The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/2633-1225.htm

Destination image branding for world heritage sites: a methodology combining GIS with sentiment analysis

Kun Sang, Pei Ying Woon and Poh Ling Tan
Department of Advertising, Xiamen University Malaysia, Sepang, Malaysia

Received 24 April 2024
Revised 30 July 2024
Accepted 16 August 2024

Abstract

Purpose – Against the background of the popularity of social media and heritage tourism, this study aims to focus on world heritage sites, proposing a method to examine and compare the digital spatial footprints left by tourists using geographic information systems.

Methodology – By analyzing user-generated content from social media, this research explores how digital data shapes the destination image of WHS and the spatial relationships between the components of this destination image. Drawing on the cognitive-affective model (CAM), it investigates through an analysis of integrated data with more than 20,000 reviews and 2,000 photos.

Innovation – The creativity of this research lies in the creation of a comprehensive method that combines text and image analytics with machine learning and GIS to examine spatial relationships within the CAM framework in a visual manner.

Results – The results reveal tourists' perceptions, emotions, and attitudes towards George Town and Malacca in Malaysia, highlighting several key cognitive impressions, such as history, museums, churches, sea, and food, as well as the primary emotions expressed. Their distributions and relationships are also illustrated on maps.

Implications – Tourism practitioners, government officials, and residents can gain valuable insights from this study. The proposed methodology provides a valuable reference for future tourism studies and help to achieve a sustainable competitive advantage for other heritage destinations.

Keywords Heritage tourism, Sentiment analysis, Destination image, GIS, Social media

Paper type Research paper

Introduction

User-generated content (UGC) from social media platforms is an essential marketing source and an important means to grasp users' perspectives in the current digital age. Due to its accessibility, scholars have actively studied UGC for various purposes, including information retrieval, destination selection and decision-making, etc. (Mirzaalian and Halpenny, 2019; Santos, 2022). In recent years, with the advent of machine learning (ML) and artificial intelligence, the vast amounts of unprocessed data on social media like Facebook, Instagram, Weibo, TripAdvisor and others can be transformed into valuable

Funding: This research was supported by Fujian Social Science Research Fund (FJ2024C128) and Xiamen University Malaysia Research Fund (XMUMRF/2024-C14/IART/0023).

Tourism Critiques: Practice and Theory
Vol. 5 No. 2, 2024
pp. 254-271
Emerald Publishing Limited
e-ISSN: 2633-1233
p-ISSN: 2633-1225
DOI 10.1108/TRC-04-2024-0012

insights that benefit businesses, governments and even individuals. As big data have expanded, traditional analytical methods have declined (Stylos *et al.*, 2021). In tourism, scholars use an increasing number of new tools to derive sentiments from UGC (Mehraliyev *et al.*, 2022), which is instrumental in identifying tourists' preferences and behavioural patterns, addressing tourists' satisfaction, evaluating destination"s images (Micera and Crispino, 2017), developing effective marketing strategies (Lin *et al.*, 2021) and tackling other issues, such as hotel occupancy (Ampountolas and Legg, 2021), consumers' activities and purchasing decisions (Liu *et al.*, 2019).

Among various tourism categories, heritage tourism is identified as one that is rapidly expanding. WHSs are, thus, proposed globally for those tangible heritages with notable ecological, cultural and historical characteristics, representing an important tourism sector (Lanen *et al.*, 2022). It involves visiting or participating in experiences that highlight specific sites, objects, activities and narratives from both historical and contemporary contexts (Rasoolimanesh *et al.*, 2021). The unique historical and cultural attributes of WHS serve as compelling factors that attract tourists to those places (Seyyedamiri *et al.*, 2022; Wang *et al.*, 2023). Moreover, a high quality of *in situ* experiences is a noteworthy factor enhancing the appeal of a WHS (Carreira *et al.*, 2022; Molinillo *et al.*, 2022). Destination marketing organisations (DMOs) actively manage these appealing site images as valuable brands in the industry, and a strong WHS brand can definitely attract more tourists (Gomez *et al.*, 2016; Wang *et al.*, 2023). However, during and after the COVID-19, increasing competition among tourism destinations and changing tourist preference necessitate that WHSs use more innovative methods to sustain their competitiveness and enhance their destination images (Richards, 2018; Sun *et al.*, 2023).

However, a gap remains between the advancement of analytical methodologies and the burgeoning amount of big data in tourism research (Jiang *et al.*, 2021). The potential of online data analysis in tourism, particularly concerning heritage sites through UGC analysis, has been widely acknowledged. Some difficulties have been identified, such as the time-consuming and costly process of manually extracting useful insights from online platforms (Paolanti *et al.*, 2021). This research tries to employ social media with text and sentiment analysis, with the help of spatial technologies, to investigate the heritage sites in George Town and Malacca in Malaysia as case studies, thereby presenting a comprehensive approach to understanding the public cognition and sentiment for the heritage sites. Though the representation of heritage in the two cities holds considerable value in attracting visitors, consumers, events and investors, there is a scarcity of research examining the performance of destination image specifically within the Malaysian heritage tourism market (Mehraliyev *et al.*, 2022). Thus, this paper contributes methodologically by employing social media with text and sentiment analysis, combined with spatial technologies, to investigate heritage sites. Theoretically, it tests the spatial relationship between cognition and affection in heritage tourism following the CAM theory. The purpose of this paper is to study and contrast the perception of various sites concerning their respective tourist destination images (TDI) with a new comprehensive method. And two primary research objectives are set: examining the spatial relationship between cognitive image and affective image through social media data; and telling the differences or similarities in tourists' perceptions between the two historical cities in Malaysia.

Literature review

Tourist destination image

Previous studies have been undertaken on the topic of TDI since the 19th century, and it has garnered considerable recognition as a crucial factor influencing visitor behaviours

(Embacher and Buttle, 1989; Carreira *et al.*, 2022; Pramanik, 2023). Especially, the CAM proposed by Baloglu and McCleary (1999) and further elaborated by Pike and Ryan (2004), etc. described how tourists' perceptions of a place are influenced through interaction with the sites. Among it, the cognitive image encompasses beliefs, perceptions and information tourists hold about a place, while the affective component relates to the emotions and sentiments visitors associate with the destination (Pramanik, 2023; Pan *et al.*, 2014; Royo Vela and Garzón Paredes, 2023). The application of CAM is crucial for assessing places, and more variables/factors have been studied, such as cognition, affection, user satisfaction and post-visit intentions (Pramanik, 2023; Pan *et al.*, 2014; Shen and Lai, 2023). It offered a systematic theory to understand the relationship between factors that influence visitor experiences and destination image formation.

Then, the relationship between cognitive and affective images has been extensively studied, too. Several studies have highlighted them. For instance, Stylidis *et al.* (2017) found that both cognitive and affective images significantly influence the overall destination image. Similarly, Woosnam *et al.* (2020) and Yang *et al.* (2022) demonstrated that affective images are significantly influenced by tourists' cognition and mediate the relationship between cognition and intention. However, the past methods mainly applied questionnaires to measure a few dimensions under cognition and affection. There is a lack of methodology to analyse the spatial relationship (the distribution and pattern) between tourists' cognition and affection of TDI. The spatial relationship between these images has been scarcely studied. Therefore, based on previous studies and theories (Baloglu and McCleary, 1999; Pike and Ryan, 2004), this research proposes a methodology to address the *RQ1*:

RQ1. Does the cognitive image of WHS significantly affect the affective image from a spatial perspective?

