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MDIVis: Visual analytics of multiple destination images on tourism user generated content

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ABSTRACT

Abundant tourism user-generated content (UGC) contains a wealth of cognitive and emotional information, providing valuable data for building destination images that depict tourists' experiences and appraisal of the destinations during the tours. In particular, multiple destination images can assist tourism managers in exploring the commonalities and differences to investigate the elements of interest of tourists and improve the competitiveness of the destinations. However, existing methods usually focus on the image of a single destination, and they are not adequate to analyze and visualize UGC to extract valuable information and knowledge. Therefore, we discuss requirements with tourism experts and present MDIVis, a multi-level interactive visual analytics system that allows analysts to comprehend and analyze the cognitive themes and emotional experiences of multiple destination images for comparison. Specifically, we design a novel sentiment matrix view to summarize multiple destination images and improve two classic views to analyze the time-series pattern and compare the detailed information of images. Finally, we demonstrate the utility of MDIVis through three case studies with domain experts on real-world data, and the usability and effectiveness are confirmed through expert interviews.

1. Introduction

According to the cognition-emotion model defined by Baloglu and McCleary (1999), the tourism destination image is separated into cognitive themes and emotional experiences, with the cognitive themes referring to tourists' knowledge and the emotional experiences exposing the emotional tendency (Huang et al., 2021). In addition, tourism user-generated content(UGC) consists mainly of online travel notes and comments on tourism platforms. With the richer and more convenient Internet applications, online travel platforms have become prevalent in people's daily lives, and they have become an important means for tourists to make travel plans and share their experiences. These platforms contain a wealth of user-generated content reflecting visitors' practical sentiments. Similarly, the tourism UGC may play a significant role in portraying the destination image, providing valuable opportunities for tourism research. By constructing and examining multiple destination images with tourists' perceptions, tourism managers can explore the commonalities and differences of multiple destination images to investigate the elements of interest to tourists and improve the competitiveness of the destinations (Agus et al., 2020).

The existing research on destination images based on tourism UGC mainly uses text mining combined with text description for single destination image construction (Sheng et al., 2020; Garay, 2019). Visual analysis of tourism destination images currently has not drawn adequate research attention, with visualization mainly used to present data processing results. Although a few studies use visual analysis for single destination image exploration, studies that focus on destination images comparison are still lacking (Li et al., 2016). Therefore, tourism managers lack specific techniques and tools to process and visualize essential data to extract valuable information and knowledge (Barroso et al., 2020), and the discovery of commonalities and differences between multiple destination images is considered a challenging task in this context.

In this paper, we introduce MDIVis, an interactive visual analytics system for tourism UGC, to assist analysts in exploring and analyzing multiple destination images. From the travel notes and comments, MDIVis extracts the cognitive entities and emotional descriptions, and the cognitive entities that make up the

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cognitive image are divided into five categories to facilitate the exploration and comparison of destination images from multiple perspectives. Meanwhile, MDIVis allows users to compare at both overview and detail levels. At the overview level, we design and employ the Sentiment Matrix View to help analysts intuitively compare the characteristics of multiple destination images. Analysts can investigate and compare the temporal evolution and detailed information of multiple destination images at the detail level. To evaluate the usability and effectiveness of MDIVis, we performed case studies with real-world data, followed by interviews with domain experts. The results show that the system can identify the commonalities and differences between multiple destination images, reveal the temporal pattern of images, and explain the elements of tourists' concerns that change the images. The main contributions of our work include:

- A set of novel visualization designs are proposed to support the interactive comparison of destination images.
- A system based on linkage views is developed. The system provides users the exploration of tourism destination images at two levels of overview and detail.
- Three case studies and an expert interview based on real-world data that demonstrate the usability and effectiveness of MDIVis.

2. Related works

Previous studies related to our work can be divided into two parts: techniques for tourism destination image analysis and visualization of user-generated content.

2.1. Techniques for tourism destination image analysis

Destination image refers to a person's overall beliefs, ideas, and impressions of the destination (Woosnam et al., 2020). Researchers primarily use three methods to identify a destination image: questionnaire surveys, UGC mining, and picture recognition methods. Jeng et al. (2019) and Han et al. (2021) conducted destination image questionnaire surveys to assist marketers in studying visitor behavior patterns and developing publicity strategies. However, the destination image research was limited by investigation time and questionnaire design. Tourism UGC data provides a reliable way for destination image research by the characteristics of easy access, popularity, authenticity, and direct participation of tourists. Qi and Chen (2019) classified the collected tourism comment texts and built destination images using analysis software. They analyzed and summarized tourists' attention to various aspects, including destination leisure, culture, etc. Since UGC is usually presented in text, some content analysis methods (LDA, etc.) are often used to transform UGC into a structured topic model, and emotional experience contained in the text can also be extracted easily (Wang et al., 2020; Gkritzali et al., 2018). Furthermore, in recent years, some studies have investigated and broadened the use of artificial intelligence technology in tourism destination research, focusing on the construction of destination images with tourism picture content mining (Zhang et al., 2019; Xiao et al., 2020). Sheng et al. (2020) combined images and text descriptions to construct a tourist destination image. They found that the destination image revealed by text descriptions is clearer than images.

