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TDIVis: visual analysis of tourism destination images*

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Abstract: The study of tourism destination images is of great significance in the tourism discipline. Tourism user-generated content (UGC), i.e., the feedback on tourism websites, provides rich information for constructing a destination image. However, it is difficult for tourism researchers to obtain a relatively complete and intuitive destination image due to the unintuitive destination image display, the significant variance in departure time and data length, and the destination type in UGC. We propose TDIVis, a carefully designed visual analytics system, aimed at obtaining a relatively comprehensive destination image. Specifically, a keyword-based sentiment visualization method is proposed to associate the cognitive image with the emotional image, and by this method, both time evolution analysis and classification analysis are considered; a multi-attribute association double sequence visualization method is proposed to associate two different types of text sequences and provide a dynamic visual encoding interaction method for the multi-attribute characteristics of sequences. The effectiveness and usability of TDIVis are demonstrated through four cases and a user study.

Key words: Tourism user-generated content; Information visualization; Destination image; Sentiment visualization; Sequence visualization

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1 Introduction

The definition of a tourism destination image in the study is broadly quoted as the sum of people's beliefs, ideas, and impressions about a destination (Crompton, 1979). Baloglu and McCleary (1999) divided tourism destination images into two categories, i.e., cognition and emotion. A cognitive image refers to the tourists' understanding of the destination attributes, and an emotional image is the tourists' emotional attitude towards the destination. Establishing an excellent image is important for attracting tourists, and it is also an important method for tourism marketing, which affects the sustainable development of destinations.

The traditional method of constructing a destination image is surveying using a questionnaire (Stylidis et al., 2017; Kotsi et al., 2018). Researchers design the questionnaire according to the research purpose and then quantify and statistically analyze the results to obtain the image of the tourist destination. This type of research is a time- and cost-prohibitive exercise. Moreover, the effectiveness of destination image construction relies on the design of the questionnaire. The arrival of the new era of mobile Internet provides researchers with new sources of data, such as social media data (Zheng et al., 2016). Increasing numbers of tourists use mobile

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Web platforms to publish travel blogs and comments for sharing and communicating. These types of original text are user-generated content (UGC). Tourism UGC contains destination image information such as tourist attraction, tourist traffic, and environmental atmosphere, which provides good materials and new opportunities for tourism studies.

At present, in most related works the UGC is used to construct a destination image through the combination of text mining and text description. This approach does not fully use the tour departure time or destination cognitive image category contained in the tourism UGC, and cannot comprehensively construct or analyze images from the perspective of time sequence evolution and classification comparison. Although visualization has been used to help construct an image, only simple visualization methods are used to provide an auxiliary explanation for text processing results (Yuan et al., 2014; Li et al., 2016). The association between the destination's cognitive and emotional images is not analyzed properly, and these images do not consider any notable properties, such as text type (travel blogs and comment texts in tourism UGC), so it is difficult to discover the effects of different attributes on the destination image.

In this study, we present TDIVis, a visual analytics system considering both travel blogs and comment texts, to help tourism researchers intuitively analyze the destination image in the context of new media and provide new ideas for the image construction of destination management organizations. We harvest tourism UGC from Baidu Travel and Mafengwo, collecting $\geq$710 000 travel blogs and 1.53 million comments, and then analyze and process the data. According to the data characteristics and our visualization tasks, we divide the analysis of the whole destination image into two parts, i.e., cognitive-sentiment analysis and travel-comment analysis. Cognitive-sentiment analysis aims at connecting cognitive images with emotional images and providing multi-perspective analyses of the overall image, time sequence, and classification. Travel-comment analysis supports the association of two text sequences to explore and analyze multiple attributes of text. For cognitive-sentiment analysis and travel-comment analysis, the keyword-based sentiment visualization method and multi-attribute association double sequence visualization method are proposed, respectively. In addition, we provide the original text content views in case some of our users want to read them. An interactive system of destination image construction is also enabled, which helps users quickly obtain a complete destination image.

The major contributions of this study can be summarized as follows:

1. We design a keyword-based sentiment visualization method to correlate the cognitive image and the emotional image of the destination. The curve is one of the correlation designs in our method, but too many curves can easily lead to visual confusion. Thus, we compare two types of curves, Bézier curve and B-spline curve. The results indicate that the B-spline curve can effectively solve the problem of visual confusion while drawing the curve.