Understanding TDI variables offers useful implications for the efforts of DMOs (Wu and Liang, 2020). The perception of a destination among tourists can be highly individualised, influenced by their subjective evaluation of the site at a given moment (Huete-Alcocera and Hernandez-Rojas, 2022; Pramanik, 2023). These perceptions are connected to tourists' experiences at the destination, influencing their plans (Li *et al.*, 2021; Zhang *et al.*, 2014). It may also have undergone distinct changes depending on the tourism experience at different stages, such as pre-visit and post-visit (Xu and Ye, 2016; Kim, 2018; Sharma and Nayak, 2019; Li *et al.*, 2021). In heritage destinations, the importance of the image linked to these destinations can be obtained by tourists through the act of visiting sites and engaging in activities that are intertwined with individuals, artefacts, traditions, historical structures or any tangible narratives from the past (Akgun *et al.*, 2020; Poria *et al.*, 2004). According to Piramanayagam *et al.* (2020), travellers who visit cultural heritage locations may form a unique view of the TDI in comparison to other kinds of destinations. To comprehend the prevailing feelings among visitors, it becomes imperative to explore the unique characteristics of the destination image as seen by heritage tourists, especially those visiting specific WHS.

Social media data

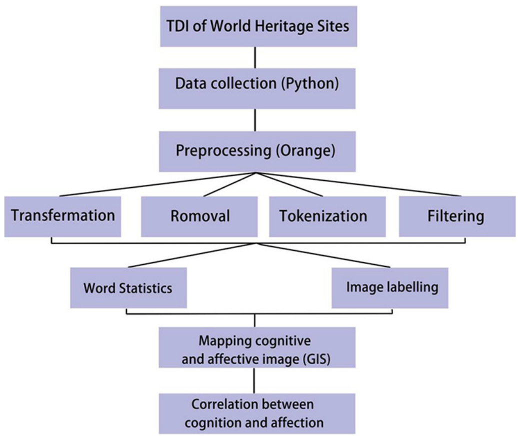
The extensive data generated by social media and review platforms significantly aids in addressing customer needs and enhancing brand promotion through sentiment analysis (Shirdastian *et al.*, 2019; Nowacki and Niezgoda, 2020). With the expansion of UGC, the tourism industry and its stakeholders can effectively use sentiment analysis for better planning and decision-making (Farhadloo *et al.*, 2016; Sun *et al.*, 2020). UGC and online platforms may reflect tourists' affective imagery of different destination aspects (Liu, 2015; Mehra, 2023; Philandera and Zhong, 2016). In addition, Geographic Information Systems

(GIS) have proven to be a valuable tool in tourism. To enhance the visualisation of sentiment analysis results, GIS can be integrated. As a powerful method for data management, spatial analysis and visualisation, it has been successfully applied in various cases using different algorithms. For example, global tourists' feelings based on reviews were mapped using GIS (Wang and Kirilenko, 2021), and in combination with a fuzzy sentiment framework, citizens' emotions towards environments and service infrastructures were also evaluated on maps (Cardone *et al.*, 2022).

For the comparisons between different destinations, previous research has mainly adopted single data sources or methods. For example, Murakami (2018) compared destination images from Japanese and foreign tourists using TripAdvisor reviews, highlighting the role of cultural context in shaping tourists' perceptions. Taecharungroj and Mathayomchan (2021) examined the destination images of France, the USA and Thailand using Flickr photos. Ling and Li (2023) compared the official published image with tourists' perceived images of Fuzhou City by internet texts. However, comparative studies for Malaysian cases are lacking. Innovatively, this research proposes the methodology that combines ML with GIS to examine the destination images of WHS in Malaysia through the analysis of various data sources (text and images) and visualises the relationship on a map to answer the *RQ2*:

RQ2. What are the differences or similarities in tourists' perceptions between the two historical cities in Malaysia?

A study of visitor emotions through social media comments is crucial for understanding the current tourism landscape in Malacca and George Town, as evidenced by existing literature. The sentiment analysis of WHSs, particularly Malaysian heritage sites, has not been extensively explored (Mehraliyev *et al.*, 2022; Puh and Bagić Babac, 2023). Traditional approaches, such as questionnaires, often used to examine the depiction of these historic towns as tourist destinations, face limitations in spatial and temporal reach, thus affecting the generalizability of findings. In contrast, employing big data from social media offers more impartial and comprehensive alternatives. Moreover, the investigation of destination image, integrating textual and visual elements from social media, remains relatively limited. A



Source: Figure by authors

Figure 1. Workflow of the study

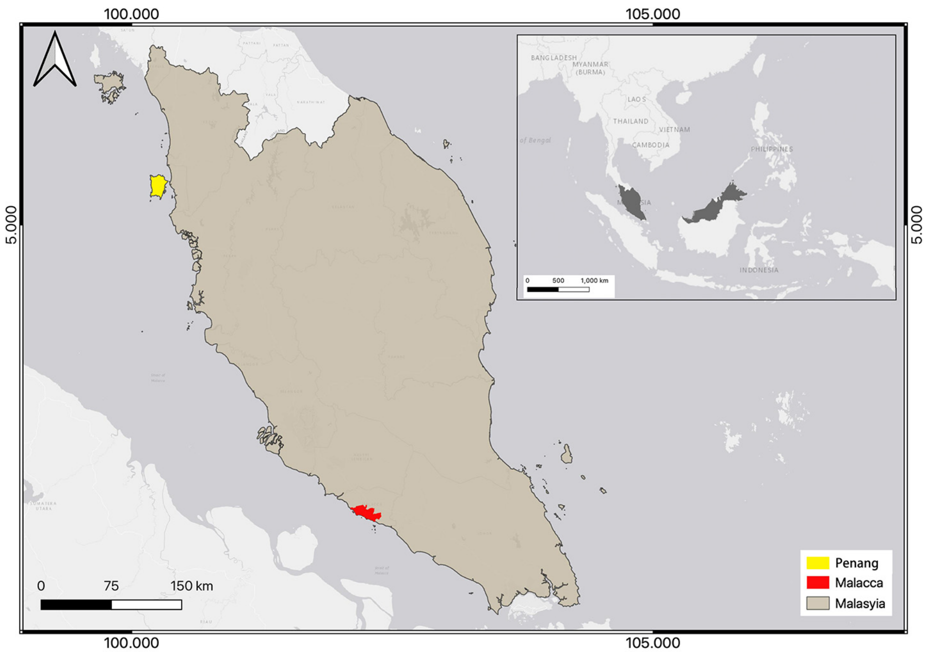
combined analysis of these data types can lead to a deeper understanding (Kirilenko *et al.*, 2021; Li *et al.*, 2023) to inform future planning and development strategies, enhance regional promotion, attract more tourists and stimulate the local economy.

