Perceptions on Cultural Ecosystem Services of World Cultural Heritages in Beijing: A cross-cultural Comparison of Social Media-based Online Reviews and Images

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Abstract

This study introduces an innovative approach combining social media text and image comments to quantify the perceptual differences of cultural ecosystem services among various sociocultural groups. For five World Heritage Sites in Beijing, natural-language processing classifies visitor perceptions using social media comments and image data, and importance-performance analysis quantifies the differences between Chinese and international visitor perceptions of these cultural ecosystem services. For the six perceived cultural ecosystem service categories, cross-cultural and local visitors exhibit the same satisfaction trends. In particular, international tourists assign higher importance scores for a given cultural ecosystem service than Chinese tourists. The proposed methods incur a lower cost than traditional methods and acquire large volumes of broad-ranging data. Additionally, the importance of–the performance analysis data-acquisition method is improved. Moreover, World Heritage Site sustainability can be promoted by understanding the different heritage tourism perceptions of different cultural groups. Furthermore, this study provides valuable insights for decision-makers to improve tourism management and conservation strategies.

Keywords: cultural ecosystem services, World Heritage Site, cross-cultural tourism, natural-language processing, importance-performance analysis

1. Introduction

World Heritage Sites are regarded as universal treasures, being the most attractive natural or cultural sites in the world (UNESCO World Heritage Centre, 2019). As World Cultural Heritage Sites are famous for their profound historical and cultural connotations and unique cultural landscapes, they attract tourists worldwide; thus, a balanced relationship between tourism, recreational activities, and the natural environment is desired (Ghermandi et al., 2020). In recent years, the study of ecosystem services for World Cultural Heritage Sites has become increasingly popular (López Sánchez et al., 2020; Venkatachalam et al., 2022), where ecosystem services are the benefits that people derive from ecosystems and include provisioning, regulating, supporting, and cultural services (MA, 2005).

Hegetschweiler et al. (2017) state that cultural ecosystem services (CESs) are relevant to people rather than ecosystems. The CESs that people obtain from an ecosystem are nonmaterial, and these intangible benefits are more prominent than material ones (Cheng et al., 2019). The reason is that they are felt and experienced directly while benefiting human well-being (Kosanic & Petzold, 2020; Liu et al., 2022; Wang et al., 2021)such as urbanisation and unsustainable land use, and human-induced drivers, such as climate change. A result is the loss of ecosystem services. The way humans benefit from diverse ecosystem services for their physical and mental wellbeing differs from place to place and between communities and social groups. While the existing research on ecosystem services is rich on the relevance of provisioning ecosystem services for human wellbeing, the role of cultural ecosystem services is not sufficiently understood. Moreover, a variety of methods and a wide range of approaches are adopted to study how landscapes provide ecosystem services and how important they are for different people. Therefore, this paper systematically reviews where and how cultural ecosystem services are studied explicitly with respect to aspects of human physical and mental wellbeing and various social groups. Our review provides an overview of research biases and gaps that need to be addressed to advance our understanding of this link, which is critical to implementing meaningful environmental conservation and protection for local communities and vulnerable populations.”,”container-title”:”Ecosystem Services”,”DOI”:”10.1016/j.ecoser.2020.101168”,”ISSN”:”22120416”,”journalAbbreviation”:”Ecosystem Services”,”language”:”en”,”note”:”Q1<2 区 >”,”page”:”101168”,”source”:”DOI.org (Crossref. Unlike provisioning, regulating, and supporting services, which provide material security for human life directly through quantifiable objective indicators of biological, physical, and socioeconomic relevance (Cheng et al., 2019), CESs satisfy intangible needs. The quantification of CESs is subjective and challenging because they operate directly on the individual and have spiritual, cognitive, and aesthetic dimensions. Moreover, individuals perceive CESs in the same environment differently according to their social and cultural backgrounds (Cheng et al., 2013; Huai & Van de Voorde, 2022; Terkenli et al., 2020). In general, however, policy developers and administrations do not consider public perceptions sufficiently because of the subjective and ambiguous nature of CESs. In addition, understanding public opinions and preferences is crucial for preserving and managing Cultural Heritage Sites and, in turn, supporting the development of local communities (Csurgó & Smith, 2021).

Public perceptions of CESs can be analyzed to establish the emotional bonds between humans and nature. Importantly, people from different sociocultural backgrounds may have different preferences towards the same ecosystem; thus, the perceptual differences between groups with different cultural backgrounds are attracting increasing research attention. For example, in a study by Madureira et al. (2015)Angers, Lisbon and Porto, respondents in four cities across two countries reported different satisfaction levels with green spaces. Similarly, in an eight-country cross-population study, Terkenli et al. (2020) found that tourist perceptions and intentions differed with nationality. Another study, in which parks in Shanghai and Brussels were taken as study sites, found that people have different landscape preferences according to their cultural context (Huai & Van de Voorde, 2022). However, most of the above works, whether cross-city or cross-national group studies, were general regarding their object of study, as they focused mostly on urban green spaces. In particular, no studies have focused on specific sites such as historic parks. Furthermore, most research has focused on the overall landscape impression of the target site rather than on the cultural perceptions of visitors.

Research on CES perception has long been based on traditional approaches involving social surveys, interviews, and self-reporting (Dou et al., 2021; Terkenli et al., 2020; Zhang et al., 2022). However, traditional methods can be time-consuming and labor-intensive in the context of data collection from cross-cultural communities, particularly for studies considering transnational tourism. With an increasing number of visitors sharing their observations on social media platforms (e.g., Twitter, Instagram, Weibo), crowdsourced data is becoming a fresh and valuable resource. Crowdsourced data refers to information collected and provided by non-experts and citizen organizations for researchers rather than professional scientists and government agencies. These non-experts volunteer to share information through means such as uploading to online platforms based on social media networks. In this process, users typically collect information using sensors (e.g., smartphones, computers) and then choose to upload, providing a continuous stream of passive crowdsourced data relevant to natural environment research. Previous studies have mentioned that crowdsourced data relies on user-generated content shared voluntarily, not specifically intended for researchers. Therefore, in this study, we particularly focus on data derived from social media sources. Furthermore, social media data (SMD) reflect the most honest and direct visitor perceptions and typically contain two types of information: social media images and comment text.

