EC will be judged as his/her principal emotion. Therefore, for a certain region A, the intensity of a particular emotion e over a period t can be expressed by the ratio of faces with the emotion e to the total number of faces detected. EII is defined as:

$$EII_{At-e} = \frac{n_e}{n} \tag{2}$$

where n_e is the number of faces with the emotion e, and n is the number of all faces that have been recognized. EII is equal to or >0. Values of this metric close to 1 present the intensity of emotion e is strong in places, and values close to 0 present the intensity of emotion e is weak in places.

Emotion Evenness Index (EEI): the concept of evenness has been regarded as one of the basic parameters of community structure in interspecific competition by ecologists, and it can be used to describe same characteristic of emotion space structure. The evenness index is based on Pielou Evenness Index with a foundation of Simpson Index (Whittaker, 1972). The metric is calculated as follows:

$$EEI_{At} = \frac{1 - \sum EII_e^2}{1 - n_b^{-1}} \tag{3}$$

where EII_e is the EII value of six basic emotions, n_b is the count of all faces of six basic emotions. This index ranges between 0 and 1. The value close to 1 means the basic emotions are evenly distributed in the emotion space of places, and the value close to 0 means the basic emotions are heterogeneously distributed in the emotion space of places.

Emotion Suppressed Index (ESI): to quantitatively explore the differences of online and offline place emotion, the difference of emotion intensity index (EII) between the two can be used to describe the extent of place emotion that has been suppressed or exaggerated. We normalized it for each place by dividing it by its offline EII. The calculation formula is as follows:

$$ESI_{At-e} = \frac{EII_{offline} - EII_{online}}{EII_{offline}} \tag{4}$$

where $EII_{offline}$ is the EII value of offline dataset, and EII_{online} is the EII value of online dataset. For the ESI, a positive value represents the emotion e is underestimated by SNS information in places, and a negative value means the emotion e is overestimated by SNS information in places.

4. Results

In this section, we revisit our research questions mentioned in Section 1 and state our findings. For the convenience of discussion, we assume that the emotion that people naturally express in their daily life are more worthy of being set as baseline. We compare online and offline
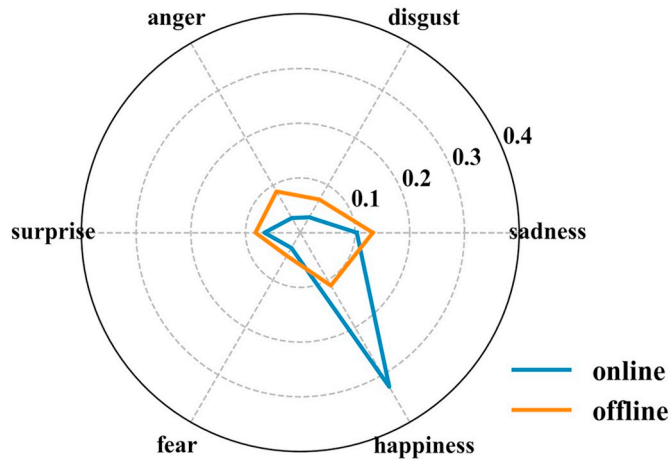
Fig. 2. EII of six basic emotions comparing online and offline datasets.

place emotion based on this assumption. In other words, offline place emotion is not the true value, although we set it as baseline.

4.1. The differences in online and offline place emotion

Research question 1 (RQ1) focuses on the emotion space structure of online and offline. Since the emotion probability index (EPI) synthesizes six basic emotions and represents the overall emotional characteristics, it can be utilized to answer RQ1. The EPI of online and offline datasets are 61.182 and 56.653 respectively. A corresponding *t*-test between the neutral's EC of the two datasets yielded a t value of -9.527 which was significant at the level $p < 0.001$. Therefore, there were indeed significant differences between online and offline place emotion, and the results suggest that online place emotion will overestimate the probability of basic emotions in our study area.