Methodology

This study used a quantitative approach, employing social media data mining with GIS within the CAM framework to analyse the TDI of Malaysian heritage towns. The methodology involved delineating the research area, collecting and cleaning social media data, applying text and sentiment analysis, analysing images, integrating the results into a GIS for mapping and spatial correlation between cognitive and affective images (Figure 1).

Study area

The selected areas, Malacca and George Town, two famous historical cities, were shaped over five centuries by East-West trade and cultural exchanges in Malaysia (Figure 2). Once key Maritime Silk Road ports, these heritage cities showcase a multicultural heritage blend of Malay, Chinese, Indian and European influences. The rich and diverse heritage not only highlights historical significance but also anchors sustainable tourism, stimulating scholarly interest and international tourism. Both Georges Town and Malacca are popular cultural cities in Malaysia that have world-renowned cultural and heritage sites that attract tourists



Source: Figure by authors

Figure 2. Study area and its global location

from across the globe. Both cities in Malaysia were awarded the WHS by the United Nations Educational, Scientific, and Cultural Organisation (UNESCO) in 2008 (UNESCO, 2021). Since then, it has been a popular global tourist destination among heritage tourists. The high-quality standard of *in situ* experiences is a notable aspect that contributes to the attractiveness of WHS destinations (Carreira *et al.*, 2022). The distinct historical and cultural characteristics contribute to the branding of the destination (Lanen *et al.*, 2022; Wang *et al.*, 2023), drawing tourists' attention to these famous destinations.

Previous researchers mostly focused on analysing the preferences and interests of tourists in these two destinations. For example, quality leisure activities were greatly valued by visitors, since they actively seek opportunities for enjoyment, exploration and cultural learning during their travels. Service experiences, encompassing outstanding customer service and immersive sensory engagement, have a significant role in enhancing overall satisfaction levels and fostering favourable referrals. It was noted that individuals who visited Malacca tended to allocate their financial resources mainly towards accommodation, shopping and dining, with relatively fewer funds towards transportation and entertainment expenditures. One of the main factors may be attributed to the reputation of Malacca as an economically viable tourism destination. A considerable proportion of tourists in Malacca have expressed their satisfaction with the local services, such as the standard of tourism infrastructure, cleanliness of attractions, quality of accommodations, pricing and the overall level of service rendered (Begum, 2014). Then, visitors also expressed admiration for the comprehensive and profound heritage, history and culture of Penang. The significance of authenticity was considered a prominent motivation in heritage tourism in George Town.

Data collection and pre-processing

The data were collected from January to July 2023 using Python programming to extract information from Weibo (https://weibo.com/, accessed on July 25, 2023) and Google Map Reviews (www.google.com/maps, accessed on July 25, 2023). These two platforms are widely used for sharing comments, reviews and images in both Chinese and English. On Weibo, the keyword "Malacca" was used for search engine optimisation. For Google Map Reviews, prominent locations in Malacca and George Town were chosen through purposive sampling, focusing on sites with over 1,000 comments. The selected sites are mainly located in the city centre (core heritage area) (Figure 3).

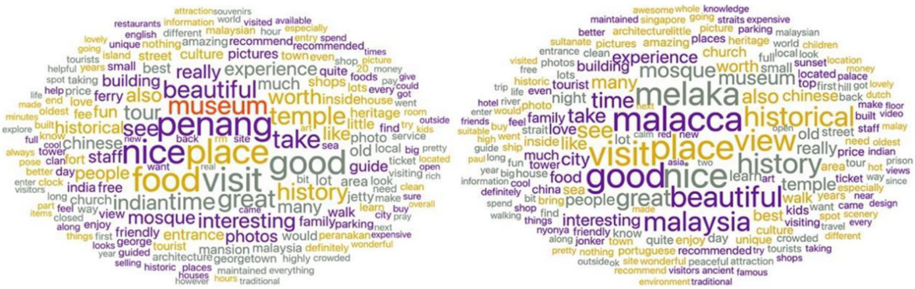
Source: Begum *et al.* (2014)

Figure 3. Location of selected samples

Table 1. Categories of the sites (M – Malacca; G – George Town)

Religious sites (M)	*Religious sites (G)*
Cheng Hoon Teng Temple	Cheah Kongsi Temple
Christ Church Melaka	Kapitan Keling Mosque
Kampung Kling Mosque	Han Jiang Ancestral Temple
Melaka Straits mosque	St George’s Anglican Church
St. Peter’s church	Church of the Assumption
Poh San Teng temple	Goddess of Mercy Temple
	Cheah Kongsi Temple
	Sri Mahamariamman Temple
Modern building and service (M)	*Modern building and service (G)*
The Orangutan House	Penang Town Hall
The Shore Sky Tower	Penang Ferry
Malacca Tower	City hall
Malacca Gateway	Persatuan Hainan
Oceanarium	Penang state museum
Updown House	Up side down Museum
Oceanarium	Wonder food museum
Baba Nyonya Heritage Museum	
Melaka Sultanate Palace Museum	
Museum Samudera	
Culture and history (M)	*Culture and history (G)*
A Famosa	Chew Jetty
Dutch Square	Leong SAN Tong Khoo Kongsi
Portugese Settlement	Fort Cornwallis
St. John Fort	Logan Memorial
Jonker Walk Melaka	Pinang Peranakan Mansion
Malacca River Walk	Queen Victoria Memorial
Little India Malacca	Penang Little India
	Syed Alatas mansion

Source: Table by authors



Source: Figure by authors

Figure 4. Word Cloud for George Town (left) and Malacca (right)

In George Town, 22 notable sites such as Chew Jetty, Cheah Kongsi Temple and Wonder Food Museum were selected for analysis (Table 1), mainly situated in the centre of George Town (Figure 3). The processing was conducted using “Orange”, an open-source ML tool based on Python. Textual data from Google and Weibo were consolidated into a single file, resulting in 12,093 records for Malacca and 9,724 for George Town after cleaning. In addition, 890 tourist photos for Malacca and 1,365 for George Town were selected. Text pre-processing in Orange involved converting words to lowercase, removing accents, HTML/URLs, tokenizing words, eliminating stop words and applying stemming and lemmatisation. Only nouns, verbs, adjectives and adverbs were retained. The resulting keywords were visualised in word clouds (Figure 4), with the size representing their frequencies.

The analysis of the social media photos was conducted using Microsoft Azure Custom Vision, a cloud-based service by Microsoft that facilitates the creation, training and deployment of vision models for tasks such as image categorisation and object recognition (https://portal.azure.com/, last accessed 25 July 2023). The classification of photos by tags primarily used convolutional neural networks, training images through layers including convolutional, pooling and fully connected ones. The iterative adjustment of network weights depended on the availability of labelled training data. This algorithm learns to identify patterns and distinctive features in the input images. A loss function quantified the discrepancy between predicted outputs and actual labels during training, aiming to minimise this difference. The optimisation process was completed using stochastic gradient descent, which iteratively updates network parameters (Dhruv and Naskar, 2020; Wang *et al.*, 2019).