Social media images contain large volumes of information, such as location data (Liu et al., 2022) and user IDs. Furthermore, this type of information is updated continuously. By analyzing the contents of these photographs, user perceptions of the landscape can be determined (Chen, 2022; Karasov et al., 2022; Richards & Friess, 2015)while importance is calculated using an adjusted association rule mining algorithm. The results are validated with earlier surveybased attributes relevant to visitors and Australia's case. The results demonstrate encouraging accuracy, suggesting that the proposed methodology offers opportunities to assess tourist satisfaction at destinations with larger sample sizes for a lower cost and greater data collection flexibility than traditional approaches. The methods proposed could be beneficial in a wide range of tourism contexts.","container-title":"Annals of Tourism Research","language":"en","note":"Q1","page":"19","source":"Zotero","title":"Assessing destination satisfaction by social media: An innovative approach using Importance-Performance Analysis","author":[{"family":"Chen","given":"Jinyan"}],"issued":{"date-parts":[["2022"]]}},"label":"page"},{"id":249,"uris":["http://zotero.org/users/9672283/items/VISUUPYX"],"itemData":{"id":249,"type":"article-journal","abstract":"Coupled usage of remote sensing and geotagged social media data responds to the growing interest in the spatially explicit operationalisation of cultural ecosystem services (CES. Currently, content-based photograph classification can be performed manually or using machine learning methods. An objective coding method for manual photograph classification has been established by experts in fields related to environmental management (Richards &

Friess, 2015). Moreover, Oteros-Rozas et al. (2018) have developed a review protocol including a set of landscape-feature and CES indicators to be identified in each photograph. The accuracy and reliability of these manual classification methods have been proven; however, they are overwhelmed when confronted with large amounts of data. Advanced computer technology is providing new methods for studying CESs. One automatic image content identification method involves the use of open-cloud platforms (e.g., Google Cloud Vision), which provide an API for image recognition, allowing users to analyze the contents of individual images and return these data as keywords (Cao et al., 2022; Fox et al., 2021; Ghermandi et al., 2022). Subsequently, researchers can classify photographs based on the tagged content. Recently, deep learning has been used for CES-based image classification. In particular, convolutional neural networks are becoming increasingly popular, and deep learning methods can be used for large-scale, low-cost, and relatively simple CES identification (Cao et al., 2022; J. Chen, 2022; Oteros-Rozas et al., 2018; Richards & Lavorel, 2022).

Moreover, researchers have examined user opinions and preferences (Huai & Van de Voorde, 2022) and satisfaction (Chen, 2022) with tourism sites by using natural language processing (NLP) algorithms to extract rich semantic and sentiment data from SMD comments. NLP methods can quantify large volumes of unstructured textual data into structured data that are more easily analyzed. The purpose of sentiment analysis is to identify the sentiment polarity of text (positive, negative, or moderate) and convert it into specific sentiment ratings (Huai & Van de Voorde, 2022; Wang et al., 2021)how these distinct spaces provide different services, if any, to human wellbeing has been seldom addressed. Using large volumes of social media data considering broad user groups and publicly available content, we developed a method to transform un structured online comments into a structured assessment of nine categories of ecosystem services. An 'ecosystem services lexicon' was created based on 6853 words under twenty-eight subcategories of parks' services to human wellbeing using the word2vec model. The application of the ecosystem service lexicon to urban parks in Beijing revealed that all ecosystem services were perceivable to urban park users; however, the perception frequency of the ecosystem services varied across different parks. Additionally, the perceived ecosystem services were bundled together; four types of bundles were identified with varied dominant services. Technically, this study offered a novel technical procedure that can transfer unstructured free comments into a structured assessment of urban parks' perceived services to human wellbeing. Theoretically, the study revealed small-scale ecosystem service bundles from users' opinions and called for a further cross-scale understanding of ecosystem service bundles. Practically, the study findings can help inform evidence-based park policies, planning, and management.","container-title":"Urban Forestry & Urban Greening","DOI":"10.1016/j.ufug.2021.127233","ISSN":"16188667","journalAbbreviation":"Urban Forestry & Urban Greening","language":"en","note":"Q1<2-3 区 >","page":"127233","source":"DOI.org (Crossref to quantify visitor perceptions intuitively. Algorithmic models, such as word2vec (Jatnika et al., 2019, p. 2; Wang et al., 2021)000 articles in the English Wikipedia as the corpus and then Cosine Similarity calculation method is used to determine the similarity value. This model then tested by the test set gold standard WordSim-353 as many as 353 pairs of words and SimLex-999 as many as 999 pairs of words, which have been labelled with similarity values according to human judgment. Pearson Correlation was used to find out the accuracy of the correlation. The results of the correlation from this study are 0.665 for WordSim-353 and 0.284 for SimLex-999 using the Windows size 9 and 300 vector dimension configurations.","collection-title":"The 4th International Conference on Computer Science and Computational Intelligence (ICCSCI 2019, can also be used to transform the text into word vector form and can be further combined with machine learning algorithms to derive the frequencies of tourist perceptions regarding landscape elements. Currently, NLP is not particularly applicable to cultural heritage site design planning. However, as visitor perceptions are crucial for the conservation and governance of cultural heritage, a method to rationally apply NLP while accurately analyzing visitor perceptions must be developed.

In general, current research has the following limitations: 1) The data-gathering approach is limited to photo content analysis or text data analysis, which cannot be used for an in-depth assessment of visitor perceptions; 2) The research subjects have the same cultural backgrounds, and any cross-cultural backgrounds are insufficiently diverse to illustrate perceptual differences in the cross-cultural context; 3) The focus of the study is substantially broad, and the cultural component is not highlighted.

In response to the above research gap, this study presents a method for quantifying the differences in CES perceptions of Chinese and international tourists by applying NLP combined with importance-performance analysis (IPA) of reviews from online travel agency (OTA) platforms for five World Heritage Sites in Beijing. Note that international tourists here refer to foreigners with different cultural backgrounds who come to China for short-term tourism, which differs from foreigners who have lived in

China for a long time. To propose culturally appropriate suggestions for the conservation and development of World Heritage Sites and to contribute to research on differences in cultural perception, this study addresses the following questions: 1) How can social media images and text data be combined to characterize tourist perceptions? 2) Which types of CES can visitors perceive? 3) What are the similarities and differences in CES perceptions among people from different cultural backgrounds? Thus, this study presents a framework for studying CES perceptions by combining picture and text data to reveal the similarities and differences in cross-cultural tourists' perceived preferences. Notably, this study implements IPA (Chen, 2022; Wang et al., 2022), which generates four quadrants based on user perception (with importance and performance on the X- and Y-axes, respectively) using a corresponding coordinate system.

2. Materials and methods

2.1. Methodological framework

The method employed in this study comprises three main steps (Figure 1): 1)First, a web crawler is used to obtain related SMD (from TripAdvisor and Ctrip in this case). 2) Second, to find the specific CES categories perceived by visitors to heritage sites, NLP and sentiment analysis are applied to the review texts. Hence, we can determine the frequencies and attitudes of user CES perceptions. The CES-perception attitude measure reflects visitor satisfaction relying on the IPA approach. Based on keywords returned from each image using an online cloud platform (i.e., Google Cloud Vision), we obtain specific CES classifications and analyze the perception frequencies; this knowledge is combined with the comment-text perception frequency in the second step to determine the IPA importance indicator. 3) Finally, we identify differences in CES perceptions among different cultural groups using IPA mapping.