To answer research question 2 (RQ2), the emotion intensity index (EII) and emotion suppress index (ESI) of six basic emotions for two datasets are computed, and the results are presented in Figs. 2 and 3. As can be seen, there is a clear peak in happiness which means EII in online dataset is much larger than in offline dataset, but other five emotions in online dataset have lower EII values. This implies that online place emotion tends to exaggerate people's happiness and suppress other emotions. This pattern is further reflected in the Fig. 3, with values of ESI for happiness being negative and for the other five emotions being positive. Furthermore, the polarity of the top three emotions in ESI

including disgust, anger, and fear are all negative. Specifically, users tend to conceal their negative emotions. Therefore, these results combined suggest that the misalignments vary in each emotion dimension. In terms of all basic emotions, emotion evenness index (EEI) of two datasets (EEI of online dataset is 0.644 and offline dataset is 0.818) also indicate the overall misalignment.

4.2. The pattern of online and offline place emotion among different demographic groups

Research question 3 (RQ3) questions the effects of diversity on the pattern of differences between online and offline place emotion. As stated in Section 3.2, each dataset was divided into six diverse groups: teen female, adult female, old female, teen male, adult male, and old male. Similarly, we can start with the comparison of EPI between diverse groups of datasets. From Fig. 4, it can be observed that female's online EPI all scored significantly higher than their offline EPI. Female's high online EPI conforms to the finding we represent in Section 4.1 that the overall online EPI is higher than the offline EPI. However, this pattern is not obvious for male groups. Teen males' online EPI (59.59) is only slightly higher than their offline EPI (55.88), and adult male's online EPI (51.76) is even lower than that of their offline EPI (53.34). Therefore, the misalignment of emotion probability of female groups between online and offline place emotion is higher than that of male groups. Moreover, teen and old females' differences between online and offline EPI are larger than adult females' EPI which suggests that the emotion probability bias of teen and old females is larger than adult females. In sum, the following result shows the online-offline emotional differences: teen female > old female > adult female > old male > teen male > adult male. In other words, the emotions of adult male are most consistent online and offline.