2. We propose a multi-attribute association double sequence visualization method correlating two different types of text sequences, aimed at discovering the similarities and differences between destination images, which are mined from travel blogs and comments. It also provides an interactive method of dynamic visual encoding to explore the influence of various attributes on destination images. For the sequence unit mapping in our method, histogram equalization is adopted to solve the visual confusion of color caused by the uneven distribution of data, after comparing it with two other color mapping methods (traditional linearization and box plot equalization).

3. We design and implement an interactive visualization system to help users build an overall image, time sequence, and classification of the tourism destination image.

2 Related work

In this section, we review related works regarding tourism destination image analysis and tourism UGC text visualization.

2.1 Tourism destination image analysis

Most of the research in this field used mainly questionnaires to construct a tourism destination image. Lu S et al. (2020) used questionnaires to explore the linguistic landscape in Hongcun, a Chinese traditional village. Jeng et al. (2019) used questionnaires to investigate the views of groups in different countries on Taiwan's destination image, helping destination marketers reposition their destinations and providing a reference for individuals who want to travel to Taiwan, China. da Silva et al. (2018) surveyed 132 Portuguese travel agencies, in view of the good tourism relationship between Brazil and Portugal to analyze the image of Brazil's tourism destinations considering the perspective of travel agencies. Papadimitriou et al. (2018) used questionnaires to investigate and analyze the views of three different groups on the destination cognition, emotion, and overall image of the Greek city of Patras. Results showed that differences between different groups could have a certain degree of impact on their perception of the destination image.

With the rise of the mobile Internet platform, some of the UGC (e.g., the travel text data of the travel platform) is analyzed through data mining and other information technology methods to complete tourism destination image analysis. Gkritzali et al. (2018) analyzed the evolution of Athens's destination image from 2005 to 2015 using TripAdvisor Athens tourism forum data and data mining methods. Wang R and Hao (2018) used the latent Dirichlet allocation (LDA) model to divide the cognitive image of travel blogs and analyzed the most important 26 cognitive images. Tseng et al. (2015) collected 630 articles published by tourists on an international travel blog website, and used text analysis tools to infer the image of Chinese destinations composed of nine themes, including people, food, trains, cities, and so on. Sun et al. (2015) constructed the image of New Zealand's tourist destinations by analyzing the text of Chinese tourists' travel blogs, and divided the image into six themes. Stepchenkova and Zhan (2013) used the UGC to establish a Peruvian destination image.

The research on construction and analysis of the destination image using questionnaire survey is limited by time and questionnaire design. In addition, sample selection and the subjective factors of researchers significantly affect the results. In the construction and analysis of the destination image based on tourism UGC, most studies constructed the analysis of the destination image by extracting words related to the destination while combining the text description. In this study, we use UGC to analyze the destination image and combine visualization with text processing to display the destination image intuitively.

2.2 Tourism user-generated content text visualization

In the study of tourism UGC text visualization, existing studies used visualization only as an auxiliary display method, adopting relatively simple methods such as line chart, word cloud, and bar chart. For instance, Li et al. (2016) proposed a visual analysis system for the emotional changes of travel network reviews; this system uses maps and bar charts to help users select travel reviews in which they are interested, and uses the stacked polyline area map to represent the changes of tourists' emotional values over time in tourism reviews. Yuan et al. (2014) proposed a method for extracting location-related practical information from a large amount of travel data and thereafter showing the relationship between locations through a node-link diagram. Based on this work, Yuan et al. (2016) used the node-link diagram to represent the co-occurrence relationship in the tourism location network, and presented the actual location represented by the tourism location vocabulary on the map to achieve the division of the tourist area and the identification of the popular tourist location. Kim et al. (2017) used a line chart to conduct an emotional analysis of tourists' comments on Paris to find out the reasons for negative comments. Oh et al. (2018) used the word cloud and a bar chart to present comments on the restaurant experience of American tourists traveling to Hong Kong, China, helping travel marketers visually understand the proportion of tourists visiting different types of restaurants. However, few of these works have focused on visual design.