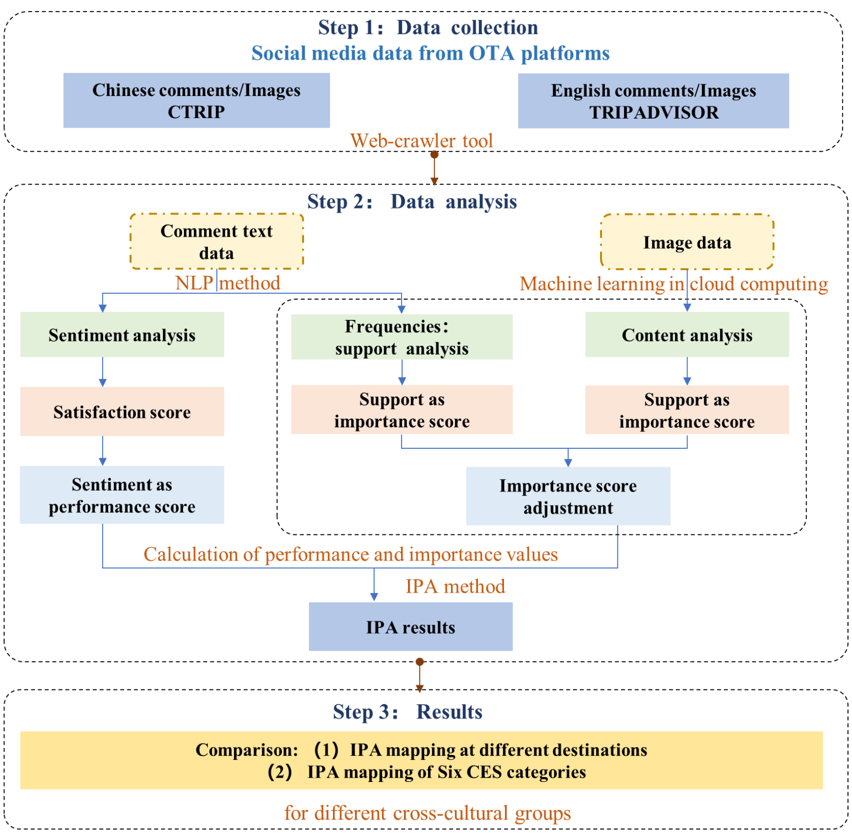


Fig. 1 Methodological framework employed in this study.

2.2. Study area

Beijing is the capital of China, its global communication hub, one of its first historical and cultural cities, and the city with the most cultural heritage in the world (UNESCO). Over 3,000 years of history have yielded world-class cultural heritage sites, such as the Forbidden

City, the Temple of Heaven, the Great Wall, the Summer Palace, and the Imperial Tombs of the Ming Dynasty, which attract both Chinese and international tourists (UNESCO). These five World Heritage Sites showcase traditional Chinese culture to international visitors in terms of fortification, garden culture, palace architecture, tomb regulations, and ritual culture. The present study attempted to identify the similarities and differences in the CES perceptions of people from vastly different international sociocultural backgrounds concerning World Heritage Sites characterized by traditional Chinese culture.

As discussed in the Introduction, investigating the perceptions of people from various cultural backgrounds of the World Heritage sites in Beijing is crucial, not only to supplement consideration of CESs in cross-cultural perception studies but also to further reduce researcher and policymaker perceptual differences of user needs from multicultural backgrounds and to propose appropriate policy recommendations for the future conservation of World Heritage sites in Beijing.

2.3. Crowdsourced SMD preparation

2.3.1. Data collection

Table 1 lists the number of online reviews and related images collected in this study pertaining to the five World Cultural Heritage Sites in Beijing; these items were obtained from Ctrip and TripAdvisor. Ctrip is one of the most popular OTAs in China and allows the public to spontaneously upload their opinions on attractions through reviews, travelogues, or pictures. According to 2019 Ctrip's first quarter financial report (https://investors.trip.com/zh-hans/financial-information/quarterly-results), Ctrip may have had more than 200 million active users in this period; thus, we chose Ctrip as our data source to collect the local Chinese people perspectives. Moreover, we chose TripAdvisor, another OTA platform, as a data source for international perspectives because this site is a world-renowned online travel information acquisition platform with over 600 million reviews from travelers worldwide (https://en.tripadvisor.com.hk/). This site is becoming a popular source for ecotourism and recreation research (Teles da Mota & Pickering, 2020)including nature-based tourism. We assess the current state of the academic literature to highlight what sources of data and methods are used, where and to assess which issues and what are the benefits and limitations of this novel source of data. Using a systematic quantitative literature review method, we identified 48 relevant pub lications mostly from Europe (18. The use of online review data for this research is permitted under the non-commercial use license of Ctrip (https://you.ctrip.com/htmlpages/eula.html) and the fair use principle for non-commercial purposes of TripAdvisor. We crawled relevant SMDs from Ctrip and TripAdvisor using keywords, collecting user IDs, post times, comment content, comment images, and comment locations for posts dated between January 2008 and May 2022. The search results were exported to a Microsoft Excel spreadsheet for data processing.

We cleaned the obtained data and, following deduplication, we obtained 29,252 Chinese and 21,022 English valid comment data items. The image data required further cleaning. Based on the literature (Cardoso et al., 2022; Oteros-Rozas et al., 2018) and our study requirements, we primarily considered photographs with specific ecosystem service perception content and filtered them according to the following rules: 1) Photographs with human subjects, such as selfies, were removed. 2) Images that were irrelevant to CES perception, such as advertisements, were removed. Following the processing step, we obtained 52,852 and 13,415 photographs from Chinese and international tourists, respectively. This study complied completely with privacy protection principles, and all data were saved in a fully encrypted folder to further protect privacy. These data were accessible only to members of the research team, and the original data were completely deleted once the study was completed.

Table 1 Data on five World Cultural Heritages of Beijing

World Cultural Heritage Site	Main cultural resources	Number of Chinese comments	Number of international comments	Number of pictures uploaded by Chinese tourists	Number of pictures uploaded by international tourists
Forbidden City	Architecture, cultural relics, court culture	10202	8274	21200	7776

Temple of Heaven	Architecture, landscape, worship	3188	3909	792	1830
Great Wall	Architecture, urban construction, military history, engineering	10154	2197	15804	2689
Summer Palace	Architecture, cultural relics, gardens, royal art	2920	6132	10459	1955
Imperial Tombs of the Ming Dynasty	Architecture, landscape, worship	2874	569	792	378

2.3.2 Identification of CES classifications

First, the types of CESs perceived by visitors must be identified. CES perceptions can vary between countries, socioeconomic levels, and the characteristics of the cultural landscapes themselves. Previous CES-perception studies concentrated on urban green spaces (Wang et al., 2021) versus other types of green spaces (Wan, 2021). In those studies, CES categories were identified based on information collected from the study sites while incorporating frameworks proposed by experts. For example, in a study of cultural services in coastal ecosystems in Hong Kong, the Millennium Ecosystem Assessment (MEA, 2005), the Economics of Ecosystems and Biodiversity (TEEB, 2021), and the Common International Classification of Ecosystem Services (Ghermandi et al., 2020) frameworks were combined to obtain a list of CES categories that fit the study-site characteristics (Cao et al., 2022). Unlike previous studies, this study proposes a method that uses NLP to obtain the most realistic CES types perceived by tourists via social media text comment data through a high-frequency word-topic clustering analysis of their most realistic travel perception comments.

In this study, public CES perceptions were characterized by analyzing descriptive comments from visitors, such as words with CES perceptual characteristics (i.e., nouns, adjectives, and verbs). In previous studies, comments in various languages were translated into the same language for subsequent processing (Wan, 2021). To avoid translation bias, authoritative dictionaries (Merriam-Webster's Collegiate Dictionary, Eleventh Edition, and Oxford Advanced Learner's Dictionary) were used. However, the translation process may affect the emotions conveyed by the original language. In contrast, in this study, NLP processing was separately applied to English and Chinese comments to characterize visitor perceptions as realistically as possible (Huai & Van de Voorde, 2022) and to avoid translation-induced misinterpretations. The following NLP-based steps were used to identify the actual CES-perception types of Chinese and international tourists.