Quantify tourists' cognition and affection

Following the Liu Hu lexicon-based method (Hu *et al.*, 2013), this research used the counting of percentage of lexicon to represent the perception of a site. Namely, if an identified lexicon is frequently mentioned, it reflects the strength of characteristics of this lexicon. And according to text statistics, noun words contained the main cognitions towards the sites (Liu *et al.*, 2023). This research used python to quantify the cognition value according to the sum of character keywords, normalised by the length of words in each review. The final score reflected the strength of cognition that a visitor expressed on the social media. The cognitive values for the sample sites were obtained using the average values of the reviews for the same site.

For sentiment values, "Tweet Profiler" tool in Orange Software facilitated the extraction of sentiment data, supporting three emotion classification models including Ekman's and Plutchik's Mood States. This study used Plutchik's taxonomy, which identifies primary emotions as fear, anger, joy, sorrow, trust, disgust, anticipation and surprise, quantifying emotions on a positive-negative scale from 0 to 7 (Colnerič and Demšar, 2018; Machleit and Eroglu, 2000). It enabled the graphical representation of emotional responses, enriching sentiment analysis in communication and tourism research. Thus, each sample site obtained one average emotional value after calculating all the reviews.

And the open-source program QGIS was used to visualise the analysed results. The process included generating raster data to visually represent the geographical distribution of emotions and cognition, highlighting areas with significant positive or negative responses. In estimating values in expansive areas with sparse data, the inverse distance weighting (IDW) method was used by leveraging data from adjacent known points, giving more weight to nearer sites and less to distant ones (Masoudi, 2021). Location data, cognition values and emotional metrics were imported into GIS, where the IDW method generated a raster data set covering the whole study area with cognitive and affective images across larger regions.

Spatial correlation

Based on the interpolated raster data, the relationship of cognitive and affective image can be checked. Due to the number of selected sites, the sampling size can be increased to improve accuracy. In each city, additional sample points were drawn on the map, and corresponding cognitive and affective values can be assigned from the rasters. A grid system with 200-m

Table 2. Word frequencies

Word (M)	Frequency	Word (M)	Frequency	Word (G)	Frequency	Word (G)	Frequency
Place	5,431	Chinese	611	Place	2,831	Many	517
Nice	2,645	Food	610	Visit	1,446	People	513
Visit	2,387	Old	584	Food	1,417	Staff	487
Good	1,858	Best	584	Nice	1,249	Chinese	483
View	1,578	Love	559	Good	1,224	Historical	479
Beautiful	1,477	Night	555	Museum	865	Photos	469
History	1,427	Walk	535	Take	850	Much	464
Historical	1,388	Building	526	Great	845	Fun	456
Great	1,146	Church	489	Temple	830	Building	443
See	1,064	Family	487	Beautiful	793	Old	430
Time	1,008	Sea	477	Time	782	Entrance	402
Mosque	957	Small	445	History	769	Guide	401
Take	892	Inside	426	See	733	Inside	363
Museum	870	Tourist	409	Tour	653	Ferry	363
Many	788	Street	396	Worth	649	Best	362
City	740	Area	388	Interesting	643	Little	360
Temple	733	Kids	383	Indian	634	Free	350
Like	720	Day	373	Really	566	Area	346
Experience	701	Enjoy	368	Experience	557	Culture	342
Really	697	Top	362	Like	549	Pictures	338
Worth	652	Amazing	360	Mosque	546	Photo	336
People	628						

Source: Table by authors

spacing was used for the two cities, and the "extract raster values to points" tool in QGIS was used. It allowed for nearly 100 samples with assigned values. Pearson correlation was then run in SPSS to examine the relationship between two samples.

Results

Text and image analysis

According to word frequency statistics, the most frequent terms are shown in Table 2. For Malacca, the top keywords were "Place", "Nice", etc. with nouns comprising 58.7% and adjectives 24.0%. Visitor motivation appeared driven by attributes like history, museums, churches, sea, food and temples. In George Town, the frequently mentioned words included "Place" and "Visit", with nouns making up 43.5%. Notably, the top words were positive, indicating prevailing emotions among visitors, such as "Nice", "Good", "Beautiful", "Great" and "Unique". Tourists of both two towns commonly used positive adjectives like "Nice", "Good" and "Great". However, some differences emerged in noun usage for the two cities. In Penang, visitors more frequently discussed food (1,417 mentions) compared to Malacca (610 mentions). Conversely, night views were mentioned more by Malacca visitors (555 mentions). Cultural tours focusing on churches and museums showed similar word frequencies in both locations. Commonly used nouns included "views", "history", "food", "museum", "temple", "people" and "buildings".

Labelled images were uploaded to the vision project and manually tagged. The model then adjusted its internal parameters, such as weights and biases, based on these labels to learn to recognise distinct patterns and features. In Malacca, 890 images were classified into:

- people (23.78%);

- river landscapes (17.78%);
- modern buildings (15.22%);
- foods (11.89%);
- churches (8.33%);
- festivals (8%);
- plants (5.22%);
- historical sites (5%); and
- animals (4.78%).

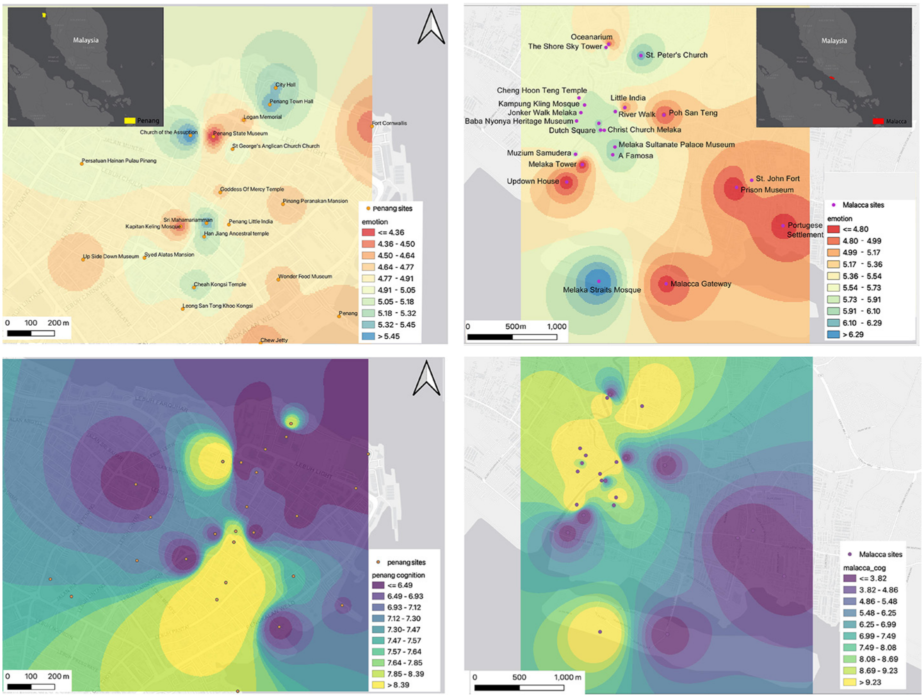
This suggested that visitors were most impressed by modern architecture, sea views, local culture, festivals and historical sites. In George Town, 1,365 images were analysed, revealing six key topics:

(1) Buildings and streets (36.48%);

(2) Nature landscapes (21.98%);

(3) Foods (21.40%);

(4) People (11.21%);



Source: Figure by authors

Figure 5. Sentiment and cognition map (George Town left and Malacca right)

(5) Sea and beaches (5.57%); and

(6) Night scenes (3.37%).