The cognition-emotion paradigm is frequently used in destination image analysis and research, and it has a favorable impact on tourist satisfaction and loyalty (Chiu et al., 2016). At the same time, not all cognitive factors influence tourists' desire to return, and categorizing cognitive entities can make destination image analysis easier (Triantafillidou et al., 2019; Leković et al., 2020). Through quantitative content analysis, Garay (2019) investigated the distribution of cognitive themes and emotional experiences of the destination image. Huang et al. (2021) established a research framework from a cognitive perspective, investigated how cognitive-behavioral characteristics and emotional experiences under various cognitive themes serve destination image and proposed novel suggestions for improving tourist experiences.

The current research focuses on constructing destination images by combining word frequency statistics with text descriptions, but the results are too complex for tourism analysts to recognize and interpret. Furthermore, most studies focus on constructing a specific destination image without considering image contrast and time-series impact.

2.2. Visualization of user-generated content

User-generated content refers to blogs, comments, notes, and other forms that include user experiences, sentiments, and opinions. In this section, we present the current state of visual analytics studies of UGC on social media and travel websites.

Social media is a growing source of user-generated content. Similar to our work to explore the destination images, many researchers focus on the abstraction and construction of hot topics using visual analytics. Knittel et al. (2021) used a clustering method to update the visualization of the topic. They integrated familiar and highly relevant visual metaphors to summarize methods for visualizing details about a specific topic of interest. Troudi et al. (2019) employ visual analytics to undertake multidimensional research of hot events, collecting data from numerous social media sources to identify events that have occurred. Kucher et al. (2020) built a text visualization analysis tool to explore and analyze sentiments and positions in social media UGC. In addition, mining temporal features has been a research focus in UGC visual analysis in recent years. TagNet was created by Chen (2018) for tag-based sentiment analysis. It combines a traditional tag cloud with an upgraded node-link graph to represent the temporal evolution of emotions through simple and intuitive visual expressions. Furthermore, the targeted view design aids users in comprehending the potential information of UGC. Hu et al. (2016) created a visualization approach for unstructured social media text that incorporates word cloud and tree cloud principles, which display keywords in social media and keep the sentence structure of the texts, allowing readers to grasp significant concepts and perspectives rapidly.

A few visual analytics of tourism UGC studies utilize the exploratory power of visual analytics (Kim et al., 2017; Zhang and Koshijima, 2019; Yuan et al., 2016; Xu et al., 2015). Francalanci and Hussain (2015) combined with k-shell analysis theory to propose a novel visual peripheral layer graphical representation to help travel experts explore and analyze the most competitive locations or events in social networks. Li et al. (2016) used visual analytics to investigate the social network relationships and uncover the tendency of hot tourism areas. Cao et al. (2020) suggested a multi-attribute dual-relationship technique to investigate the relationship between knowledge and pictures but did not consider the difference of multiple destination images.

Based on the above work, we focus on the cognitive and affective elements of destination images and design a visual analysis framework to support interactive exploration and comparative analysis of multiple destination images.

3. Scenario and task analysis

To better identify the scenario for the need to investigate the commonalities and differences of multiple destination images, we invite four domain experts (E1–E4) to gather the requirements and find the design candidate. E1 is a strategy analyst working in the tourism management department. E2 and E3 are product managers of the tourism industry. E4 is a professor at the school of tourism.

In this section, we first discuss and organize analysis tasks with experts, then introduce the research scenario data and formulate the requirements accordingly based on the tasks.

3.1. Task abstraction

Different tourist attractions have different attraction elements, and people perceive them differently. Our overall analysis goal is to explore and compare multiple destination images, which will assist tourism managers in discovering the most interesting destinations for tourists and the competitive elements of each destination. Furthermore, an exploratory analysis approach from overview to detail is well accepted. The characteristics of each destination image in terms of overview need to be intuitively discovered to narrow down the set of candidates of interest. At the same time, the user needs to explore the details of the destination image in terms of its temporal characteristics and the factors that are of widespread interest from multiple perspectives. After a roundtable with tourism experts, we formed the following specific tasks:

- **T1 Summarize multiple destination images.** To investigate the multiple destination images comprised in the dataset, experts need to summarize and examine the general situation of these destination images. Three main areas are included as follows:
  - **T1.1 Summarize the overall images of the destination set.** The analysts first need to generalize the overall images of the destination set and discover the distribution of cognitive and affective images.
  - **T1.2 Summarize the cognitive themes of the destination set.** Cognitive themes are a form of expression of people's perception of destinations. The analysts need to perceive the richness of cognitive themes of destinations and further analyze the information about each cognitive theme category.
  - **T1.3 Summarize the emotional experiences of the destination set.** Emotional experiences point to the emotional tendency of tourists toward destinations, which usually presents a positive or negative state. For example, experts want to know which destination image of landscapes performs more positively than others.
- **T2 Explore the time-series evolution of destination images.** Over the years, multiple destinations have changed in popularity in a competitive environment with each other. Analysts need to analyze and compare the temporal patterns of different destinations with the temporal characteristics of travel UGC data.
- **T3 Analyze and compare detailed information of individuals.** After the overview analysis, the experts can find some destinations of interest as a subset to be dissected to develop a comprehensive understanding of the relevant destination images and compare them. The following requirements are considered:
  - **T3.1 Compare the cognitive themes of individuals.** Each destination image contains its exclusive cognitive themes, and comparing cognitive themes is looking for differences in the cognitive entities that make up the cognitive themes. For example, experts want to know the main elements of the attractiveness of some destinations and different values for tourists.
  - **T3.2 Compare the emotional experiences of individuals.** Similar to T1.3, detailed comparisons for sentiment analysis are needed to be combined with cognitive themes, and the analysts need to compare specific sentiment descriptions of cognitive entities.
  - **T3.3 Compare the perceived/projected image of a single destination.** A single destination usually includes two images, a perceived image based on visitor feedback and a projected image constructed by the official portrayal. The analysts need to compare these two images to understand their differences, which helps propagandists optimize their propaganda strategies.
  - **T3.4 Exhibit raw user-generated contents.** In the raw user-generated content, travelers share their perceptions of destination images in detail. Therefore, analysts need to incorporate the complete descriptions of the UGC during the analysis to better comprehend the destination images.