(1) Biterm topic model

The topic model is a statistical model that is primarily applied to text-clustering scenarios in NLP to discover abstract topics within a series of documents. For this study, we chose the Biterm topic model (BTM), which was proposed by Yan et al. (2013)such as tweets and instant messages, has become an important task for many content analysis applications. However, directly applying conventional topic models (e.g. LDA and PLSA as a more suitable topic model for short-text research based on the LDA model. The BTM uses an entire corpus of short texts for modeling, presents short texts as word pairs, and uses the topic distribution of the entire corpus to describe the topics of individual documents, thereby enriching the semantic information of the documents. In particular, this approach maintains word-to-word correlation and estimates the distribution probabilities of different topics.

(2) Topic inference based on online reviews

In this study, the Chinese and international tourist comment data were first pre-processed. 1) Data cleaning was performed to ensure the validity and relevance of the comment text and to reduce noise within the comments, for example, by removing ads and duplicate comments. 2) Word separation was performed using the Jieba word separation tool (a Python platform tool) for Chinese comments and the Natural Language Toolkit (NLTK) for English comments.

The following equation was used to represent the perplexity degree, to determine the optimal number of

topic values K, and to apply the BTM to the pre-processed comments. The K value was used to evaluate the model generalization ability, with a smaller K indicating an improved modeling result. From Yan et al. (2013)
such as tweets and instant messages, has become an important task for many content analysis applications. However, directly applying conventional topic models (e.g. LDA and PLSA,

$$K = \exp\left\{-\frac{\sum \ln p(b)}{|B|}\right\} \tag{1}$$

where $|B|$ denotes the total number of word pairs, and $p(b)$ denotes the joint probability of word pair b, as the following Equation shows. From Yan et al. (2013)

$$p(b) = \sum_z p(z)p\left(w_i \middle| z\right)p\left(w_j \middle| z\right) = \sum \theta_z z_{i|z}\Phi_{j|z}, \tag{2}$$

where $p(z)=\theta_z$ denotes the probability distribution of topic z, $p\left(w_i \middle| z\right)$ denotes the probability distribution of the topic-z feature word w_i, and $p\left(w_j \middle| z\right) = \Phi_{j|z}$ denotes the probability distribution of the topic-z feature word w_j.
From Figure 2(a), when the BTM modeled the pre-processed Chinese comments, the optimal perplexity was obtained when K and the number of topics were both 9. On the other hand, the perplexity of the English reviews is shown in Figure 2(b). In this case, when the results were combined with manual screening, the best classification results were obtained when K was 18.

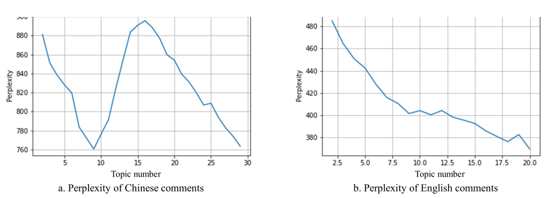


Fig. 2. Perplexity indicator values for different topic numbers.

The distribution based on subject terms allows for an intuitive matching of topics to specific ecosystem cultural service domains; thus, the results can be used to classify ecosystem cultural services. In Figure 3, the 15 words with the highest probability of occurrence are listed in a word cloud for each topic according to the topic-word probability distribution; the font size indicates the probability of occurrence of that word in relation to that topic, considering Chinese reviews as an example.

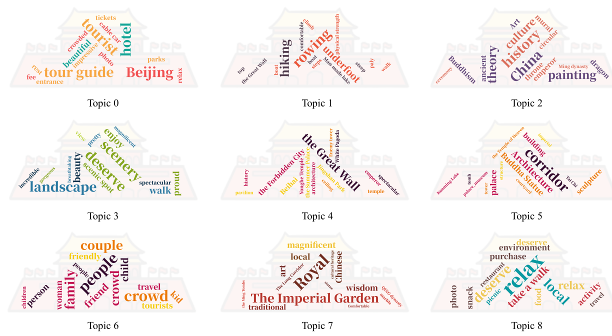


Fig. 3. Wordcloud graph for Topic 0–8.

We divided the aforementioned subject terms into CES categories, summarised the CES visitor perception categories consistent with the Beijing World Heritage Sites based on the subject term distributions, and combined the BTM results for the Chinese and international reviews. The following six CES categories were established in this study based on the perceived characteristics of the visitor comments, prior literature, and MA (MEA, 2005): 1) Aesthetic services, corresponding to visitor appreciation of the landscape and its many natural scenic elements, such as those at the Great Wall; 2) Recreation and tourism services, being those providing leisure or recreational activities for visitors, including scenic recreational facilities and family experience programmes; 3) Heritage and cultural services, corresponding to the wealth of cultural heritage services related to Beijing's regional characteristics provided by the World Heritage Sites (such as those of the Great Wall, the Forbidden City, and other ancient buildings); these sites also have deep cultural connotations; 4) Physical and mental recovery services, which facilitate relaxation and activities such as jogging, cycling, rock climbing, and boat trips; 5) Social relation services, corresponding to the locations for social interaction provided by the World Heritage Sites (additionally, sites potentially promoting human interaction); 6) Spiritual services through which the World Heritage Sites satisfy the spiritual needs of visitors from various cultural backgrounds and allow cross-cultural visitors to perceive different social customs and habits. A CES classification system for the five World Heritage Sites was created, as presented in Table 2.

Table 2 Cultural ecosystem service categories of 5 world heritage sites

Categories of Cultural Ecosystem Service	Description of CES	Examples of representative keywords	Included Topics
Aesthetic services	Appreciation of the landscape	Scenery, landscape, beauty, spectacular	Topic 3
Recreation and tourism Services	Provide recreational activities for tourists	Tour guide, tourists, visit, tourists	Topic 0, 8
Heritage and cultural services	Preserve historical and cultural heritage	The Great Wall, royal, architecture, Temple of Heaven	Topic 4, 5
Physical and mental recovery services	Engage in physical and mental health-promoting activities	Physical strength, rowing, hiking, walk around	Topic 1
Social relation services	Promote interpersonal communication	People, friends, family, child, baby	Topic 6
Spiritual services	Meet the spiritual needs of different types of tourists	Painting, theory, knowledge, Buddhism,	Topic 2, 7

2.3.3 Sentiment analysis

This study argues that tourist satisfaction with the expressive nature of a destination is expressed through the sentiment values of their reviews. Thus, tourist perceptions of and attitudes toward Cultural Heritage Sites can be quantified through sentiment analysis. Sentiment analysis, also known as review mining, can assign objective values to subjective reviews using computer algorithms. We quantified the perceptions of Chinese and international visitors by using the Baidu (https://ai.baidu.com /tech/NLP) and Google (https://cloud.google.com/natural-language) NLP platforms to perform a sentiment analysis of the selected Chinese and English texts. These platforms are based on pre-trained state-of-the-art machine learning models and can perform high-accuracy computations for sentiment analysis tasks. Low to high sentiment scores indicate negative, neutral, and positive emotional polarity, respectively. We obtained the sentiment score for each online review by accessing the APIs of the selected platforms and obtained the average sentiment score of each World Cultural Heritage Site as the visitor satisfaction level for the site. To improve the comparability of the Chinese and English comments, we normalised the Google NLP sentiment scores using the min–max normalisation method.