As a result, the main labels from images and noun words from texts are seen as the cognition keywords for Malacca and George Town.

Mapping results

A GIS-based representation and visualisation of cognition and affection across the geographic areas was created to illustrate the distribution and intensity of various images in Malacca and George Town. This involved integrating GIS with emotional and cognitive data extracted from the reviews. The average emotion and cognition scores, detected by Orange for each review, were linked to the specific locations of 23 places in Malacca and 22 sites in George Town, as shown in Figure 5. The spatial resolution was 10 m, with a dimension of 324 rows and 383 columns. In the GIS map, lower emotion scores are indicated by reddish colours, while higher scores are represented by blue-greenish colours, reflecting visitors' expressed emotions. And bluish colours in cognition mean lower value, and yellowish colours mean higher values for cognition.

As is seen, most places in Malacca were positively associated with experiences of joy. Conversely, in George Town, the Church of Assumption and Penang Town Hall garnered more positive emotions, whereas Penang State Museum, Fort Cornwallis and Chow Jetty had fewer positive responses. A noticeable trend showed that tourists were more satisfied with the western part of George Town compared to the eastern part. For both Malacca and George Town, religious sites liked churches and temples received more positive reviews than other cultural and historic sites. Overall, the emotional scores were higher in Malacca than in George Town. For cognition, the higher values for Malacca belonged to St. Peter Church and Malacca Straits Mosque. For George Town, the higher cognitive images were from Church of Assumption and Penang Town Hall.

At last, the spatial correlations (Pearson correlation value) between cognition and affection of TDI were carried out according to the sample points. It showed that the correlation value in Malacca was 0.41 (moderate correlation, p value < 0.001). And for George Town, the correlation was 0.91 (high correlation, p value < 0.001). It can be seen that increasing cognition values were highly related to the growth of affective values (Figure 6).

Correlation

id	affection	cognition
1	5.605	9.152
2	5.689	9.449
3	5.753	9.920
4	5.794	8.993
5	5.775	9.616
6	5.557	8.925
7	4.851	2.233
8	5.178	5.370
9	5.317	6.254
10	5.458	7.025
11	5.629	7.833
12	5.927	9.124
13	6.256	10.585
14	5.521	6.300
15	5.569	9.415
16	5.655	9.228
17	5.726	9.633
18	5.847	11.412
19	5.872	7.714

Correlation

id	affection	cognition
1	4.924	7.168
2	4.921	7.121
3	4.914	7.108
4	4.898	7.191
5	4.880	7.333
6	4.872	7.471
7	4.874	7.585
8	4.931	7.051
9	4.932	6.933
10	4.930	6.794
11	4.900	6.972
12	4.852	7.274
13	4.844	7.479
14	4.863	7.664
15	4.941	6.998
16	4.947	6.793
17	4.974	5.970
18	4.921	6.547
19	4.750	7.238
20	4.782	7.461

Source: Figure by authors

Figure 6. Correlations between cognition and affection

Discussions

First, this research explored how the TDI can be perceived from social media data, the findings indicated that online data, encompassing both texts and images, offer valuable insights into tourism industry perceptions (Jiang *et al.*, 2021; Li *et al.*, 2023; Lin *et al.*, 2021; Lozano-Monterrubio and Huertas, 2020). In terms of destination image formation, both Malacca and George Town were predominantly perceived as heritage locations. GIS modelling, using digital and electronic big data (Zhou *et al.*, 2020), and text analysis highlight prevailing tourist perceptions centred around themes like “Food”, “Place”, “Visit” and “History”. For *RQ1*, these findings aligned with the cities’ heritage status, with the understanding of TDI’s cognitive and affective components (Baloglu and Brinberg, 2016; Iordanova and Stylidis, 2019; Pramanik, 2023; Wang *et al.*, 2020). Consistent with Piramanayagam *et al.* (2020), travellers visiting cultural heritage sites develop distinct TDIs compared to those visiting other destination types. This research tested the spatial relationship between cognitive image and affective image. In accordance with previous research used questionnaires, the results are consistent (Kim, 2018; Akgun *et al.*, 2020; Alcocer and Ruiz, 2020; Bigart *et al.*, 2022; Yang *et al.*, 2022; Pramanik, 2023; Shen and Lai, 2023). Namely, using spatial methods to quantify the cognitive and affective image also supported the conclusion of a positive relationship between these two factors in the TDI.

Research question two examined tourists’ perceptions of Malacca and George Town. The findings revealed shared positive perceptions in both cities. Common adjectives like “nice,” “good,” and “great” and nouns such as “views,” “history,” “food,” “museum,” “temple,” “people,” and “buildings” were frequently mentioned, reflecting overlapping cognitive images in aspects of natural and cultural sceneries, tourist facilities and leisure activities (Guo *et al.*, 2014; Pereira *et al.*, 2022; Liu *et al.*, 2023). Both cities’ statuses as WHS further reinforce their identities as centres of cultural and heritage significance (Abu Hassan *et al.*, 2014; Chia, 2020). And the cognitive image is also echoed in the catering industries, with both cities recognised for the Malaysian foods (Mohamad *et al.*, 2022). Distinct differences emerged as George Town was characterised by more images of food, buildings and streets, indicative of its popularity for street arts. Conversely, Malacca showed a preference for photographs of people and river scenes, underscoring its proximity to the straits. These unique characteristics highlighted the distinct appeal of each city (Katahenggam, 2020; Najd *et al.*, 2015; Yin *et al.*, 2020).

Practical implications

This study’s exploration of destination image confirms that TDI is a complex, multi-dimensional construct encompassing various interrelated elements (Alcocer and Ruiz, 2020; Bigart *et al.*, 2022; Pramanik, 2023; Wang *et al.*, 2020). Based on the image perceived by tourists, local DMOs should strategically position these sites within target markets to foster a favourable image. Effective strategies should highlight both the distinctive features of the sites and the emotions they evoke. They should leverage these insights to promote the unique attributes of their destinations, effectively attracting tourists. The distinct characteristics identified through UGC offer opportunities to distinguish these destinations, creating unique brands for an increasingly discerning tourism market. And these insights can be used to gain a sustainable competitive advantage for the destination, particularly benefiting heritage areas (Guo *et al.*, 2023).

Theoretical implications

Methodologically, by integrating text and image analytics with ML and GIS, this research introduces a novel approach to examining spatial relationships within the CAM. This comprehensive method can serve as a valuable reference for future studies in tourism and related fields. Then, the application of CAM theory to analyse integrated reviews and photos offers a robust framework for understanding the cognitive and affective components of destination image. This enhances the theoretical understanding of how tourists perceive and emotionally respond to heritage sites. And the introduction of GIS to visualise the spatial distribution of tourists' perceptions and emotions represents a significant advancement in tourism research methodologies. Further studies can be developed based on the spatial concept of CAM and more related variables.