3.2. Data description

Travel UGC is the main source of data for building destination images. Various travel community platforms have emerged in daily life, providing people with rich channels to exchange travel experiences and generate different UGC data forms. One type of UGC data is travel notes information, in which travelers publish travel notes which are long-form content after visiting a city or province, such as www.mafengwo.cn, and www.youxiake.com, etc. The other type is the comments information, which is the short-form content tourists post after visiting a specific site attraction, such as www.ctrip.com, www.tripadvisor.cn, and www.qyer.com. After comparing various travel websites, this work selects travel notes from 'mafengwo' (long text) and comments from 'tripadvisor' (short text) as the primary research data. The travel notes information contains records and experiences of people and objects experienced by tourists during the tour. Each paragraph of travel notes has different description objects, which is a comprehensive embodiment of the image of a destination. The comments contain more explicit time information and describe the visitor's feelings after visiting a destination.

First, we use a network crawler to resolve the UGC data from 2014 to 2020, collecting 560,000 tourism comments and approximately 1.57 million comments. Second, we refer to the type of destination in the 'mafengwo' website and classify destinations into five categories museums, religious sites, city parks, ancient towns, ecological sites, and others, so that users can make an initial selection of destinations based on their preferences, while the commonalities and differences in the images of similar destinations better indicate tourist concerns and potential competitiveness. After that, we remove the deactivation words from the UGC and use the TextRank algorithm to extract nouns and adjectives as cognitive and emotional elements of the destination image. Furthermore, we associate cognitive entities with emotions with textual contexts to help users understand what visitors are really thinking. In inspiration by Beerli and Martin (2004), we divide the cognitive themes into five categories: foods, scenes, landscapes, facilities, and atmospheres. Finally, we calculate the emotional score of key phrases using SNOWNLP, with negative to positive degrees mapped from -1 to 1. This value will be used to visualize visitors' real emotional tendencies towards destinations.

3.3. Design requirements

To address the above analysis tasks, we combine the data characteristics of UGC to formulate the following design requirements.

Fig. 1. MDIVis allows users to investigate and compare multiple destination images on UGC from multiple aspects. Setting panel (A) helps users to roughly filter destinations of interest, the Sentiment Matrix View (B) presents an overview of images of multiple candidate destinations, the Timing View (C) describes changes in the ranking of several destinations over the years, the Keywords Radar View (D) provides detailed information to explore and compare the destination images, and the Auxiliary View (E, F) offer extra information for users.

DR1. Provides an overview of multiple destination images. The system should support effective identification and interpretation of the cognitive themes and emotional experiences of the destination images. The visualization of a destination image encodes its emotional tendency and the richness of the cognitive entities (**T1**).

DR2. Visualize the temporal changes of destination images. The changes of tourist destination images per year should be visualized. The views should provide an overview and comparison of how the destination images have changed over the years (**T2**).

DR3. Compare the detailed information of destination images. In order to discover and comprehend the common and different elements between destination images, the views should show the detailed features of the image from different aspects and support the independent selection of destinations for comparative exploration (**T3**).

4. MDIVis system design

4.1. System pipeline

We design MDIVis, an interactive visual analytics system to explore multiple tourism destination images based on UGC, integrating the requirements and data characteristics. The pipeline of the system is shown in Fig. 2. After acquiring UGC and processing the dataset, we save the formed structured data in the database.

We design and implement a series of visual linkage views, which are combined with rich interactive means to assist users in analyzing and exploring destination images from various perspectives.

The view components and interactions of MDIVis follow an analysis model from overview to detail. The overview level views serve as the entry point for analysis, with the Sentiment Matrix View providing the user with an overview of multiple destination images in the dataset, and the Cognitive View shows comprehensive statistical information on cognitive entities (**T1**). The detailed level views are designed to provide more specific image information to help users compare destinations. Specifically, the Timing View presents the destinations' ranking in recent years (**T2**), the Keywords Radar View illustrates the differences in the images of the destination under each category (**T3**), and the UGC view shows the original UGC that supports the destination image.

4.2. Sentiment Matrix View

With multiple destination images in a dataset, users first need a quick overview of these destination images (DR1). We summarize the destination image into two parts: cognition and emotion. To better comprehend and compare them, we provide classification and overall visual design.

As shown in Fig. 1(B), multiple destination images are displayed in a matrix. Each row represents a destination image, including image units of five cognitive types (food, attraction, scenery, service, and atmosphere) and the overall image unit. Analysts can compare the distribution of the same destination image across different cognitive categories horizontally and multiple destination images within a single cognitive type or the overall situation vertically.