2.4 Analysis of social media images

2.4.1 CES classification identification from images

Several studies have confirmed that the photographic content uploaded by visitors is related to their landscape preferences (Cao et al., 2022; Oteros-Rozas et al., 2018). In this study, an automatic image content recognition platform (https://cloud.tencent.com/) was used to crawl the images using keyword tag recognition. The following three steps were implemented: 1) We used an online cloud platform (i.e. the Tencent Cloud platform) to perform keyword recognition on images uploaded by Chinese and international tourists. A confidence-to-score was returned with the results each time and, for each image, we only considered the first six keywords; hence, sample results were obtained, as presented in Table 3. 2) We classified the obtained keyword tags, matching them with the six previously determined CES categories, and ignored irrelevant tag words. The specific categories are presented in Appendix A. 3) The images were classified according to particular criteria. Note that each image could correspond to more than one CES category.

Table 3 Sample image recognition results

Image sample	Sample image recognition result
 Pic_1	[' 水 (water)', Confidence: 92; ' 自然 (nature)', Confidence: 79; ' 倒影 (reflection)', Confidence: 73; ' 树 (tree)', Confidence: 56; ' 叶子 (leaf', Confidence: 41] Number of tags: 5
 Pic_2	[' 纪念碑 (monument)', Confidence: 93; ' 艺术 (art)', Confidence: 80; ' 雕像 (statue)', Confidence: 65; ' 墙壁 (wall)', Confidence: 40; ' 建筑 (architecture)', Confidence: 33] Number of tags: 5

 Pic_3	[‘ 地质学 (geology)’, Confidence: 86; ‘ 山岳 (mountain)’, Confidence: 79; ‘ 岩石 (rock)’, Confidence: 55; ‘ 地形 (terrain)’, Confidence: 43; ‘ 风景 (landscape)’, Confidence: 32] Number of tags: 5

The classification validity was ensured by randomly selecting 100 images by experts for manual identification of the image CES type, and the manual identification results were compared with the automatic identification results and assessed for reliability based on Cohen’s kappa coefficient κ. The CES-type classification exhibited strong consistency (κ = 0.701), exceeding the suggested value (0.6). This outcome indicated that the CES-type identification performed using image content analysis was statistically significant.

2.5 IPA method

CESs are difficult to quantify because of their subjective nature. In this study, quantification was performed using the IPA method, which is an intuitive method of analyzing the importance and performance of a destination as perceived by a tourist. Unlike direct questionnaires, which are based on IPA importance and performance indicators, web-based Big Data were used in this study. Therefore, one focus of this study was the effective transformation of the crawled web data into IPA indicators. Previously, Wang et al. (2022) compared the similarities and differences of data obtained from SMD and questionnaires and found that the results were essentially the same; however, those derived from SMD were more biased towards public rather than personal services. Further user categorisation is required, and thus, this study further categorised users into Chinese and international tourists.

2.5.1 Importance and performance evaluation using SMD

This study hypothesized that the sentiment tendency of each review is associated with the tourist’s perceived satisfaction with the CESs. Thus, performance scores were generated for each CES by calculating the performance sentiment score based on an open artificial intelligence (AI) platform; this was an automatic method of returning sentiment categories ('1' and '0' for very satisfied and dissatisfied, respectively) to represent, to some extent, the visitor satisfaction levels for each World Heritage Site. In particular, the mean sentiment score for each Cultural Heritage Site and comments relating to a particular CES category was used as an indicator of visitors’ perceived satisfaction with this CES type for this site.

In this study, the perceived importance of a CES was assumed to be correlated with the number of mentions by heritage site users (Chen, 2022). Thus, the importance metric was based on a correlation-rule learning approach calculating support to obtain the adjusted occurrence frequencies of each CES type in the textual comments and images pertaining to each World Heritage site. The importance *i* was the arithmetic mean of the adjusted frequencies for the textual comments and images, which were determined separately.

The degree of support was calculated as follows (Chen, 2022):

$$\text{Support}\left(A_d\right)=\frac{\left[p\in T;A_d\in p\right]}{\text{N}} \tag{3}$$

where *T* was defined as the entire dataset consisting of *N* reviews for the five selected World Heritage sites, and *Support*(A_d) for attribute *A* of destination *d* was defined as the proportion of CES-related reviews of a particular type *p* in *T*. The importance scale was restricted to 0–5 (with 5 being the most important attribute) to match the performance level. The following relation was used to adjust the scale (Chen, 2022):

$$\text{Imortance}\left(A_d\right)=5*\frac{\left[p\in T;A_d\subseteq p\right]}{\left[\max\left(N_{Ad}\right)\right]} \tag{4}$$

where max $\left(N_{Ad}\right)$ indicated the maximum number of times a CES type (*A*) was mentioned at a particular destination.

Table 4 briefly lists the Chinese tourists' perceived importance values of the various CES categories for the Forbidden City.

Table 4 Sample of importance values perceived by Chinese tourists for the Forbidden City

CES categories	Chinese comments	imp_1	Chinese images	imp_2	imp_ave
Aesthetic services	4018	2.83	10304	5	3.92
Recreation and tourism services	4533	3.19	9768	4.74	3.96
Heritage and cultural services	7102	5	7397	3.59	4.29
Physical and mental recovery	819	0.58	1596	0.77	0.68
Social relations	735	0.52	1778	0.86	0.69
Spiritual services	3337	2.35	3403	1.65	2.00

3. Results

3.1 Satisfaction and importance characteristics of World Heritage Site CESs

From the analysis of online comments and photographic content regarding the five targets Cultural Heritage Sites, Chinese and international visitors differed significantly regarding their perceived CES satisfaction and importance. Because our study had a large number of results, the Forbidden City was chosen as a representative example to illustrate the results; however, the results for each of the five World Heritage Sites are presented in Appendix B. Table 5 reports the calculated satisfaction and importance scores, where the CES satisfaction was determined from the sentiment value of each comment, and the CES importance was determined from the number of times the CES is mentioned in comments and images. The two sources of importance were assessed separately in this study, with the highest perceived frequency being assigned a value of '5', and the remaining scores being assigned based on a scale according to Equation (4). Combining CES satisfaction and importance scores may reflect public demand for cultural services.