Limitations and future research

Furthermore, this study has limitations that highlight areas for future research. The focus on Melaka and George Town may not fully capture sentiments towards all UNESCO heritage sites in Malaysia, as each site has unique characteristics that were not individually considered (Le *et al.*, 2021). In addition, the analysis was limited to two online platforms and a selection of specific locations, potentially excluding other significant touristic attractions. This limitation might have affected the comprehensiveness and objectivity of the findings, not fully representing all tourists' sentiments. The emotion map used in the study associated feelings with location names rather than precise geographical coordinates, suggesting a need for more accurate techniques. Future studies could expand the scope to include a broader array of data sources and stakeholders, as well as enhance geo-visualisation accuracy, to provide a more holistic understanding of tourist sentiments at heritage sites.

Conclusion

Theoretically, this study reveals that the formation of TDI is dynamic. Applying the CAM, provides empirical data that deepens the understanding of TDI formation and its effective exploration among tourists. While prior research has investigated TDI in the context of social media and through CAM (e.g. Sukiman *et al.*, 2023; Omo-Obas and Anning-Dorson, 2023), this study examines spatial TDI components of UNESCO heritage sites in Asia using CAM. The findings affirm that image is a multi-dimensional phenomenon, encompassing both cognitive and affective factors, which correlated with each other. The differences and similarities between Gorge Town and Malacca are also provided by the proposed method. And the findings suggest that the GIS-based method can detect destination images with greater detail compared to traditional empirical approaches, tested the context-specific theoretical model for analysing online destination images using extensive textual data from tourists.

References

Abu Hassan, Z., Jailani, M.A.K. and Abdul Rahim, F. (2014), "Assessing the situational analysis of heritage tourism industry in Melaka", *Procedia – Social and Behavioral Sciences*, Vol. 130, pp. 28-36.

Akgun, A.E., Senturk, H.A., Keskin, H. and Onal, I. (2020), "The relationships among nostalgic emotion, destination images and tourist behaviors: an empirical study of Istanbul", *Journal of Destination Marketing and Management*, Vol. 16, pp. 1-13.

Alcocer, N.H. and Ruiz, V.R.L. (2020), "The role of destination image in tourist satisfaction: the case of a heritage site", *Economic Research*, Vol. 33 No. 1, pp. 2444-2461.

Ampountolas, A. and Legg, M.P. (2021), "A segmented machine learning modeling approach of social media for predicting occupancy", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 6, pp. 2001-2021.

Baloglu, S. and Brinberg, D. (2016), "Affective images of tourism destinations", *Journal of Travel Research*, Vol. 35 No. 4, pp. 11-15.

Begum, H., Er, A.C., Ferdous Alam, A.S.A. and Sahazali, N. (2014), "Tourist's perceptions towards the role of stakeholders in sustainable tourism", *Procedia-Social and Behavioral Sciences*, Vol. 144, pp. 313-321.

Baloglu, S. and McCleary, K.W. (1999), "A model of destination image formation", *Annals of Tourism Research*, Vol. 26 No. 4, pp. 868-897.

Bigart, E., Freimund, W. and Dalenberg, D. (2022), "Exploring peace within the cognitive-affective structure of the destination image of Glacier National Park", *Leisure Sciences*, pp. 1-24.

Cardone, B., Di Martino, F. and Sessa, S. (2022), "GIS-based fuzzy sentiment analysis framework to classify urban elements according to the orientations of citizens and tourists expressed in social networks", *Evolutionary Intelligence*, Vol. 15 No. 3, pp. 1-10.

Carreira, V., Gonzalez-Rodriguez, M.R. and Diaz-Fernandez, M.C. (2022), "The relevance of motivation, authenticity and destination image to explain future behavioural intention in a UNESCO world heritage Site", *Current Issues in Tourism*, Vol. 25 No. 4, pp. 650-673.

Chia, L. (2020), "Penang's historic George Town: a heritage theme park?", Channel News Asia, available at: www.channelnewsasia.com/asia/penangs-historic-george-town-heritage-theme-park-1033051

Colnerič, N. and Demšar, J. (2018), "Emotion recognition on twitter: comparative study and training a unison model", *IEEE Transactions on Affective Computing*, Vol. 11 No. 3, pp. 433-446.

Dhruv, P. and Naskar, S. (2020), "Image classification using convolutional neural network (CNN) and recurrent neural network (RNN): a review", Machine Learning and Information Processing: Proceedings of ICMLIP 2019, pp. 367-381, doi: 10.1007/978-981-15-1884-3_34

Embacher, J. and Buttle, F. (1989), "A repertory grid analysis of Austria's image as a summer vacation destination", *Journal of Travel Research*, Vol. 27 No. 3, pp. 3-7.

Farhadloo, M., Patterson, R.A. and Rolland, E. (2016), "Modeling customer satisfaction from unstructured data using a Bayesian approach", *Decision Support Systems*, Vol. 90, pp. 1-11.

Gomez, M., Fernandez, A.C., Molina, A. and Aranda, E. (2016), "City branding in European capitals: an analysis from the visitor perspective", *Journal of Destination Marketing and Management*, Vol. 7, pp. 190-201.

Guo, A., Huang, F. and Sun, X. (2014), "Research on the impact of tourism motivation on destination image", *Research on Financial and Economic Issues*, Vol. 6 No. 367, pp. 132-139.

Guo, X., Wang, Y., Tao, J. and Guan, H. (2023), "Identifying unique attributes of tourist attractions: an analysis of online reviews", *Current Issues in Tourism*, Vol. 27 No. 3, doi: 10.1080/13683500.2023.2165904.

Hu, X., Tang, J., Gao, H. and Liu, H. (2013), "Unsupervised sentiment analysis with emotional signals", *Proceedings of the 22nd international conference on World Wide Web*, pp. 607-618.

Huete-Alcocera, A. and Hernandez-Rojas, D.R. (2022), "Does local cuisine influence the image of a world heritage destination and subsequent loyalty to that destination?", *International Journal of Gastronomy and Food Science*, Vol. 27, p. 100470.

Iordanova, E. and Stylidis, D. (2019), "The impact of visitors' experience intensity on in-situ destination image formation", *Tourism Review*, Vol. 74 No. 4, pp. 841-860.

Jiang, Q., Chan, C.S., Eichelberger, S., Ma, H. and Pikkemaat, B. (2021), "Sentiment analysis of online destination image of Hong Kong held by mainland Chinese tourists", *Current Issues in Tourism*, Vol. 24 No. 17, pp. 2501-2522.

Katahenggam, N. (2020), "Tourist perceptions and preferences of authenticity in heritage tourism: visual comparative study of George Town and Singapore", *Journal of Tourism and Cultural Change*, Vol. 18 No. 4, pp. 371-385.

Kim, J.H. (2018), "The impact of memorable tourism experiences on loyalty behaviors: the mediating effects of destination image and satisfaction", *Journal of Travel Research*, Vol. 57 No. 7, pp. 856-870.

Kirilenko, A.P., Stepchenkova, S.O. and Dai, X. (2021), "Automated topic modeling of tourist reviews: does the Anna Karenina principle apply?", *Tourism Management*, Vol. 83, p. 104241.

Lanen, R.J.V., Van Beek, R. and Kosian, M.C. (2022), "A different view on (world) heritage. The need for multi-perspective data analyses in historical landscape studies: the example of Schokland (NL)", *Journal of Cultural Heritage*, Vol. 53, pp. 190-205.