Figs. 5 and 6 show EII and ESI of six basic emotions of six diverse groups. In general, we find that all groups are more expressive in happiness on the internet compared to daily living, with female groups having a more conspicuous tendency than others. Even more, adult and old groups suppress their other five emotions. This coincides with the findings of complete datasets in Section 4.1. However, teens not only enjoy exaggerating their happiness (ESI: female -4.17 male -0.81), but also enjoy exaggerating their sadness (ESI: female -0.14 male -0.61) slightly. Moreover, the polarity of the top suppressed emotion of all groups except old females are also all negative emotions. It is interesting that old females are found to suppress the surprise emotion (ESI: 0.69). We notice that ESI of happiness of male groups decreased with age growth. Along with the growth of the age, the bias of happiness of male is increasing. Nevertheless, there is no evidence that this
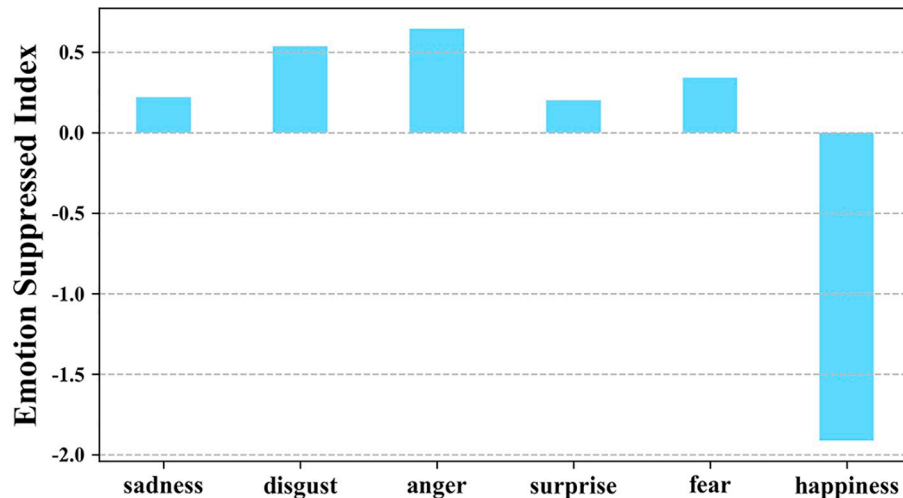
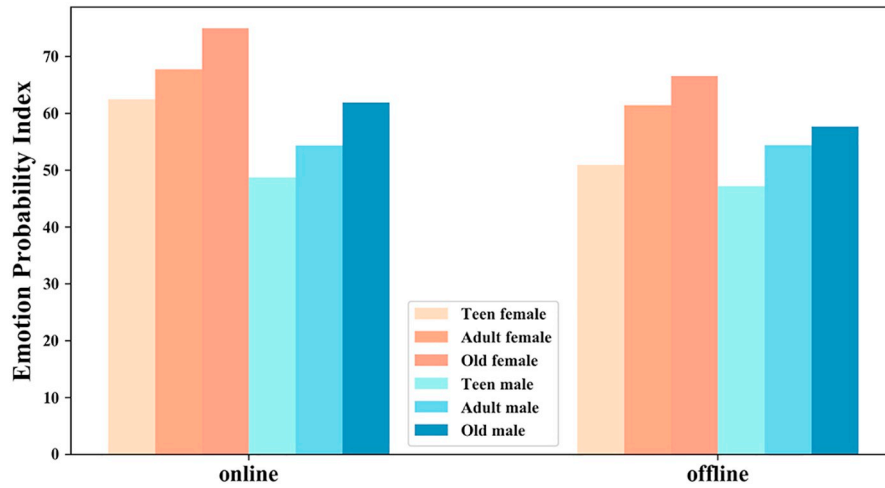

Fig. 3. ESI of six basic emotions.

Fig. 4. EPI of six diverse groups comparing online and offline datasets.

pattern applies to female groups.

The EEI of groups (see Fig. 7) indicates offline emotion evenness of all groups is almost identical with some differences in online emotion evenness. It is apparent from Fig. 7 that all groups are misaligned. The result is consistent with the finding in Section 4.1 that online place emotion is misaligned, and this pattern of females is also significantly obvious. Together, these results suggest that there are differences between groups in online and offline emotion evenness.

5. Discussion

This paper aims to contribute to the discussion of the representativeness of place emotion extracted from SNS (online place emotion). This discussion focuses on two aspects: 1) what are the differences between online and offline place emotion, and 2) whether demographic diversity influences the pattern of these differences. We notice that results of the analysis are quite similar for the overall datasets and diverse groups. This consistency lends credence to the observations made.