An image unit identifies the emotional tendency of visitors to a destination in a specific cognitive category. As shown in Fig. 3(a), each image unit is encoded with four rectangles, two large rectangles $LArea_1$ and $RArea_1$ and two small rectangles $LArea_2$ and $RArea_2$ embedded inside. Color depths used by $LArea_1$ and $RArea_1$ encode positive and negative emotional degrees, respectively. The area size by $LArea_2$ and $RArea_2$ map the number of positive and negative cognitive entities.

An overall image unit (Fig. 3(b)) provides general information of the image, including the integrated distribution of cognitions and emotions of the destination. In travel notes or comments, not all cognitive entities are associated with emotional expression. We mine the distribution of entities with emotional descriptions and non-emotional entities in the text to help users identify the credibility of destination images with the overall image unit. The pie charts at the top of the unit show the distribution of cognitive entities with emotional descriptions after classification, while the horizontal stack chart shows the overall distribution. The length of the line segment with two points encodes the difference between negative emotion value and positive emotion value. The distance *negNum* between the starting point of the line segment and the left border of the rectangle encodes negative emotion value, and the corresponding distance *posNum* encodes positive emotion value.

4.3. Timing View

Each tourist destination is visited by numerous tourists every year, and its popularity varies annually. In this view, we follow

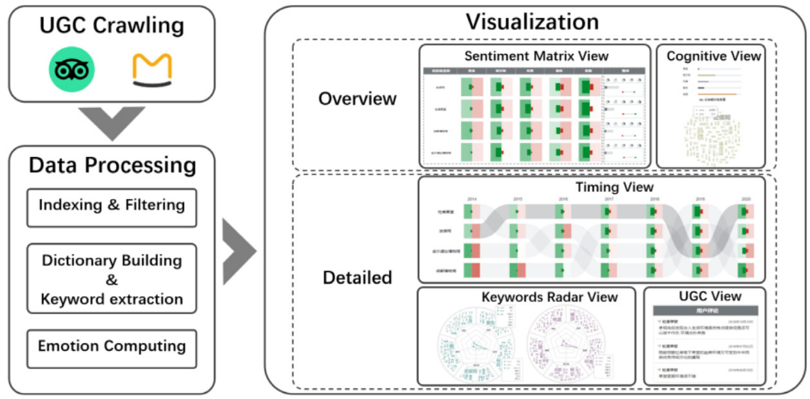


Fig. 2. The pipeline of MDIVis, contains UGC crawling, data processing, and visualization.

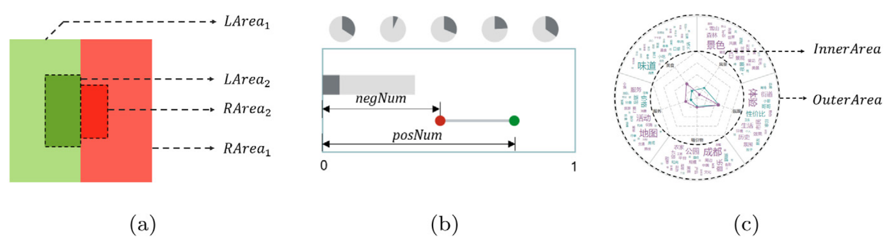


Fig. 3. Design of multiple views. (a) A cognitive image unit consisting of $LArea_1$, $LArea_2$, $RArea_1$ and $RArea_2$. (b) An overall image unit with pie charts, bar charts, and a points-and-line graph. (c) A Keywords Radar View contains *InnerArea* and *OuterArea*.

the sentiment matrix units to represent the destination's image each year. In addition, in conjunction with the work of Zhang et al. (2020) on visual ranking channels, we use visual channel chains showing the ranking of multiple destination images over the years (DR2).

As shown in Fig. 1(C), the time-series design adds a temporal dimension to the dimensional image units of the sentiment matrix, with the destination name text arranged vertically on the left and the temporal information juxtaposed horizontally above. The central part comprises image units arranged by a matrix-like layout, in which represents the overall image in a specific year. For a destination, the image units per year are connected by a chain of channels on a light background, and each chain reflecting the change in the ranking of images over the years. When the experts hover over a destination or image unit, the associated image chain will be highlighted, to help experts to focus on the selected destination and mine its temporal evolution pattern. For example, in Fig. 1(C), the images of the destination Temple of Marquis Wu are highlighted.

4.4. Keywords Radar View

The Keywords Radar View has been designed to explore and compare the detailed characteristics of multiple destination images. As shown in Fig. 1(D), we add the visual mapping of the points' area on the axes to the classical radar map to present the sentiment image of the cognitive dimensions. We combine it with the annular word cloud to provide a detailed comparison of the images (DR3). The view uses a radial layout and contains *InnerArea* and *OuterArea* parts, as shown in Fig. 3(c). In the *InnerArea* part, a modified radar map is used to encode the image information of the destination in multiple cognitive dimensions to facilitate visual comparison. The corresponding cognitive attribute values are encoded by the distance between the intersection on the axis and the axis center in the radial axes. The area of points encodes the emotional attributes of the destination in that dimension. In the *OuterArea* part, the word clouds represent the cognitive entities of the destination image, and different colors are used to distinguish the destinations. This view supports the comparative analysis between different dimensions (different sectoral word clouds) and enables the content comparison of a single dimension (the same sectoral word cloud).