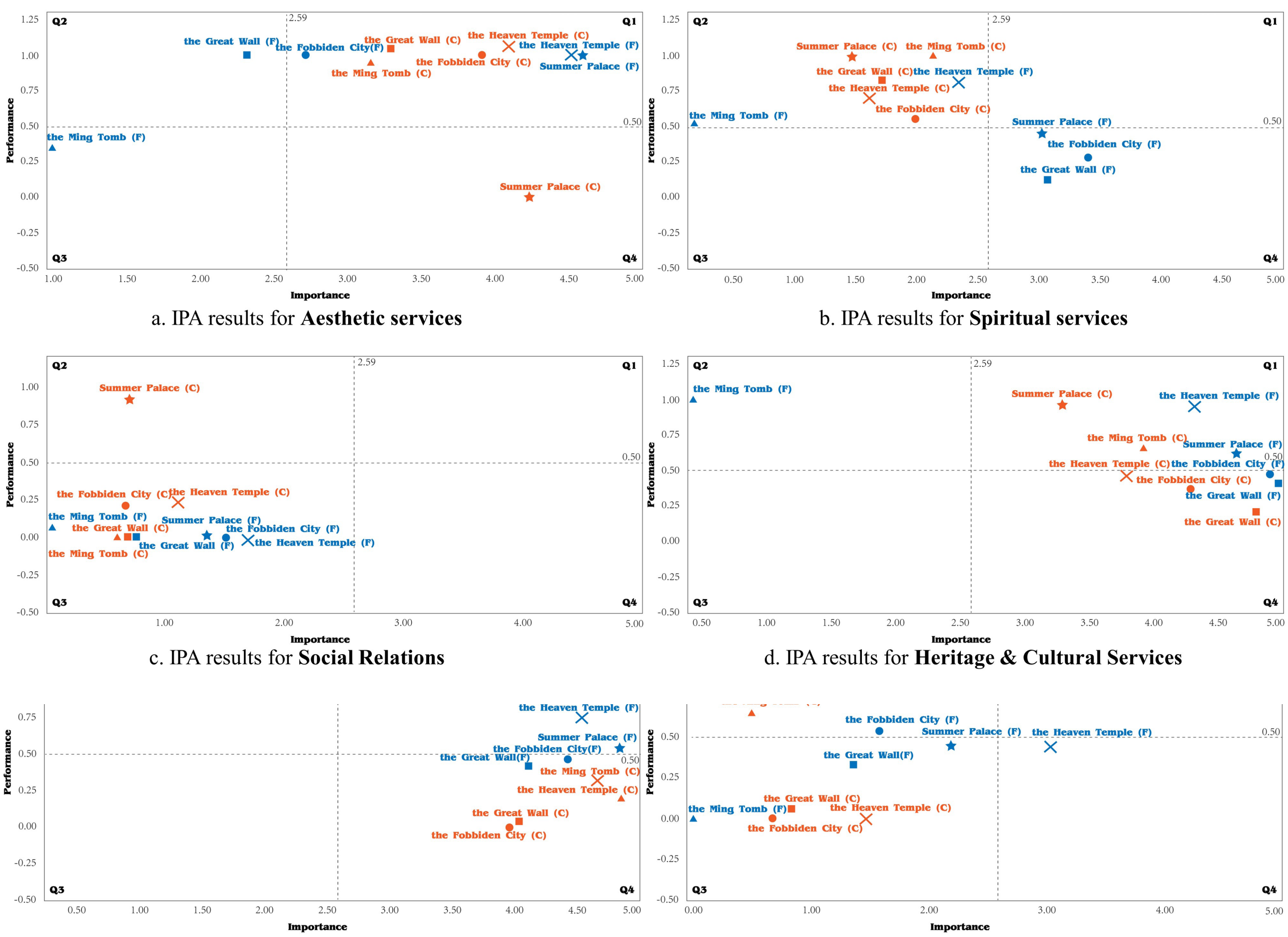
Table 5 Satisfaction and importance results for CES perception of Forbidden City

Category	Performance (Chinese)	Importance (Chinese)	Performance (Internationalers)	Importance (Internationalers)
Aesthetic services	1.00	3.92	1.00	2.71
Recreation and tourism services	0.00	3.96	0.47	4.43
Heritage and cultural services	0.39	4.29	0.45	4.99

Physical and mental recovery	0.00	0.68	0.54	1.58
Social relations	0.21	0.69	0.00	1.54
Spiritual services	0.57	2.00	0.29	3.41

3.2 IPA comparisons of perceived CESs

The use of both data-centred and scale-centric approaches has advantages and disadvantages. In particular, from the findings of Chen (2022), a data-centred approach in conjunction with a detailed analysis of each destination facilitates the presentation of greater volumes of information. In this study, an IPA quadrant map was constructed using the mean of importance and performance as the dividing line to compare perceptions of six CES types at the five World Heritage Sites of Beijing.



a. IPA results for **Aesthetic services**

b. IPA results for **Spiritual services**

c. IPA results for **Social Relations**

d. IPA results for **Heritage & Cultural Services**

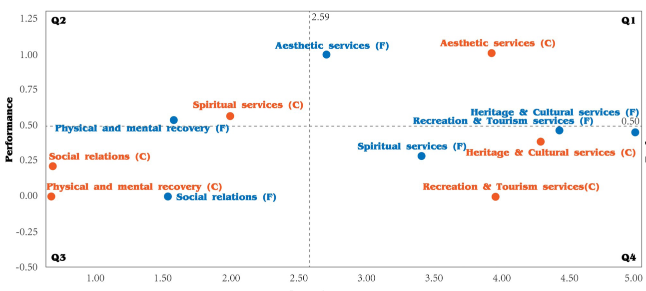
e. IPA results for **Recreation & Tourism services**

f. IPA results for **Physical and mental recovery**

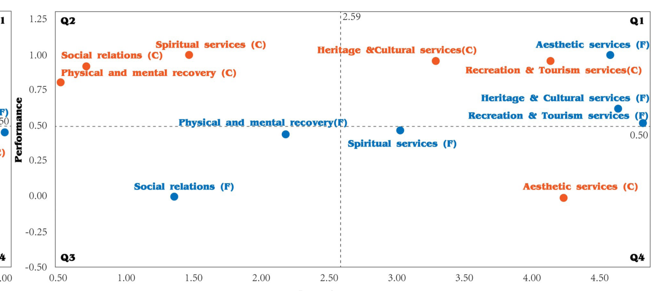
Fig. 4. IPA results for (a) aesthetic services, (b) spiritual services, (c) social relations, (d) heritage and cultural services, (e) recreation and tourism services, and (f) physical and mental recovery.

Figure 4 shows the IPA results for each of the six CES categories. Figure 4(a) indicates that, in general, the aesthetic services CES was perceived well by Chinese and international tourists at all destinations, with most points falling into the first quadrant (indicating high importance and high performance). In contrast, a large difference was observed between the Chinese and international visitor perceptions of the spiritual services CES. Chinese visitors perceived spiritual aspects well across destinations but perceived them as being less important (Fig. 4(b)). Conversely, international tourists attributed a higher importance value to this CES but a lower performance score when visiting for multiple purposes. This result implies that cross-cultural tourists find it challenging to perceive the expression of inspirational spiritual services when visiting World Heritage Sites, even though they consider them important. This is because various objective factors can impede the complete perception of these services by international visitors. For example, English-speaking tourists visiting these destinations may be hindered by the differences in the language systems of China and the West, differences in expression, and inaccurate translations through direct translation; these problems may dilute or even degrade the historical and cultural connotations of Chinese tradition for international visitors. Social relations as a CES did not generally receive a high-performance score, falling almost entirely into the third quadrant (low performance and low importance) (Fig. 4(c)). Finally, international tourists more strongly emphasized heritage and cultural services, recreation and tourism services, and physical and mental recovery than Chinese tourists and assigned higher importance and performance values to their CES perceptions for each Cultural Heritage Site overall (Figs. 4(d)–(f)).

