Destination image: A consumer-based, big data-enabled approach

Purpose - This research aimed to use a bottom-up, inductive approach to derive destination image attributes from large quantities of online consumer narratives and establish a destination classification system based on relationships among attributes and places.

Design/methodology/approach - Content and social network analyses were used to explore the consumer image structure for destinations based on online narratives. Cluster analysis was then employed to group destinations by attributes, and ANOVA provided comparisons.

Findings - Twenty-two attributes were identified and combined into three groups (core, expected, latent). Destinations were classified into three clusters (comprehensive urban, scenic, and lifestyle) based on their network centralities. Using data on Chinese tourism, the most mentioned (core) attributes were determined to be landscape, traffic within the destination, food and beverages, and resource-based attractions. Social life was meaningful in consumer narratives but often overlooked by researchers.

Originality/value - This research produced empirical work on Chinese tourism by combining a bottom-up, inductive research design with big data. It divided the 49 destinations into three categories and established a new system based on rich data to classify travel destinations.

Practical implications - Destinations should determine into which category they belong and then appeal to the real needs of tourists. DMOs should provide the essential attributes and pay attention to creating a unique social life atmosphere.

Keywords: Destination image; content analysis; social network analysis; user-generated content; big data mining

1. Introduction

A good destination image is crucial for tourism development, and every destination has unique image attributes and characteristics. Determining competitors is challenging for destination management organizations (DMOs) and tourism businesses (Caber et al., 2017). However, identifying the image characteristics of destinations assists DMOs with better positioning competitors and developing core advantages (Dwyer et al., 2004).

Tourist destination image (TDI) refers to the overall consumer impressions of the tourist destination (Kotler, 2002). While there is no unified concept of TDI so far, most scholars believe that cognitive, affective, and overall images exist (Beerli and Martín, 2004). Studies have highlighted the criticality of destination image to tourism marketing success (Li et al., 2021). With a burgeoning domestic tourism market of over six trillion trips (TravelChinaGuide, 2020), China provides a unique opportunity to investigate destination images from a consumer perspective (Zhong et al., 2015). Most destination image literature focuses on Western tourists, but Chinese tourists differ culturally and economically (Pearce, Wu and Osmond, 2013). The development of Chinese destination smart tourism and advancements in information and communication technologies may provide insights for other countries (Wang et al., 2019). Previous research has shown that Chinese tourists are consistent and enthusiastic in seeking different activities, experiences, and scenery (Wang et al., 2008; Yu and Weiler, 2001), suggesting that their online reviews are connected with destination image attributes (Qi and Chen, 2019).

Prior destination image studies have taken a top-down approach, measuring pre-determined attributes quantitatively but ignoring the qualitative data (Xu et al., 2018). Gartner (1994) studied the formation process and classification of images and demonstrated that consumer data constitute organic images and are highly credible. As the Internet has developed rapidly, tourism research has entered the era of big data, and tourism is considered an important field of big data application (Li et al., 2018). With big data, previous tourism studies can overcome their limited sample sizes and offer a new way of studying tourism behaviour (Yang et al., 2015).

Based on big data mining and a staged research design, this study used a bottom-up inductive approach to explore customer-created destination images of Chinese destinations. The research question was, taking popular tourist destinations in China as examples, which are their similar and dissimilar image attributes? The specific research objectives were to:

1. Identify images across multiple destinations through online tourist comments.
2. Determine the importance of individual destination attributes and the relationships among them.
3. Explore similarities and differences among destinations based on image attributes.
4. Conduct a cluster analysis for the destination image attributes and selected destinations.

2. Literature review

2.1 Tourism destination image

Since the term tourism destination image (TDI) was introduced (Hunt, 1975), extensive research has been conducted on the topic, which provides valuable insights into destination differentiation and tourism marketing (Wang et al., 2020; Xiao et al., 2022). TDI can be defined as "the beliefs, ideas, and impressions of tourists concerning the attributes of destinations" (Echtner and Ritchie, 1993; Lin et al., 2021; Sahin and Baloglu, 2011). Although images can be understood as the mental combinations of discursive attributes and holistic impressions of destinations (Murphy et al., 2000; Zhang et al., 2014), discussion about TDI has existed since Crompton (1979) first proposed destination image's cognitive components (attributes). Previous research shows that many image attributes have accumulated since the 1970s (Table 1). The current study focused on the image attributes of destinations, which can be understood as the "key cognitive and perceived image attributes of tourists" (Eom et al., 2020; Guo and Pesonen, 2022; Lai et al., 2018).