4.5. Interactions

In this section, we describe the interactions between the visual components involved in MDIVis. Interactions are designed to assist users in exploring and comparing multiple destination pictures and completing relevant analysis tasks.

Before conducting a formal analysis, users need to roughly filter destinations by category in the Setting panel (Fig. 1(E)), or manually search for destinations to add to the candidate list to be analyzed. While the user generates or changes the set of candidate destinations, the Cognitive View presents comprehensive cognitive information about them, and the Sentiment Matrix View provides overall emotional images of the multiple destinations in each cognitive category. Then, users can interactively sort the candidate destinations in the matrix to facilitate the selection of specific destinations of interest, and switch to the detailed level views for detailed comparison and exploration by clicking on the tabs in the setting panel. The Timing View shows how multiple destination images have changed in ranking over time, allowing users to hover over an image to notice which destination it belongs to and explore the context of that destination with the highlighted bar. Moreover, users can investigate more information by hovering over the visible elements with the mouse to expand the bubble tooltips in the Keywords Radar View. In addition, when the user explores a specific destination image by interacting with the view component, the view will automatically update the UGC information that supports the destination image.

5. Evaluation

Destination image is one of the popular subjects in tourism, and tourism managers are concerned about the differences in multiple destination images. To evaluate the effectiveness and availability of MDIVis, we conduct three case studies and an expert interview in real-world data.

5.1. Case studies

In the following, we present three case studies and highlight insights gathered from real-world data, with an example from Chengdu, Sichuan Province, China. The three case studies jointly cover all tasks described in Section 3.1.

5.1.1. Summarize and compare multi-destination images

Summarizing tourists' emotional tendencies and the richness of cognitive entities towards each destination in Chengdu is an important prerequisite for understanding the commonalities and differences in destination images. In this case, we describe how our system helps experts understand multiple destination images from various perspectives.

First, we select the destinations in the Museum category in the setting panel to get an overview of the destination. Fig. 1(E) shows the distribution of cognitive themes for these destinations, with atmospheres being the most popular, followed by attractors, and foods being the least. Then, we analyze the cognitive word cloud by selecting the atmosphere cognitive histogram. In the bottom, some terms, such as history, characteristics, and children, have been discussed extensively, which means that tourists prefer to bring their children to broaden horizons and experience the sense of history and culture.

The destination images in the museum category are shown in the Sentiment Matrix View (Fig. 1(B)). Then we can find that light gray takes up more area than dark gray in overall image units generally, indicating that the cognitive entities of visitors' rich experience are unrelated to emotion. In addition, the emotional line segments in the bottom all deviate to the right, indicating that tourists have good experiences of the destinations (**T1.1**). The emotional matrix depicts the classified emotional situation of the various destinations, and the most popular destinations are Temple of Marquis Wu, Du Fu Thatched Cottage, Chengdu Museum and Jinsha Site Museum, according to the overall ranking. For each cognitive category, the green embedded rectangle on the left of the image units occupies more area than the red rectangle on the right, indicating that tourists develop more positive impressions of the destinations, and the overall destination images are pleasant (**T1.3**). In addition, it is noticeably that almost every destination has the highest frequency of cognitive themes in the category of atmosphere, followed by attraction, and services least, which is consistent with the distribution of cognitive classification word cloud (**T1.2**). In general, all destinations present positive images, i.e., more positive feelings among visitors. Also, the museum destinations focus on enhancing attractions and landscapes to create a historical atmosphere but lack reputations of service (**T1**).

5.1.2. Explore the temporal characteristics and details

Exploring the development of destination images over the years, combined with detailed information on destination images, can help experts identify specific differences in destination images and further provide a basis for improving the competitiveness of destinations. In this case study, we describe how MDIVis helps experts explore image differences and potential competitiveness of destinations.