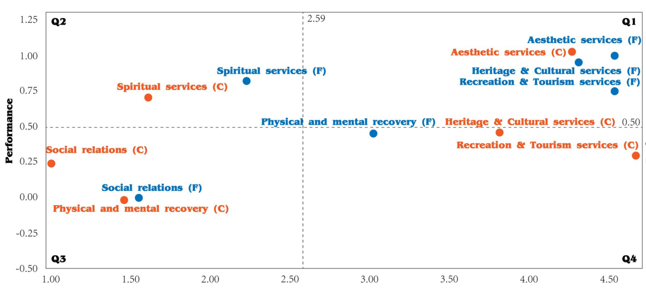
3.3 IPA comparisons of perceived CESs for each site



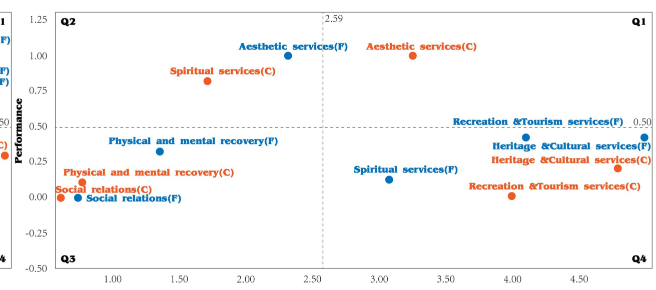
a. IPA results for **the Forbidden City**



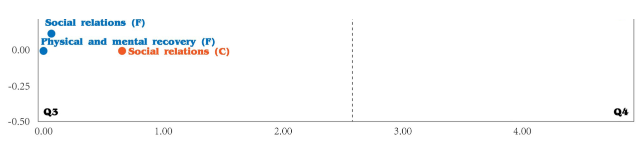
b. IPA results for **the Summer Palace**



c. IPA results for **the Heaven Temple**



d. IPA results for **the Great Wall**



e. IPA results for **the Ming Tomb**

Fig. 5. IPA results for the (a) Forbidden City, (b) Summer Palace, (c) Heaven Temple, (d) Great Wall, and (e) Ming Tomb.

Figure 5(a)–(e) illustrate the differences in CES perceptions between Chinese and international visitors to each destination. Both Chinese and international tourists apparently considered aesthetic services to be the most important CES type when visiting World Heritage Sites. Moreover, these services were generally highly satisfactory and well-perceived by both groups. In addition, the heritage and cultural services and the recreation and tourism services were well perceived by both Chinese and international tourists, falling in the first quadrant (high satisfaction and high performance); these results are similar to the findings of Dou et al. (2017) and Gai (2022)with both positive and negative consequences. One major challenge is how to secure the long-term quality of life for urban residents. Many studies on quality of life are based on 'material' ecosystem services (i.e., provisioning and regulating services. Similarly, for both the Chinese and international visitor groups, the physical and mental recovery and social relations CESs were perceived as unimportant and poorly represented, falling in the third quadrant (low performance and low importance), again agreeing with the findings of Gai (2022). These results indicate that visitors focus more on the cultural heritage services and enjoying the scenery. They are less interested in communicating in person. It is difficult for visitors to perceive sports services at World Heritage Sites, except for destinations (i.e., the Great Wall), which require considerable physical effort.

In general, significant cultural differences exist between Chinese and international tourists. Therefore, international tourists often need help to grasp the spiritual connotations of Chinese history and culture shortly. Visiting these heritage sites is an emotional experience for tourists, and it is worth considering the future promotion of Cultural Heritage Sites to improve international tourists' understanding of the spiritual and cultural services they provide.

4. Discussion

4.1 Innovation of the proposed method

As tourism flourishes at World Heritage Sites, a balanced relationship must be established between tourism, recreational activities, and the natural environment. This balance is essential for sustainability and to promote the sociocultural needs of visitors. Ordinary urban green spaces have been shown to provide recreational and exercise opportunities for visitors while also promoting stress reduction and improving mental health (Dadvand, 2018; Schrammeijer, 2021)including green spaces, has a crucial role in brain development in children. Currently, however, we are not aware of evidence linking such exposure with potential effects on brain structure. OBJECTIVE: We determined whether lifelong exposure to residential surrounding greenness is associated with regional differences in brain volume based on 3-dimensional magnetic resonance imaging (3D MRI. In this study, we selected specific sites, that is, World Heritage Sites.

Currently, social media Big Data are being widely used as a major source of research data (Dadvand et al., 2018; Schrammeijer et al., 2021) to understand visitor perceptions. However, social media photograph-related metadata only (Cao et al., 2022; Lee et al., 2022; Sinclair et al., 2019) or online review texts (Huai and Van de Voorde, 2022) have primarily been used. In addition to visualizing realistic visitor perceptions, SMD can be used to identify specific cultural services through content recognition. In particular, text data can provide a broader overview of cultural service perceptions than image data. Therefore, this study provides a new framework for combining two different types of data, text and image, to reveal the full extent of the differences in the CES perceptions of Chinese and international visitors. Combining text and image content can overcome the limitations of pure text- or image-based classification. SMD are also valuable for the future development of historical and cultural heritage sites. In the post-pandemic recovery era, determining the true perceptions of international tourists visiting Chinese historical and cultural heritage sites is possible to promote heritage tourism on the international market by valuing the experiences of these international tourists.

This study also proposes an innovative approach that overcomes the limitations of traditional questionnaire methods for data collection. From multi-source SMD, we can indirectly measure CES importance and performance, as perceived by Chinese and international tourists, through IPA. The performance scores were calculated by converting CES-related comments into sentiment values based on sentiment analysis via an online NLP platform; this was performed following the identification of tourists' specific CES-perception categories, which reduced self-reporting bias. The importance scores were measured based on the number of individual CES-related comments and images associated with each destination, with the two data types (text and image) being combined to provide greater accuracy.

4.2 Common understanding of CES perception

The results of this study show that CESs are widely perceived during visits to World Heritage Sites. However, the perceived importance and performance of each CES vary among different social groups. From the IPA analysis performed in this study, both Chinese and international visitors placed greater emphasis on aesthetic services, followed by heritage and cultural services and recreation and tourism services. This outcome echoes previous findings (Gai, 2022) that heterogeneity among tourists does not affect their perception of CES performance. This finding also suggests that visitors from different backgrounds and cultural contexts tend to focus on the direct cultural, historical, and natural resources of a Cultural Heritage Site. In this study, visually driven aesthetic services received significant attention (pertaining to landscape perception), as human attention was drawn to objects with ornamental qualities (Grahn, 1991). The five World Heritage Sites in Beijing have considerable ornamental resources, as the Summer Palace is the largest and most culturally rich royal garden in the world(UNESCO), and the Temple of Heaven is the site of large rituals held by former rulers and the bearer of ancient Chinese philosophy. The Great Wall has limited accessibility because of its location but offers pleasant natural scenery on mountainous terrain. Thus, cultural heritage and scenic appreciation services are well-perceived. In contrast, the three service categories of social relations, sports and fitness, and inspiration and spirituality are less prone to be perceived when visiting one of the Beijing World Heritage Sites. Visitor groups are less concerned with the process of communicating with each other in person or are indifferent or dissatisfied with their attitude towards communication. In the case of World Heritage Sites, tourists are less likely to focus their attention on them, except for physically demanding destinations such as the Great Wall. In addition, the motivations of heritage tourists vary according to their type, with the corresponding motivations being the desire to be associated with history and the desire to learn, a background of cultural knowledge, and a strong connection to the heritage destination itself. The majority of tourists, however, do not have this motivation, particularly international tourists with completely different cultural backgrounds, and are less likely to perceive its essence in terms of inspirational spiritual services.