In Section 4.1, we found that there are significant differences in online and offline place emotion, and the differences appear in each emotion dimension. This does not come as a surprise as the reliability and representativeness of big data have been doubted in recent years (Boyd & Crawford, 2012; David et al., 2014). Although big data helps obtain large-scale and copious data of human behavior and perception, it is hardly to neglect that UGC is produced as by-products of communication between users. The most interesting finding was that online place emotion underestimates people's negative emotional side and overestimate their happiness. People in real life living are not as happy as they present in SNS. A possible explanation is that many of the smiles in social media settings may be "posted" (Singh et al., 2017) and people tend to show their positive and optimistic images to others (Vaate, 2018), which maybe based on humans' social instincts of emotional linkage (Waxer, 1977). It can, therefore, be assumed that the place emotion extracted from SNS information makes little sense as representations of real-world situations. Overall, it is necessary to reconsider the findings in prior works using SNS information to measure
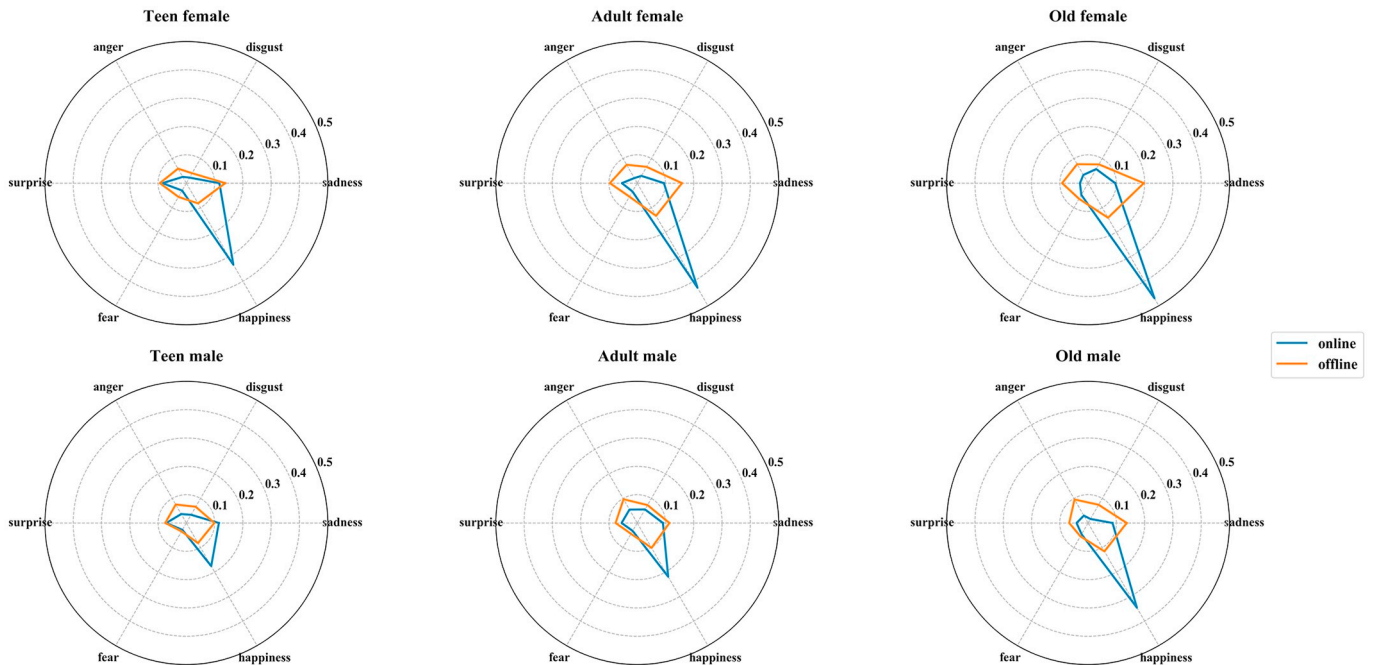