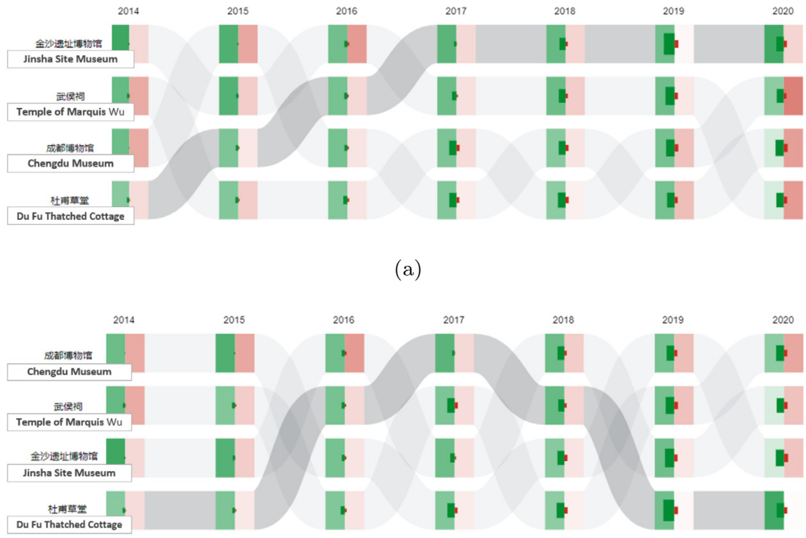
In the preceding analysis, the experts are interested in the destinations of the Temple of Marquis Wu, Du Fu Thatched Cottage, Chengdu Museum, and Jinsha Site Museum, which occur with high frequencies of appearance, and we investigate the temporal patterns of these destination images. Fig. 1(C) illustrates that the image units for all destinations show a similar trend from 2014 to 2019. The areas of inner rectangles grow increasing over the chain, which means that the impression of tourists grows richer over year. It is worth noting that the areas of the inner rectangles decline significantly from 2019 to 2020. Based on actual events, it may be due to the social impact of COVID-19 in early 2020, which reduced the number of tourist trips and weakened their perception of the destinations. It is also worth mentioning that, while the ranking of Temple of Marquis Wu fluctuates in the overall ranking, the general trend is improving. The ranking rose from the second in 2014 to the first in 2015 and remained in 2018 before dropping in 2019, but it climbed back to the top two in 2020. Next, we examine the temporal evolution of sentiment images of the atmosphere category and sort them by positive images, as shown in Fig. 4a. Similar to the overall situation, in the image units of each year, the green rectangular area of the embedded left side is larger than the right red rectangle, indicating that the destinations had left more positive impressions for the tourist. When we hover over the name text of the Du Fu Thatched Cottage, the relevant image units are connected by a chain. Since 2014, its ranking has increased year by year. It rose to the first place in 2017 and remained its place until 2020, indicating that the destination positively impacts tourists.

We then sort them by negative images, and the result is shown in Fig. 4b. The negative ranking of Du Fu Thatched Cottage varies greatly, increasing year after year and decreasing year after year. It returned to fourth place in 2019 and maintained a certain level. It has been discovered that while tourists' positive impressions of Du Fu Thatched Cottage are increasing year by year, there are also more negative impressions. However, the increase in negative impact has gradually decreased since 2017. It can also be seen that the color depth of the units' right rectangles declines to about 0 from 2019 to 2020, indicating that tourists' negative perception of this destination is decreasing. As a result of the above observation and analysis, due to environmental changes and competition among various tourist destinations, the images of multiple destinations have undergone big or small changes over the years (**T2**).

We continue to compare and analyze the images of the Temple of Marquis Wu and Du Fu Thatched Cottage in the Keywords Radar View (**T3**). In the positive perception of tourists, as shown in Fig. 5(a, b), both destinations have the same cognitive entities such as *history*, *culture*, and some synonyms, which indicates that tourists prefer to feel the influence of the Chinese excellent traditional culture (**T3.1**). In negative perception, as shown in Fig. 5(c, d), the two destinations have similar entities per category, including *scenery*, *taste*, *ticket*, *price*, *cost performance*, indicating that the destinations leave some similar negative impression on tourists (**T3.2**). To support this insight, we browsed through the relevant original user-generated content, and many tourists said they would go there frequently if the tickets were not very expensive (**T3.4**). The above examples show that museum destinations perform well in terms of historical and cultural heritage. However, the service elements, mainly the entrance fee, may become the key competitive element for the destination in the subsequent development.

5.1.3. Compare the perceived/projected images

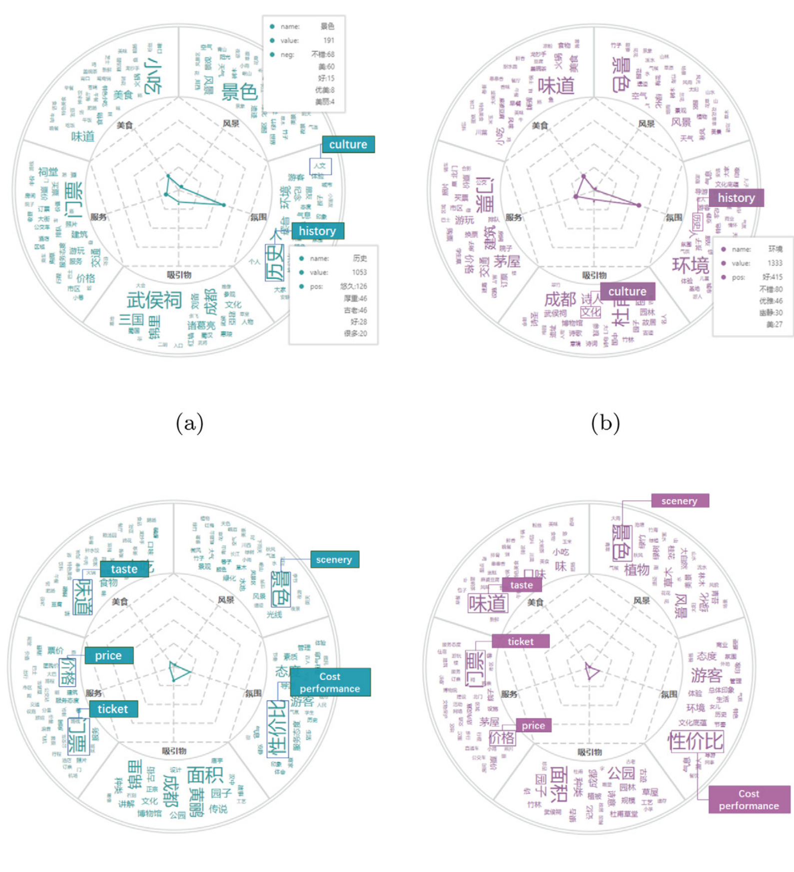
Destination image can be divided into the perceived image and projected image, where perceived image refers to tourists' overall impression and feeling of the destinations, and the projected image is defined as the ideal image assigned to the destination by tourism management. Tourists' impressions of destinations in UGC provide valuable data to construct perceived images. In this case, we take Chengdu city as an example with publicity data to explore the divergence between perceived and projected images.