Le, T.H., Arcodia, C., Novais, M.A., Kralj, A. and Phan, T.C. (2021), "Exploring the multidimensionality of authenticity in dining experiences using online reviews", *Tourism Management*, Vol. 85, p. 104292, doi: 10.1016/j.tourman.2021.104292.

Li, X., Zhang, Y. and Liyang Mei, L. (2023), "Analyzing online reviews of foreign tourists to destination attractions in China: a novel text mining approach", *Asia Pacific Journal of Tourism Research*, Vol. 28 No. 7, pp. 647-666, doi: 10.1080/10941665.2023.2255315.

Li, H., Lien, C.H., Wang, S.W., Wang, T. and Dong, W. (2021), "Event and city image: the effect on revisit intention", *Tourism Review*, Vol. 76 No. 1, pp. 212-228.

Lin, M.S., Liang, Y., Xue, J.X., Pan, B. and Schroeder, A. (2021), "Destination image through social media analytics and survey method", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 6, pp. 2219-2238, doi: 10.1108/IJCHM-08-2020-0861.

Ling, L. and Li, X. (2023), "Analysis of discrepancies between destination image and tourists' perceived image: taking Fuzhou as a case", *Communications in Humanities Research*, Vol. 23 No. 1, pp. 14-22.

Liu, B. (2015), *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions*, Cambridge University Press, Cambridge.

Liu, Y., Huang, K., Bao, J. and Chen, K. (2019), "Listen to the voices from home: an analysis of Chinese tourists' sentiments regarding Australian destinations", *Tourism Management*, Vol. 71, pp. 337-347.

Liu, J., Liu, Y., Fan, X. and Shan, S. (2023), "Research on the perception of destination terrain image of vacation tourism based on network text: take Hunan province as an example", *Journal of Yangtze Normal University*, pp. 18-27, doi: 10.19933/j.cnki.ISSN1674-3652.2023.04.003.

Lozano-Monterrubio, N. and Huertas, A. (2020), "The image of Barcelona in online travel reviews during the 2017 Catalan independence process", *Communication and Society*, Vol. 33 No. 3, pp. 33-49, doi: 10.15581/003.33.3.33-49.

Machleit, K.A. and Eroglu, S.A. (2000), "Describing and measuring emotional response to shopping experience", *Journal of Business Research*, Vol. 49 No. 2, pp. 101-111.

Masoudi, M. (2021), "Estimation of the spatial climate comfort distribution using tourism climate index (TCI) and inverse distance weighting (IDW) case study: Fars province, Iran", *Arabian Journal of Geosciences*, Vol. 14 No. 5, p. 363.

Mehra, P. (2023), "Unexpected surprise: emotion analysis and aspect-based sentiment analysis (ABSA) of user generated comments to study behavioral intentions of tourists", *Tourism Management Perspectives*, Vol. 45, p. 101063.

Mehraliyev, F., Chan, I.C.C. and Kirilenko, A.P. (2022), "Sentiment analysis in hospitality and tourism: a thematic and methodological review", *International Journal of Contemporary Hospitality Management*, Vol. 34 No. 1, pp. 46-77.

Micera, R. and Crispino, R. (2017), "Destination web reputation as 'smart tool' for image building: the case analysis of Naples city-destination", *International Journal of Tourism Cities*, Vol. 3 No. 4, pp. 406-423.

Mirzaalian, F. and Halpenny, E. (2019), "Social media analytics in hospitality and tourism: a systematic literature review and future trends", *Journal of Hospitality and Tourism Technology*, Vol. 10 No. 4, pp. 764-790.

Mohamad, N., Devandran, S.P., Roslan, M.A. and Nasron, A.Z. (2022), "Predictors of behavioural intention among tourist: the case of revisiting street food spots in Penang, Malaysia", *Journal of Foodservice Business Research*, Vol. 25 No. 4, pp. 475-497.

Molinillo, S., Japutra, A. and Ekinci, Y. (2022), "Building brand credibility: the role of involvement, identification, reputation and attachment", *Journal of Retailing and Consumer Services*, Vol. 64, p. 102819.

Murakami, K.H. (2018), "A comparison of destination images from three different perspectives", *Journal of Global Tourism Research*, Vol. 3 No. 2, pp. 107-114.

Najd, M.D., Ismail, N.A., Maulan, S., Yunos, M.Y.M. and Niya, M.D. (2015), "Visual preference dimensions of historic urban areas: the determinants for urban heritage conservation", *Habitat International*, Vol. 49, pp. 115-125.

Nowacki, M. and Niezgoda, A. (2020), "Identifying unique features of the image of selected cities based on reviews by TripAdvisor portal users", *Scandinavian Journal of Hospitality and Tourism*, Vol. 20 No. 5, pp. 503-519.

Omo-Obas, P. and Anning-Dorson, T. (2023), "Cognitive-affective-motivation factors influencing international visitors' destination satisfaction and loyalty", *Journal of Hospitality and Tourism Insights*, Vol. 6 No. 5, pp. 2222-2240, doi: 10.1108/JHTI-05-2022-0178.

Pan, S., Lee, J. and Tsai, H. (2014), "Travel photos: motivations, image dimensions, and affective qualities of places", *Tourism Management*, Vol. 40, pp. 59-69.

Paolanti, M., Mancini, A., Frontoni, E., Felicetti, A., Marinelli, L., Marcheggiani, E. and Pierdicca, R. (2021), "Tourism destination management using sentiment analysis and geo-location information: a deep learning approach", *Information Technology and Tourism*, Vol. 23 No. 2, pp. 241-264.

Pereira, V., Gupa, J.J. and Hussain, S. (2022), "Impact of travel motivation on tourist's attitude toward destination: evidence of mediating effect of destination image", *Journal of Hospitality and Tourism Research*, Vol. 46 No. 5, pp. 946-971, doi: 10.1177/1096348019887528.

Philandera, K. and Zhong, Y.Y. (2016), "Twitter sentiment analysis: capturing sentiment from integrated resort tweets", *International Journal of Hospitality Management*, Vol. 55, pp. 16-24.

Pike, S. and Ryan, C. (2004), "Destination positioning analysis through a comparison of cognitive, affective, and conative perceptions", *Journal of Travel Research*, Vol. 42 No. 4, pp. 333-342.

Piramanayagam, S., Rathore, S. and Seal, P.P. (2020), "Destination image, visitor experience, and behavioural intention at heritage centre", *Anatolia*, Vol. 31 No. 2, pp. 211-228.

Poria, Y., Butler, R. and Airey, D. (2004), "Links between tourists, heritage and reasons for visiting heritage sites", *Journal of Travel Research*, Vol. 43 No. 1, pp. 19-28.

Pramanik, S.A.K. (2023), "Influences of the underlying dimensions of destination image on destination loyalty in a cultural heritage destination", *Asia Pacific Journal of Tourism Research*, Vol. 28 No. 9, pp. 984-999, doi: 10.1080/10941665.2023.2283001.