Fig. 5. EII of six basic emotions of six diverse groups comparing online and offline datasets.
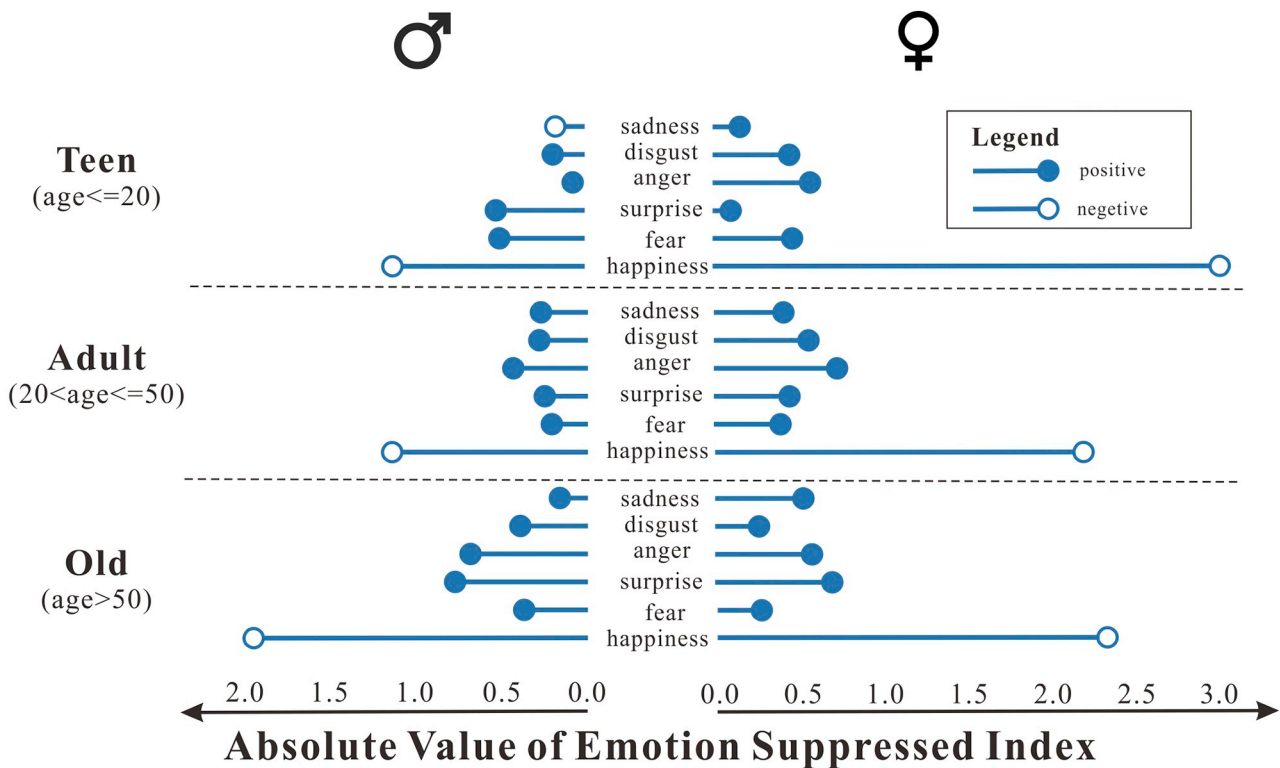
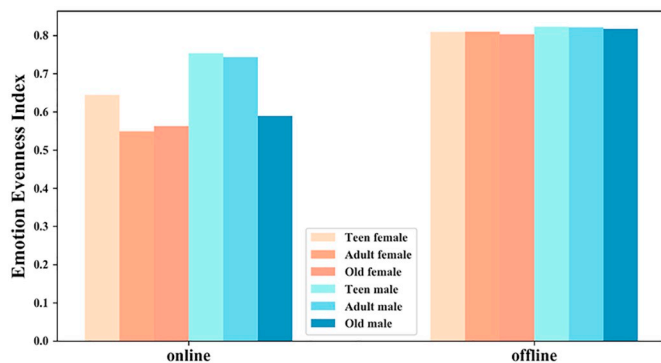Fig. 6. ESI of six basic emotions of six diverse groups.

Fig. 7. EEI of six basic emotions of six diverse groups comparing online and offline datasets.

place emotion.

Specifically, this paper provides a great insight into the effects of demographic characteristics on patterns of differences between online and offline place emotion. A striking result in Section 4.2 is that online place emotion of females is more biased than males. This is supported by a meta-analysis (Mcclure, 2000) that females have an advantage in facial emotional expression, from as early as infancy, and through childhood and adolescence. Moreover, Ottoni et al. (Ottoni et al., 2013) found women prone to describe themselves using affectionate vocabulary and men prone to use assertive vocabulary. As for the SNS setting, users post their photos out of choice, and it is possible that female users may amplify their daily emotional pattern in SNS. One unanticipated finding was that along with the growth of the age, the online place emotion of males in happiness is more biased. This pattern is absent in female groups probably due to females' cultural backgrounds of China (Marianne, Hecht, & Elizabeth Levy, 2003; Yanping & Yongshe, 2009) which often advocate females to be kind and gentle ever since they were very young. However, since males don't have such rules, they learn to mask their emotions with their social experiences growing.