[Insert Table 1]

As the image-forming agents (Beerli and Martín, 2004), user-generated content (UGC) has been examined to provide insight into understanding their conceptualization (Qi and Chen, 2019), formation (Kislali et al., 2016, 2020), framework (Bui et al., 2022) and components (Lojo et al., 2020) of TDI. Researchers have also explored the structure of TDI by combining theoretical models, such as the core-periphery structure (Wang et al., 2017). The core-periphery structure (C/PS) has been proven to help structure mental images (Deutsch and Merritt, 1965). A conceptual model of the core-periphery structure was developed by Lai and Li (2012), which demonstrated the feasibility of using cognitive image attributes in UGC to explain the TDI's structure. For better marketing, destinations must select appropriate attributes and labels (Nautiyal et al., 2022). Therefore, it is necessary to identify the destination's core attributes based on tourists' perceptions (Wang et al., 2017; Guo and Pesonen, 2022).

2.2 Big data and TDI

As the Internet deepens its influence on tourist behaviour, big data research is becoming increasingly important to enhance destination marketing capabilities and understand images from the consumer perspective (Li et al., 2018; Mariani, 2020; Bui et al., 2022). Since tourists co-create value for destinations, they should cater to their needs and preferences (Kozak and Buhalis, 2019). For valuable insights into tourism destinations, it is necessary to collect and analyse UGC, such as online reviews (Lalicic et al., 2021). Recent studies have taken up this call for greater use of big data and UGC when investigating destination images (He et al., 2022).

Most recent research studies used methods such as content analysis (Alrawadieh et al., 2019) and text mining (Wong and Qi, 2017) to explore UGC and identify connections between attributes of TDI. Marine-Roig et al. (2019) used online travel reviews from Tripadvisor to examine the gastronomic image of the Canary Islands. Meng et al. (2021) employed a big-data analysis technique to explore the destination image of Sanya. Generally, big data analytics is considered a data-driven approach, but it can also guide research design or contribute to improving theories (Chen et al., 2021; Mazanec, 2020). For example, Buhalis et al. (2020) combined both deductive and inductive analysis to bridge marketing theory and big data analytics; Bui et al. (2022) proposed a holistic measurement framework based on complex textual and visual data.

The scale and volume of big data can compensate for sample size limitations and provide a new choice for in-depth analysis of tourist behaviour (Chen et al., 2021). However, only adopting the big data research method may also face issues of analyses that are distinct from the actual situation (Lyu et al., 2022). Some significant explanatory variables might be ignored due to the massive size of big data (Fan et al., 2014). Also, a few common destination image attributes would be exacted by only focusing on big data analysis (Deng et al., 2019). Thus, more precise and detailed analytical methods are now required. Analyzing UGC with a combination of social network and statistical analyses may offer a new alternative to structuring tourism destination images (Wang et al., 2021; Williams et al., 2017).

3. Research methods

3.1 Research design

A staged design followed for a more organized and logical research process. The first step involved gathering online tourist comments, representing the primary data set. The second step was to derive destination attributes through content analysis of the data set. Third, social network and statistical analysis were applied to develop a classification structure for the destination attributes. The fourth step involved categorizing a set of 49 destinations into clusters and then comparing the perceived differences among the clusters, using social network analysis along with ANOVA and K-means cluster analysis (SPSS).

3.2 Acquisition of destination commentaries

This research used tourist-authored online narratives to derive the attributes comprising destination images. The textual reviews uploaded by tourists on social networks are numerous, varied in scope, and easy to obtain, and they constitute a bottom-up source to explore destination images. Therefore, this research selected www.ctrip.com (Ctrip), a travel website with the most significant number of users in China, as the online data source. Compared to other data sets, Ctrip offers a variety of products, attracting a wide range of consumers. Recently, Ctrip has been the data source of many studies on big data in China's tourism research (Lan et al., 2021; Yang et al., 2022). Therefore, using Ctrip as the data source made the sample widely representative.

Because tourist comments on cities (prefectural and county level) are the majority of Ctrip's data, this research focused on cities to increase the number of textual review materials and avoid low reliability from having too few responses. More specifically, the China Excellent Tourist Cities in the destination part of the Ctrip platform were chosen. The data were collected from January 1, 2008, to December 31, 2021. The codes had become saturated with no new attributes appearing. Therefore, no further data were added to the dataset.