Puh, K. and Bagić Babac, M. (2023), "Predicting sentiment and rating of tourist reviews using machine learning", *Journal of Hospitality and Tourism Insights*, Vol. 6 No. 3, pp. 1188-1204.

Rasoolimanesh, S.M., Seyfi, S., Hall, M.C. and Hatamifar, P. (2021), "Understanding memorable tourism experiences and behavioural intentions of heritage tourists", *Journal of Destination Marketing and Management*, Vol. 21, p. 100621.

Richards, G. (2018), "Cultural tourism: a review of recent research and trends", *Journal of Hospitality and Tourism Management*, Vol. 36, pp. 12-21.

Royo Vela, M. and Garzón Paredes, A. (2023), "Effects of heritage on destination image: multi-method research based on an appraisal approach to emotional response in-situ", *Journal of Heritage Tourism*, Vol. 18 No. 4, pp. 531-555.

Santos, M.L.B.D. (2022), "The 'so-called' UGC: an updated definition of user-generated content in the age of social media", *Online Information Review*, Vol. 46 No. 1, pp. 95-113, doi: 10.1108/OIR-06-2020-0258.

Seyyedamiri, N., Hamedanian Pour, A., Zaeri, E. and Nazarian, A. (2022), "Understanding destination brand love using machine learning and content analysis method", *Current Issues in Tourism*, Vol. 25 No. 9, pp. 1451-1466.

Sharma, P. and Nayak, J.K. (2019), "Understanding memorable tourism experiences as the determinants of tourists' behaviour", *International Journal of Tourism Research*, Vol. 21 No. 4, pp. 504-518.

Shen, H. and Lai, I.K.W. (2023), "The value of craft souvenirs induces travel intention by shaping destination image: from the perspective of souvenir gift recipients", *Asia Pacific Journal of Tourism Research*, Vol. 28 No. 11, pp. 1311-1326, doi: 10.1080/10941665.2023.2293787.

Shirdastian, H., Laroche, M. and Richard, M.O. (2019), "Using big data analytics to study brand authenticity sentiments: the case of Starbucks on Twitter", *International Journal of Information Management*, Vol. 48, pp. 291-307.

Stylidis, D., Shani, A. and Belhassen, Y. (2017), "Testing an integrated destination image model across residents and tourists", *Tourism Management*, Vol. 58, pp. 184-195.

Stylos, N., Zwiegelaar, J. and Buhalis, D. (2021), "Big data empowered agility for dynamic, volatile, and time-sensitive service industries: the case of tourism sector", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 3, pp. 1015-1036.

Sukiman, M.A., Chew, Y.Y. and Tan, P.L. (2023), "Exploring the impact of user-generated content on place branding: a study of UNESCO world heritage sites in Malaysia on Instagram", *Search Journal of Media and Communication Research*, Vol. 15 No. 3, pp. 15-32.

Sun, T., Li, Y. and Tai, H. (2023), "Different cultures, different images: a comparison between historic conservation area destination image choices of Chinese and Western tourists", *Journal of Tourism and Cultural Change*, Vol. 21 No. 1, pp. 110-127.

Sun, B., Ao, C., Wang, J., Mao, B. and Xu, L. (2020), "Listen to the voices from tourists: evaluation of wetland ecotourism satisfaction using an online reviews mining approach", *Wetlands*, Vol. 40 No. 5, pp. 1379-1393.

Taecharungroj, V. and Mathayomchan, B. (2021), "Traveller-generated destination image: analysing Flickr photos of 193 countries worldwide", *International Journal of Tourism Research*, Vol. 23 No. 3, pp. 417-441.

UNESCO (2021), "World heritage list 2021", available at: https://whc.unesco.org/en/list/

Wang, L. and Kirilenko, A.P. (2021), "Do tourists from different countries interpret travel experience with the same feeling? Sentiment analysis of TripAdvisor reviews", Information and Communication Technologies in Tourism 2021: Proceedings of the 2021 eTourism Conference, January 19–22, 2021, Springer International Publishing, pp. 294-301.

Wang, R., Hao, J.X., Law, R. and Wang, J. (2019), "Examining destination images from travel blogs: a big data analytical approach using latent Dirichlet allocation", *Asia Pacific Journal of Tourism Research*, Vol. 24 No. 11, pp. 1092-1107, doi: 10.1080/10941665.2019.1665558.

Wang, Z., Liu, W., Sun, Z. and Zhao, H. (2023), "Understanding the world heritage sites' brand diffusion and formation via social media: a mixed-method study", *International Journal of Contemporary Hospitality Management*, Vol. 36 No. 2, pp. 602-631, doi: 10.1108/IJCHM-02-2023-0190.

Wang, J., Li, Y., Wu, B. and Wang, Y. (2020), "Tourism destination image based on tourism user generated content on internet", *Tourism Review*, Vol. 76 No. 1, pp. 125-137, doi: 10.1108/tr-04-2019-0132.

Woosnam, K.M., Stylidis, D. and Ivkov, M. (2020), "Explaining conative destination image through cognitive and affective destination image and emotional solidarity with residents", *Journal of Sustainable Tourism*, Vol. 28 No. 6, pp. 917-935.

Wu, G. and Liang, L. (2020), "Examining the effect of potential tourists' wine product involvement on wine tourism destination image and travel intention", *Current Issues in Tourism*, pp. 1-16.

Xu, H. and Ye, T. (2016), “Dynamic destination image formation and change under the effect of various agents: the case of Lijiang, ‘the capital of Yanyu”, *Journal of Destination Marketing and Management*, Vol. 7 No. 3, pp. 131-139.

Yang, S., Isa, S.M., Yao, Y., Xia, J. and Liu, D. (2022), “Cognitive image, affective image, cultural dimensions, and conative image: a new conceptual framework”, *Frontiers in Psychology*, Vol. 13, p. 935814.

Yin, C.Y., Bi, N. and Chen, Y. (2020), “You exist in my song! how a destination-related popular song enhances destination image and visit intentions”, *Journal of Vacation Marketing*, Vol. 26 No. 3, pp. 305-319, doi: 10.1177/1356766720904773.

Zhang, H., Fu, X., Cai, L.A. and Lu, L. (2014), “Destination image and tourist loyalty: a meta-analysis”, *Tourism Management*, Vol. 40, pp. 213-223.

Zhou, B., Cheng, C., Ma, G. and Zhang, Y. (2020), “Remaining useful life prediction of lithium-ion battery based on attention mechanism with positional encoding”, *IOP Conference Series: Materials Science and Engineering*, Vol. 895 No. 1, p. 12006, doi: 10.1088/1757-899X/895/1/012006.

Further reading

Demšar, J., Curk, T., Erjavec, A., Gorup, Č., Hočevar, T., Milutinovič, M. and Zupan, B. (2013), “Orange: data mining toolbox in Python”, *Journal of Machine Learning Research*, Vol. 14 No. 1, pp. 2349-2353.

Li, Q., Li, S., Zhang, S., Hu, J. and Hu, J. (2019), “A review of text corpus-based tourism big data mining”, *Applied Sciences*, Vol. 9 No. 16, p. 3300, doi: 10.3390/app9163300.

Corresponding author

Poh Ling Tan can be contacted at: pohling.tan@xmu.edu.my