The quality of crowdsourcing geographic information is always a key topic since it was proposed by Goodchild and Glennon (2010). The existing literature has revealed the biases of crowdsourcing geographic information in different forms such as in spatial and semantic characteristics (Stephens, 2013). As an example, in a study that quantifies geographic bias of OpenStreetMap mapping in 40 countries, a significant geographic bias is found between the spatial information provided by top contributors and the rest of OpenStreetMap community, as the top contributors have a clearly different demographic and spatial characteristics from the crowd (Quattrone et al., 2015). Likewise, this study discusses and quantifies the biases of crowdsourcing geographic information in the form of collective human emotion related to places. We hope it will enrich the efforts of exploring and improving the quality of emotion-related crowdsourcing information, for more effective policymaking in smart cities. Furthermore, there are already some studies tried to extract social media-based place emotion for citizen-centric urban planning practices (Resch et al., 2016; Zeile et al., 2015). However, emotional information extracted from user-generated data usually has inherent biases which may give rise to inaccurate or even distorted results. In this study, we found such biases have statistically significant correlations with user groups' demographical characteristics. With the methodology framework we proposed, we may deduce and calculate more accurate place emotion from numerous geotagged UGCs. The existing literature has illustrated a vision of how citizen-centric planning equipped with accurate volunteered geographic information may look like in the near future, and our study is one step closer to this vision.

From the perspective of urban planning, how people in the city perceive their environment depends not only on the mood of the people but also on a variety of dynamic and static external factors such as resource availability, the feeling of safety, comfortability, urban aesthetics, *etc.* These subjective perceptions can trigger different emotions, which enable additional insights into the spatial and temporal configuration of urban planning. Citizen-centric urban planning can be achieved by analyzing UGC such as photos and posts from social

network services and extracting emotional information of general citizens related to certain places. However, due to inherent nature of UGC caused by users' social intention, the bias in UGC data has always been criticized, which thereby prevents the applications on emotion extraction from UGC data and its guidance for citizen-centric urban planning. Our experimental results show the potential of identifying and rectifying the emotional bias existed in photos uploaded to SNS. On the basis of demographic groups, the place emotion extracted from SNS mapped with the *in-situ* emotional expression, and then the patterns and correlations between the two were observed. With the help of these quantitative observations, a more accurate place emotion can be calculated. Our approach bears extensive potential to reveal unbiased insights into citizens' perceptions of the city.

This paper defined a campus as one 'place' to study the human emotions presented at the site. However, it is worth noting that the 'place' can also be defined at other spatial scales, such as functional areas like teaching areas, dormitory areas, sports areas in campus. Buildings such as lecture halls and canteens can also be defined as 'places' that "possess" their own human emotional attributes. Since the distribution of emotions is no doubtfully heterogeneous in campus, incorrect placement of cameras may make the measurements of human emotion unrepresentative and may also severely affect the accuracy of the measurement of offline data. In order to avoid this, we have chosen representative sampling points which satisfied multiple pre-requirements, including high pedestrian flow, uniform spatial distribution in the campus, and diverse functional areas on the campus, to ensure representative emotional data collected for the place of the campus.