The research team designed a text-extraction program to acquire comments. After searching for these destination names on Ctrip's official website, a systematic process was followed to obtain all comments about them. The reviews were written in Chinese, and the data were collected from Chinese tourists. Manual data cleaning was used to ensure data reliability, conducted by the researchers who were native Chinese speakers with five to six years of research experience. Two researchers separately read and filtered the data, removing comments with limited value, such as repetitive comments in texts of less than 100 words. The items were passed to a third researcher if these two people gave different judgments. Given the limitations of manual reading, all the data were downloaded, and comments were extracted from each destination using an interval sampling method (Teeroovengadum and Nunkoo, 2018). The sampling interval was ten. The number of reviews collected in different cities was not even; in first-tier cities like Beijing and Shanghai, comments were more abundant. Thus, an interval sampling method was employed to extract 2,000 comments. Cities with less than 2,000 tourist comments were excluded. Each comment was guaranteed a high-quality tourist narrative that could be used for further content analysis. Finally, a total of 21,354 reviews of 49 destinations remained.

3.3 Content analysis of text

An inductive approach (Thomas, 2006) was followed to derive codes from the text data set. The researchers carefully read the text and extracted inherent meanings, creating initial categories for meaningful text fragments. Then, according to the relationship between the initial categories, they were summarized into more general categories, namely the final categories. The coding was done by three researchers who were native Chinese speakers with rich experience in qualitative text coding. The first and second coders were each given half of the data and coded in parallel independently. After initial coding, they compared coding categories to establish the extent of overlap and merged the data into a combined set. If the overlap between the categories was low, a third researcher was added for further analysis and discussion.

3.4 Social network analysis of destination attributes

Social network analysis provides a set of tools for tourism research, allowing a better understanding of the structures of different elements (Casanueva et al., 2016). There have been many relevant applications in tourism research (He et al., 2022; Köseoglu et al., 2021; Wang et al., 2021). This research adopted this method to further explore the relationship characteristics among destination images' complex attributes. By converting 21,354 comments into a code table through matrix operations, the co-occurrence relationships among attributes were obtained. Calculations exercised by UCINET, a network analysis software program, detailed the coupling structure of image attributes. Centrality analysis identified all the perceived attributes and the most frequently mentioned of these. Eigenvector centrality better reflects the centrality index of complex nodes according to the basic principles of network analysis (Ruhnau, 2000). Therefore, this research adopted eigenvector centrality values to depict the centrality index of destination image attributes. The analysis using UCINET was weighted according to the importance of different locations, and the network was not automatically binarized. The formulas for social network analysis were based on the research of Wasserman and Faust (1994) and the work of Borgatti et al. (2013).

3.5 Categorization of selected destinations

SPSS was used to analyze whether there were differences in perceived image attributes for the selected destinations. K-means cluster analysis was used to cluster the 22 destination image attributes and 49 destinations according to their eigenvector centralities. Furthermore, a univariate analysis of variance (ANOVA) identified any statistically significant differences between clusters in terms of variables.

3.6 Ethical considerations

Ethical considerations regarding using UGC data have long been debated (Snee, 2008). Some researchers argued that there is no set access to UGC data, so there are no ethical issues.

However, to avoid criticism of ethical issues, this research was as cautious as possible in the data collection. When collecting data, the researchers retained the title and text of the comments without collecting identity information, as previous studies based on big data (Wang et al., 2019), to protect privacy and security as much as possible (Yallop and Seraphin, 2020).

4. Results

4.1 Destination image attribute frequency analysis and hierarchy

Contemporary researchers suggest that only simple conclusions can be determined if attention is not paid to the interrelationship among parts or attributes. At the same time, the wholeness of the entity cannot be grasped, and the relationships and interactions among parts cannot be reflected (Skyttner, 2005). Many tourism observers agree with this view because tourism is quite a complex system (e.g., McKercher, 1999; Morrison, Lehto and Day, 2018). Content analysis was used to sort tourist reviews, and quantitative analysis then supplemented and extended these qualitative data results. By analyzing the attributes of different tourist destinations, Table 2 shows the frequency of mentions of each of the 22 attributes for the 49 destinations. The number of comments from each destination was also listed. For example, in Beijing, the most frequently cited attribute was traffic within the destination (n = 630), while for Sanya, it was landscape (n = 459). This indicated variations in the images of attributes within particular destinations. Overall, the most frequently mentioned attribute was landscape (n14(n) = 7,555) followed by traffic within the destination (n16(p) = 6,124), food and beverages (n6(f) = 5,461) and resource-based attractions (n1(a) = 5,400).