4.3 Different CES perceptions in different cultural backgrounds

Our study considered group differences between travellers with different cultural backgrounds and found that, overall, for the same type of CES, international tourists assign higher importance to the service than Chinese tourists. This is similar to previous findings (Weiermair, 2000; Zheng et al., 2022)the tourists' various subcultures and the organisational culture of tourism enterprises in the tourism receiving region. A differentiated approach is developed which distinguishes between global, national and sub-national cultural constructs.","container-title":"Managing Service Quality: An International Journa l","DOI":"10.1108/09604520010351220","ISSN":"0960-4529","issue":"6","language":"en","page":"397-409","source":"DOI.org (Crossref. In particular, Weiermair (2000) has argued that the greater the cultural distance of a destination, the less demanding and, simultaneously, the more accommodating tourists are towards various services in that destination. This suggests that international tourists tend to perceive the importance of CES but find it difficult to understand abstract concepts because of their significant cultural differences, which leads them to assign lower expressivity values. Despite being far more familiar with the history and culture of the site than international visitors, local visitors do not show a greater appreciation for CES services, possibly because the more familiar they are with a region, the more they overlook the importance of CES and take their existence for granted.

One of the biggest differences in CES perceptions between Chinese and international visitors is the perception of inspired spiritual services. Except for Ming Tombs, international visitors gave them extremely high importance scores for the other four destinations, particularly the Forbidden City. Thus, the Forbidden City's inspired spiritual services are valued by international visitors. Moreover, the Forbidden City attracts many international visitors as a Chinese cultural symbol, but generally with cultural adaptation problems. The perception that travellers are strangers entering a new cultural environment in the host country and that psychological uncertainty arises when local values, emotional attitudes, and beliefs are unfamiliar leads to a failure to deeply perceive the inspired spiritual services of their expressive nature. The results suggest that World Heritage sites, such as these, could improve their scenic promotions in the future by considering the cultural adaptation of intercultural travelers, for example, by optimizing text translation in crucial areas, including tactful explanations of unique cultural connotations, while ensuring content readability and considering misunderstandings and ambiguities caused by cultural differences.

4.4 Policy recommendations and implications

This study demonstrates that combining the analysis of text and image comment data uploaded to social media platforms may serve as a valuable alternative and supplement to existing methods that exclusively rely on image content recognition analysis. Although not all photos are directly related to the description of cultural ecosystem services, they still reflect the authentic perceptions of tourists to a certain extent. Sentiment analysis of text comments can correspondingly complement image content analysis. Future research on social media data should focus on systematically integrating these two types of data. Overall, the findings of this study are crucial for the sustainable management of natural resources and cultural heritage sites in the study area. This management could help tourists from culturally diverse backgrounds better understand their preferences and improve the cultural heritage tourism environment. In addition, the results of this study may be useful to local authorities in planning, managing, and promoting tourism at World Heritage tourism destinations. It would be practical for government managers and design practitioners to reflect on the findings. There is research evidence (Arslan and Kaymaz, 2020) that long-term neglect of visitor characteristics and socio-spatial data can affect public perceptions of ecosystem services and long-term development plans. This study elucidates the current state of CES perceptions at World Heritage Sites and explains why specific types of services are not adequately perceived. It is necessary to organically integrate the differences in needs expressed by Chinese and international visitors to satisfy the full range of tourism needs of visitors from all cultural backgrounds and make recommendations for each historical and Cultural Heritage Site consistent with sustainable development.

4.5 Limitations and future work

Although our proposed framework combines online data and images to provide a new method of measuring CES perception, some limitations should be considered with regard to future applications. First, online Big Data were used as a source; thus, the complete user population (primarily the younger generation) could not be covered. For example, children and the elderly were excluded, and hence, the results were biased. The demographic details were also unknown, which is why demographic data were excluded from the study. Although the Internet is widely disseminated, the current primary audience is still young people, and other groups have less access to voice their opinions. Given the data acquisition limitations, future research should consider social group stratification and age demographics to enrich the composition of social media user samples. Second, linguistic ambiguity is still a limitation of SMD analysis, and the presence of different languages in comments adds to the difficulty of subsequent content analysis. Additionally, studies have shown that people tend to share positive information (i.e. things they enjoy) on social media platforms, which may lead to incomplete data collection. Third, this study was based on a small sample of five historical and cultural heritage sites in one city. Subsequent studies could expand the scope of the study population to quantify the differences in Chinese and international CES perceptions on a national scale.

In addition, future research should consider the integration of big and traditional data to explore social issues in cases where clear differences exist between big and traditional data sources, including the population sampled, data collection, and data analysis. Finally, further research should consider how to organically link these two data sources to obtain more reliable and comprehensive results.

5. Conclusion

In this empirical study, an innovative framework of text-based commentary sentiment analysis and image-based content analysis was proposed to quantify the differences in the CES perceptions of Chinese and international visitors using NLP and the IPA method. This approach is both an innovation in data acquisition for the IPA method and a contribution to the understanding of CES perception at historical and cultural heritage sites by visitors with different historical and cultural backgrounds. The main contributions of this study are as follows: 1) The differences in perceptions of historical and cultural heritage sites due to cultural background were elucidated. 2) A thematic model was used to classify CES categories based on the analysis of visitor review text, replacing the direct use of existing classification systems. 3) A combination of text and image content analysis was performed, which overcame various limitations of pure text-based or image-only content recognition. The data sources were enriched, and the data integrity was improved. 4) SMD was used as a source, and relevant IPA indicators were extracted; this approach enriched the data sources for the subsequent IPA model to a certain extent.

In conclusion, this study supports the view that online web-based social Big Data can be an important source of information without privacy implications and that publicly available information obtained through legitimate ways can facilitate understanding of how cultural heritage impacts CES perceptions. Understanding the differences between Chinese and international perceptions is crucial for infrastructure development institutions. This information will allow consider socio-ecological impacts when promoting sustainable tourism. Hence, the conservation and sustainable management of natural resources and cultural heritage can be included in policy considerations and decision-making processes. Park planners and policymakers should consider differences in CES perceptions according to different cultural contexts and balance the needs of different user groups. Moving ahead, researchers will also need to look to other parts of the world, increase the diversity of the platforms used in the analysis, and provide a deeper analysis of the motivations behind cultural perception differences. As social media plays an increasing role in our lives, it will become a crucial data source for monitoring cultural tourism in the future.

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