It also should be noted that the study area was only restricted to a campus, which means results cannot be generalized to other places with different functionality and demographic characteristics. Further studies need to verify the results with various representative places. Moreover, the demographic descriptors utilized in this work are limited. Accordingly, we acknowledge that other factors contributing to the differences between online and offline place emotion still exist, such as ethnicity and culture. For instance, Diener & Diener (1995) found that self-esteem is strongly related to subjective well-being (analogous to general positive emotions such as happy) in individualist cultures such as the United States, but only moderately so in collectivist cultures such as China. In future work, with the availability of detectors for a wider gamut of factors, we might be able to explore a more nuanced version of place emotion research. Concerning that it is still unclear how the demographic factors influence the differences in online and offline place emotion, further studies should focus more on the interaction between people and place emotion, and explore models to calibrate the bias between online and offline place emotion in kinds of places.

Other limitations include: facial image with low resolution may not be accurately detected and analyzed on emotion. For our experience, a frontal facial image has to be at least 40×40 pixels to be correctly recognized and analyzed; Additionally, there is a lower limit on the number of faces collected at one place, to ensure an accurate reflection of the place emotion. One prior study showed that 15,000 valid faces can be set to the limit for stable results (Kang et al., 2018).

6. Takeaway for practice

These findings provide supports for policy recommendations of citizen-centric urban planning in both local and international practice. As for local practice, with observations on more accurate human emotional information from SNS bond to places, policymakers can identify specific sections of cities that failed to meet citizen's expectations. Concrete (re-) planning issues such as poorly timed traffic lights at crossroads, roads with worse walkability became detectable from unbiased collective human emotions. Even the expression of pedestrians can be used to infer the sense of security of city streets. These minor/subtle dissatisfactions can hardly be observed from traditional municipal reports or citizens' formal complaints. Our study illustrates the possibility of

monitoring the dynamics of unbiased emotional landscape of a place in a city from SNS, works towards to transfer the urban management mechanism from report-driven to auto-adaptive. In terms of international practice, obtaining more accurate place emotion over the world leads to more reliable policies made by the policymakers responding to the world events such as the prediction of political elections (Tumasjan et al., 2010) and major stock market fluctuations (Kang et al., 2017b), and the responses to natural and man-made disasters (Chien, Comber, & Carver, 2017), *etc.*

7. Conclusion

Since this paper calculated the differences between six-dimensional online and offline place emotion based on four emotion indices (including EPI, EII, EII, and ESI), it provides quantitative evidence of these intangible phenomena and the methodologies allowing future research in this area to validate results more specifically. Furthermore, it may help to fix models based on SNS emotion collection of facial expression for places that have similar demographic characters.

To conclude, this study tapped into a novel domain within place emotion research and made the next step in investigating underlying differences between place emotion extracted from different resources. The study proposed four emotion indices to describe place emotion, and a stratified analysis of online and offline place emotion based on gender and age was carried out. The results indicate that place emotion extracted from SNS information, in general, tend to exaggerate people's happiness and suppress their negative emotions. Further, there are noticeable differences across diverse groups with varying gender and age. This study provides quantitative evidence of these intangible phenomena and the methodologies allowing future research in this area to validate results more specifically. Investigators should be wary of place emotion extracted from photos of SNS when conducting research on place emotion. Place emotion extracted from SNS information, although informative, may provide a skewed picture of the emotional life of a place—a picture skewed in the direction of exaggerating happiness and suppressing negative emotions. This paper presents a methodology framework which rectifies place emotion extracted from petabytes of user-generated images with much smaller samples collected from the real world. The framework was applied to a university campus in our case, and the result indicates that groups with different demographic characteristics tend to have different patterns of bias in revealing emotions in UGC. This method can be easily transplanted to other places and spatial scales, for more accurate information of place emotion obtained from UGC; however, it still needs to be confirmed by further studies whether the patterns found in our study (*e.g.* females tend to show more happiness expression in SNS photos than males do) are cross-cultural.

CRediT authorship contribution statement

Yingjing Huang: Methodology, Software, Writing - original draft. **Jun Li:** Formal analysis, Data curation, Visualization. **Guofeng Wu:** Validation, Writing - review & editing. **Teng Fei:** Conceptualization, Writing - review & editing.

Declaration of competing interest

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

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