[Insert Table 2]

Then, social network analysis (SNA) was completed to develop a general hierarchical structure of attributes. The values of node (attribute), closeness, betweenness, and eigenvector centralities of the attributes were calculated by UCINET software. The data in Table 2 was transformed into text format and imported into UCINET software to obtain the co-occurrence matrix. Then, to better show the links between the 22 attributes, the matrix was imported into Gephi 0.9.2 software for visualization. Figure 1 shows each of the 22 attributes as nodes (circles). The deeper the color, the more critical the node (attribute) in the network.

[Insert Figure 1]

According to the connotation of eigenvector centrality, it is appropriate to assume that the attribute with the highest centrality is the most significant image attribute. Table 3 shows the centrality values for the 22 attributes derived from social network analysis and their brief explanations. Landscape, traffic within the destination, food and beverages, and resource-based attractions had the highest eigenvector centrality values at 0.549, 0.450, 0.408, and 0.351, respectively. At the other end of the spectrum, sports and wellness (0.016), public services (0.015), and festivals and events (0.013) had lower Eigenvector centralities.

[Insert Table 3]

Using K-means cluster analysis, all attributes were clustered according to their eigenvector centralities (Table 3). ANOVA showed that the F-value was significant, indicating that the eigenvector centralities could cluster these 22 attributes. The final clustering centre refers to the means of the clusters. The first attribute group was named “core images,” with the highest value of the final clustering centre and means of eigenvector centralities. The second group comprised eight attributes and was called “expected and perceived.” The third group remained with ten attributes, with the lowest value of the final clustering centre and the means of eigenvector centralities. They were classified as “latent” attributes. The nomenclature for the three groups was adapted from Kotler’s Product Hierarchy Model

(Achrol and Kotler, 1999) and core-periphery structure (Wang et al., 2017). Figure 2 is a visual image of the levels of these three groups of attributes with the core attributes at the centre of the diagram and the latent as the outer ring. A brief description follows:

Core: The most crucial or influential part of tourist interactions with destinations, including tourism resources and functional attributes meeting basic needs (e.g., traffic within destination, food and beverages). They are the most crucial part of destination image, and whether they perform well significantly influences the overall destination image.

People have certain expectations for these attributes, and their appearance and performance often positively influence destination image. Tourists would have higher expectations of accommodations and price levels in most destinations.

Latent. Attributes are usually less obvious or actively perceived by tourists. Therefore, their absence does not strongly affect the destination image, and their performance does not significantly change images. However, poor performance usually negatively affects the destination image as a whole.

[Insert Figure 2]

4.2 Clustering of destinations

The eigenvector centralities of the perceived attributes for the 49 destinations were used as an independent variable to perform a hierarchical cluster analysis by K-means cluster analysis. The results are shown in Table 4. As a result of the ANOVA analysis, the eigenvector centrality could be used to cluster these 22 attributes, and the results were valid. Figure 3 shows the locations and geographic visualization for the three clusters of destinations.

[Insert Figure 3]

[Insert Table 4]

For identifying each destination type's "core-expected-latent" structure, the eigenvector centrality for each group was calculated using UCINET software, and a K-means cluster analysis was conducted based on the eigenvector centrality of 22 attributes.

[Insert Figure 4]

[Insert Table 5]

Figure 4 and Table 5 show three clusters of destinations and their "core-expected-latent" structures, ranked by the importance of different attributes. ANOVA was used to test the classification of the destinations into the three clusters. The grid marked with the grey shading of attributes was more important in the cluster, indicating that this is the core attribute. A brief description follows:

Cluster 1. The reviewers commenting on the destinations in the first cluster more frequently mentioned traffic within destinations and landscapes. These were mainly cities with significant economic development, like Beijing and Shanghai. These cities could be defined as “comprehensive or integrated urban destinations.” Tourists' primary purpose is to experience the comprehensive atmosphere of the whole city, such as in Hangzhou and Shanghai. Traffic density and congestion in these cities can adversely affect visitor experiences and leave deep impressions.