Researchers have also studied text visualization related mainly to social media UGC. Wu et al. (2018) designed a tree structure based visualization method for presenting social flow changes in social media UGC. They chiefly focused on analyzing the evolution of UGC over time, but their method cannot correlate key information in the UGC (e.g., association analyses of cognitive words and emotional words) or make full use of attributes in text data other than time (e.g., text type and number of text views). Hu et al. (2017) combined the frequent itemset mining method with a word cloud and a tree cloud to design a visualization method for unstructured social media UGC. They displayed high-frequency words and preserved the text sentence structure. Liu MC et al. (2016) proposed a visual analysis method for uncertainty perception, demonstrating the relationship among three key dimensions of Twitter data (keywords, users, and labels) through graph-based visualization. However, all the above studies used short-text data such as Twitter, which cannot meet the requirement of the comparative analysis between different types of text sequences (e.g., travel blog long text and comment short text). To help analysts link multiple text media data sources, Lu YF et al. (2018) designed a bubble chart to display keyword information, but the correlations between different types of keywords were not shown properly.

The analysis of emotion is also a major research direction for social media UGC text visualization. Most research works tend to study changes in emotional values over time (Zhao et al., 2014; Wang XT et al., 2016; Chen, 2018). For instance, Chen (2018) combined the word cloud with the node-link diagram to analyze the temporal emotional changes of a large number of tags.

Among these works, few tourism UGC text visualization studies focus on visual design. Text visualization research on social media UGC cannot achieve the comparison or correlation analysis of different types of text. In this study, we use visual analysis methods to analyze the destination image from the two aspects of the cognitive image and emotional image, and thereafter consider the influence of other attributes (e.g., time and text type) of the text on the destination image. Similar to Wu et al. (2018), the time factor is considered in our methods.

3 Background

In this section, we summarize the design requirements and basic tasks. Datasets and processing methods used in this study are also introduced.

3.1 Requirement analysis

The overall goal is to help tourism managers or tourism researchers build a relatively complete destination image via exploration. Through investigation and discussion with experts, we found that tourism destination images are based mostly on the "cognitive-emotional" destination image model proposed by Baloglu and McCleary (1999) and characteristics of tourism UGC (Hernández-Lobato et al., 2006; Papadimitriou et al., 2018; Rekha, 2018). Based on this observation, two requirements are considered in this study: (1) what are the cognitive and emotional images of a destination and (2) what impacts do the tourist comments and travel blogs have on the destination image? Thus, we define a series of visualization tasks based on these two requirements.

T1: cognitive image analysis

The cognitive image is the cognition expression of the destination attribute. It is necessary to extract the cognitive image from tourism text data for visualization. This task consists of two aspects: (1) analysis of the overall cognitive image and (2) analysis of the cognitive image category.

T1.1: overall cognitive image presentation and analysis

To enable the analyst to have an overall perception of the destination image, it is necessary to provide image descriptions from multiple angles according to the user requirements.

T1.2: category definition of the cognitive image

The destination image includes various categories, such as tourist attractions, tourism infrastructure, tourism environment, and local atmosphere.

T2: emotional image analysis

The emotional image is the emotional expression of destination attributes. An emotional image is generally used to describe the cognitive image. It is necessary to correlate the emotional image with the cognitive image. This task consists of two aspects: (1) detailed analysis of a single category and (2) comparative analysis of different categories.

T2.1: detailed analysis of a single category

It requires the analysis of the emotional image of each category for different cognitive categories. For example, what are the positive and negative ratings of the tourist attraction category? What are the positive and negative evaluations of the tourist's description in the cognitive image?

T2.2: comparative analysis of different categories

Referring to the comparative analysis of various categories of emotional images and the analysis of the causes for the negative evaluations, analysts can find corresponding solutions.

T3: image temporal evolution analysis

Tourism text data have a time attribute that is used to analyze the temporal pattern of the image.

This task consists of two aspects: (1) temporal analysis of the cognitive image and (2) temporal analysis of the emotional image.

T3.1: temporal analysis of the cognitive image

It requires an analysis of the difference between the cognitive images at different time granularities. For example, which sites in different years are mentioned more frequently? How do the cognitive images of destinations change in different quarters?

T3.2: temporal analysis of the emotional image

It requires the combination of cognitive image analyses of changes in the emotional image at different time granularities. For example, does the destination have a lot of negative evaluations at a certain point in time? What is the reason behind this situation?

T4: comparative analysis of image text

Tourism UGC includes the travel blog text and comment text. The travel blog text is quite long compared to the comment text. This task can compare and analyze the similarities and differences between the images presented by the travel blog text and the comment text. Are cognitive and emotional images consistent over the same period in time? Do they show similar temporal patterns over time?

T5: original text analysis

In addition to the cognitive image and emotional image analyses, reviewing the original text's complete description of the destination helps the analyst better understand the destination image.