(a)

(b)

Fig. 4. Timing view. The images are sorted by their positive degree (a) or negative degree (b).

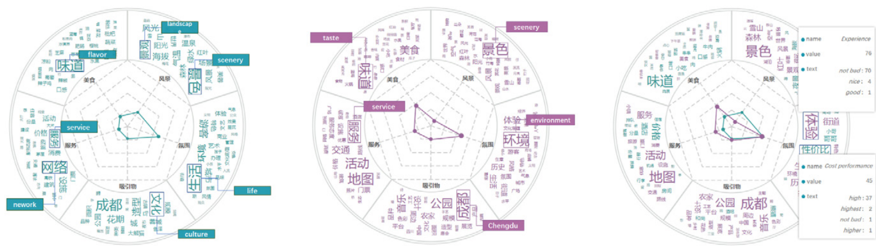


(a) (b)

(c) (d)

Fig. 5. Detailed comparative analysis with the Keywords Radar View. The destination image of Temple of Marquis Wu is divided into two parts: a positive image (a) and a negative image (c). And the destination image of Du Fu Thatched Cottage is divided into two parts: a positive image (b) and a negative image (d).

From the perspective of tourists (Fig. 6(a)), it is observed that the terms mentioned more often by tourists for the landscape category are *scenery* and *landscape*. The most frequently mentioned entity of food category is *flavor*, and the words *network* and *service* are often mentioned in the service category. In the cognitive type of atmosphere, travelers often mention *life* and *environment*, and *Chengdu* and *culture* are frequently used in the attraction category. Fig. 6(b) shows the details of the projected image. There are more high-frequency entities, including *map*, *event*, *transportation* for services, and *park*, *music* for attractions,



(a) (b) (c)

Fig. 6. Detailed comparative analysis of perception and projection. The perceived image (a) and the projected image (b) are displayed under the juxtaposition layout, respectively. And the perceived image and the projected image are displayed together under a overlay layout (c).

Table 1
Questionnaire of expert evaluation.

Usability	Q1	Is it easy (difficult) to choose some destinations for comparison analysis?
	Q2	With the sentiment matrix view, is it easy (difficult) to compare the images of the destination subset globally?
	Q3	Is it easy (difficult) to understand the temporal evolution of images between destinations?
	Q4	Is it easy (difficult) to select a subset of destinations of interest and compare them in detail?
Effectiveness	Q5	Is it easy (difficult) to analyze the difference between the perceived image of visitors and the official projected image of Chengdu?
	Q6	Overall, is it easy (or difficult) for you to use MDIVis to compare multi-destination images?
	Q7	Is it easy (difficult) to learn and use MDIVis?
	Q8	Is it easy (difficult) to understand the visual designs in MDIVis?

etc. It indicates that the projected image is more prosperous and dedicated to promoting destination diversity, which still needs to be experienced and felt by tourists in-depth.

To further compare the perceived image of tourists with the official projected image, the juxtaposition layout is replaced with an overlay layout. As shown in Fig. 6(c), the green is used to indicate tourist perceptions and purple with official projections. The internal radar diagram compares the information of the perceived image and projected image in five dimensions. It is observed that tourists mention more about the scenery category. The officials make a lot of publicity in the food, service, and attraction types, and they are more consistent in the atmosphere category with tourists. We further focus on the detailed descriptions of each dimension. The tourists feel more strongly about *taste*. In contrast, there are more cognitive entities in the projective image, such as *scenery*, *park*, *music*, etc. Then, we focus on the detailed comparison of images in the atmosphere category (Fig. 6(b,c)) and find that tourists are more concerned about *cost-effectiveness*, which is mainly described as *high* and *highest* while the official focus more on *experience* (**T3.3**). This case illustrates differences between the perceived image and the projected image, and it may be a challenge or an opportunity to shape the image according to the interests of tourists.

5.2. Expert evaluation

The above case studies have validated the utility of the MDIVis proposed in this paper. We develop the following expert evaluation to demonstrate the system's effectiveness and usability.

There are 10 exports invited to participate in the expert evaluation phase, including 2 tourism managers, 4 visual analysis researchers, and 4 researchers with tourism research backgrounds. We designed a questionnaire (Table 1), where Q1–Q4 correspond to general requirements to verify the usability of MDIVis, and Q5–Q8 involve the overall evaluation of MDIVis in the comparative analysis of destination images to evaluate the effectiveness of MDIVis. Second, we briefly introduce the background of our work and the user interface of MDIVis, followed by an explanation of MDIVis's function via an operation example. Finally, participants were encouraged to explore the MDIVis freely and respond to relevant evaluation questions.