Cluster 2. Landscape and resource-based attractions scored significantly higher than average. Some provincial capitals were included (e.g., Changsha, Nanning, Kunming, Zhengzhou). This group had cities with more tourist attractions, such as natural landscapes and good man-made attractions. They can be called “scenic city destinations” because they mainly offer beautiful scenery, abundant accommodations, and recreational amenities.

Cluster 3. This group included 15 cities that are well known for their local food, leisure experiences, and social life, such as Chengdu and Chongqing. Some are also significant for their unique cuisines, such as Guilin and Lijiang. They are often visited and referred to as "lifestyle destinations."

5. Conclusions and implications

5.1 Main conclusions

The main contribution of this research is the use of a combination of big data and qualitative analysis to investigate destination images. According to the results, core-expected-latent attributes existed within the TDI structure (Lai and Li, 2012). A new hierarchical model was built with three attributes (core, expected, and latent). With social network analysis, three clusters (urban, scenic, and lifestyle) of destinations were identified, indicating the relative importance and centricity of attributes in the system. Some of the destination image attributes identified are not frequently mentioned in previous studies, such as “social life”. “Social life” refers to the scenes of residents' life and the local atmosphere. Berlet al. (2004) deemed local atmosphere an important image category, with descriptors such as luxurious, familial, exotic, mysterious, and leisurely. Murphy et al. (2000) also mentioned that sense of place is composed of image attributes. The textual data set mentioned social life for almost all destinations. However, as in Table 1, it was rarely mentioned in previous studies. In addition, previous studies often classified attractions into two groups, natural and cultural (Lascu, 2018). This research, however, found that Chinese tourists did not draw such a significant distinction between natural and cultural attractions. They appeared to differentiate between cultural and natural resource-oriented attractions and man-made venues.

5.2 Theoretical implications

This research identified destinations' core, expected, and latent attributes based on a core-periphery structure by combining content, social network, and cluster analyses. A new destination classification system based on big data was established through bottom-up data analysis. Studies of this magnitude have rarely been done before. Multiple destinations, a large data set, and a new classification system provide much scope for future research applications.

In addition, one of the contributions is in the research design and the combination of methods used to derive the findings. Previous destination image studies have adopted a top-down approach in which pre-determined attributes were quantitatively measured through closed-ended questions (Qian et al., 2022). This research, however, enhanced the understanding of destination image from the bottom up by utilizing feedback from those who had visited destinations (Wang et al., 2019).

The attributes of destination images extracted through big data technology may be incomplete or inaccurate. Therefore, this research responded to numerous calls in previous studies to employ qualitative methods in destination image analysis (Isaac and Eid, 2019; McCreary et al., 2020). Qualitative content analysis was used to analyze many tourist comments and combined social network analysis and quantitative cluster analysis to analyze the destination image attributes in a systematic, detailed, and accurate way.

5.3 Managerial implications

Although previous studies have found many destination image attributes (Wang et al., 2019), the bottom-up identification of image attributes from a tourist perspective enables DMOs to understand better a destination's unique characteristics (Wang et al., 2020). The methods followed in this research clarify the competitive destination attributes for the 49 cities covered. This destination classification system will provide destination marketing, branding, and image communications guidelines. As part of the marketing process, DMOs should first identify which cluster their destinations belong to and then focus on the core attributes of that cluster. The results show that the "traffic within destinations", "landscape", and "food and beverages" attributes were most important for comprehensive urban, scenic, and lifestyle destinations, respectively. A thriving destination should address its landscapes and traffic conditions, which are the core and fundamental elements of destination images and influence destination identity and loyalty (Eom et al., 2020). The research further shows that social life contributes significantly to a destination's image and is often overlooked by destination management organizations. Therefore, destinations should provide unique social and leisure life atmospheres to differentiate themselves from their competitors (Uysal and Sirgy, 2019).

6. Limitations and future research directions

Although this research may provide insights into the research about destination image, some limitations must be acknowledged. First, the demographic or personal information from each tourist who commented was not collected because of ethical considerations in this research. It may be questioned whether the text taken from e-commerce sites like Ctrip is representative and authentic. Thus, future research should consider actual scale-based data collection to verify results further. Second, the data were collected from Chinese tourists and domestic destinations in China. Different results and conclusions on destination attributes may arise from this research on other populations. There is the possibility of employing similar methods in other countries as well.

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