Fig. 7 shows the results of an expert evaluation of problems Q1–Q8, demonstrating the usability and effectiveness of MDIVis. In terms of destination analysis subset selection, all participants believe that MDIVis makes it very simple to determine a subset of destinations via destination search or type selection for comparative analysis (Q1). In the overview analysis (Q2), participants by the emotional matrix view carry on the preliminary analysis to the selected destination collection, believe the design of image unit can depict the cognitive and emotional information related to intuition, and easily reflect the differences in the set of destinations in different dimensions. Furthermore, they can perform the comparative analysis of the destination collection with the type of interaction. After the overview analysis, participants interactively select destinations of interest and further analyze temporal and detailed features. In the aspect of time sequence comparison (Q3), participants prefer the Timing View to discover the trend of image's annual evolution over the year intuitively. For example, participants chose the overall ranking method, and they found that the image of Du Fu Thatched Cottage fluctuated wildly, which is difficult to obtain directly through questionnaires or raw UGC data in previous studies. In terms of detailed comparison (Q4), nine of the 10 participants thought they could complete a comparative analysis of detailed information of destination images. They agreed that it is beneficial for a complete contrast to multiple destination images that the Keywords Radar View presented classified detailed information. When comparing the visitor's perceived image with the official projected image, participants agreed that this feature was very effective for a comprehensive understanding of the Chengdu destination image (Q5). For example, participants mentioned that they could identify apparent differences between the images only by the image overview view. Participants agreed that MDIVis is effective for comparative destination images based on the above exploration and analysis experience (Q6). According to Q7 and Q8, it is easy for experts to use MDIVis and understand its visual design. Users who have never used the visual analysis system can also efficiently conduct a comparative analysis of the destination images. Moreover, most experts agree that the Sentiment Matrix View presents an overview of destination images in a table-like

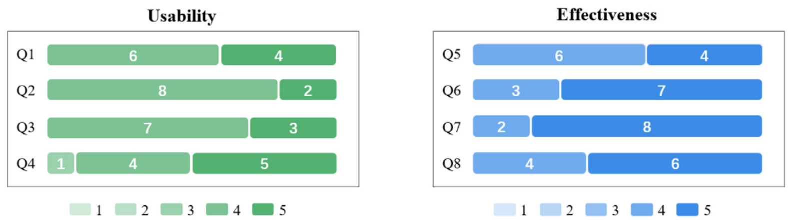


Fig. 7. Expert evaluation result.

format, reducing learning costs, and visualizes the data in a clear form, while the custom graphic design of the matrix cells offers obvious advantages in performing comparisons of multiple destination images. Experts also think that the Timing View and the Keywords Radar View support a detailed comparison of selected destination images and can effectively address users' analytical needs. However, some experts suggested that destination image indicators such as transportation, accommodation, and surrounding facilities, can be added in future work to make the analysis results more comprehensive and specific.

6. Discussion

Although the usability and effectiveness of MDIVis have been confirmed in our evaluation, there are some limitations that may serve as meaningful references for future studies.

Scalability. In the above case studies, we demonstrated the effectiveness of MDIVis for task exploration, but its scalability might be improved. The Sentiment Matrix View presents destination images in the form of a matrix, and the users get limited information about the destination at each observation. If there are massive destination images in the dataset, the overall distribution information is challenging to capture. In this work, experts tend to investigate the outstanding destinations under each category after classification, and the matrix layout is a suitable way to meet that need.

Generalization. In the current research work, MDIVis has been applied only to explore multiple destination images, where some of the visual analysis methods and views can be referenced to other domains. The Keywords Radar View and the Sentiment Matrix View are not limited to comparing destination images. They are also suitable for demand for fine-grained classification and comparison involving keywords, emotions, and time series in other fields related to text visualization, such as education. For example, we can analyze student comments on online courses to find differences by adapting the proposed methods in such a context.

7. Conclusion

We propose MDIVis for tourism destination images analysis to help users explore and understand destination image features from UGC and discover competitive elements of destinations in comparative analysis. Specifically, we firstly combine literature review and expert interviews to extract the system requirements and analysis tasks. Then, we design and implement a novel sentiment matrix view and improve two classic views, which assist users in comparing the destination images from various perspectives at the overview and detail levels. Finally, we use UGC in the actual environment for case analysis and expert evaluation to verify the usability and effectiveness of MDIVis.

In the future, we plan to add data forms to capture more information about the travel experience. The tourism destination image contains a variety of contents. This paper only analyzes the travel notes and comment information from the tourism platform. The other forms are not considered, such as transportation, accommodation, social environment, and other aspects of destination images. Also, geographical features are equally meaningful for destination image analysis, and some top-rated tourist attractions are likely to popularize the surrounding tourist places.

CRediT authorship contribution statement

Changlin Li: Writing – original draft, Methodology, Visualization, Writing – reviewing. **Mengqi Cao:** Data curation, Investigation. **Xiaolin Wen:** Investigation, Resources, Software. **Haotian Zhu:** Writing – review & editing, Formal analysis. **Shangsong Liu:** Writing – review & editing, Formal analysis. **Xinyi Zhang:** Writing – review & editing, Formal analysis. **Min Zhu:** Supervision.

Declaration of competing interest

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

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Ethical approval

This study does not contain any studies with human or animal subjects performed by any of the authors. All data used in the study are taken from public databases that were published in the past.

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