3.2 Data processing

We use the data from the websites of Mafengwo and Baidu Travel as examples for our method. Mafengwo is a tourism forum website that uses UGC as its core competitiveness. The monthly average number of active users reaches 100 million, with users writing $\geq$135 000 high-quality travel blogs per month. Mafengwo's travel blogs provide tourism UGC in the form of long text. Baidu Travel is a tourism information community service platform under Baidu; users can share travel experience on the platform, thus helping those who are ready to travel make travel plans faster and better. Baidu Travel offers a comment function that provides users with short-text UGC information about destinations. We therefore chose Mafengwo and Baidu Travel as the data sources for research.

We crawled the Mafengwo travel data (long text) and Baidu Travel's comment data (short text). The travel data include the destination information and tourists' feelings described with words after visiting a tourist destination, including $\geq$710 000 texts about the travel subjects and platform feedback. The travel subjects include the departure place, departure time, destination, travel content, the number of travel days, and so on. The platform feedback includes the travel view number, comment number, favorite number, and so on. The comment data comprise legitimate and effective concise text information about the destination written by tourists, which is composed mainly of the comment subjects and platform feedback, totaling 1.53 million. The comment subjects include the destination, comment user information, comment content, destination rating, and so on. The platform feedback includes view number, comment number, favorite number, etc.

To extract useful information from complex travel texts, we perform data processing as follows:

1. Custom dictionary building

The travel text usually includes the vocabulary of the tourism field, such as the destination and food. To ensure the accuracy of the subsequent Chinese word segmentation stage, we collect the destination and food vocabulary through the Baidu Travel website to construct a travel custom dictionary. The custom dictionary consists of 32 124 destination words and 2077 food words.

2. Keyword extraction

We use the LDA model provided by Gensim to obtain the theme model and then extract keywords based on the TopicPageRank method (Liu ZY et al., 2010). Using these methods we can obtain keywords that describe the cognitive destination image.

3. Emotional word extraction

We need to analyze not only the emotional value of the travel text but also the specific aspects of the positive or negative evaluation. Therefore, we need to extract the specific comments on the corresponding keywords in the text, i.e., the emotional words about the keywords. Applying the commentary extraction function of the natural language processing module under the Baidu AI open platform, we obtain the emotional word collection related to each keyword.

4 System overview

We design TDIVis for visual exploration of the tourism destination image from tourism UGC. TDIVis builds a relatively complete destination image from multiple aspects, such as the overall image, time sequence, and classification. The system interface (Fig. 1) consists of four main views, the overall view, association double sequence (ADS) view, original double sequence (ODS) view, and auxiliary view. The overall view shows the cognitive and emotional images of the destination. Based on the basic layout, we design two new layouts to provide a comparative analysis of the cognitive and emotional images from different dimensions. The ADS view provides the summary information of each attribute of the text aggregated by time, including the number of texts, the number of cognitive words, and the number of emotional words. Users can perform horizontal or vertical comparison analysis of the text summary at a certain point in time. Based on the selection of the ADS view, the ODS view shows the image distribution of the travel blog sequence and the comment sequence at a certain time. The auxiliary views help users better understand the destination image, including an original text view for viewing more detailed text information and a bar chart for viewing the amount of UGC.

TDIVis is a Web-based system with two components: (1) a back end for collecting and processing tourism UGC and (2) a front end for visualizing the analysis results.

In TDIVis, users first type in the destination name in the search area of the control panel and then select different analysis modes (e.g., overall image analysis or comparative analysis) to present different view results (e.g., the overall image view of the destination or the multi-attribute association double sequence view). In different views, users can combine the control panel with the requirement for sorting, i.e., TOP-N selection and attribute mapping scheme selection, to construct and analyze the destination image. Based on the different choices, users can build and analyze destination images contained in the tourism UGC.

5 Visual design

In this section, we describe details on the visual design of the TDIVis interface, which contains three main parts that assist in the exploration to build a relatively complete image of the destination, including overall image view, double sequence view, and auxiliary view.

5.1 Overall image view

According to the data features and visualization tasks, we adopt the keyword-based sentiment visualization method, which summarizes and analyzes the cognitive and emotional images of a tourism destination (i.e., T1.1 and T2.1). To support T1.2, T2.2, and T3, we design two new layouts, namely, the temporal evolution layout and classification comparison layout.

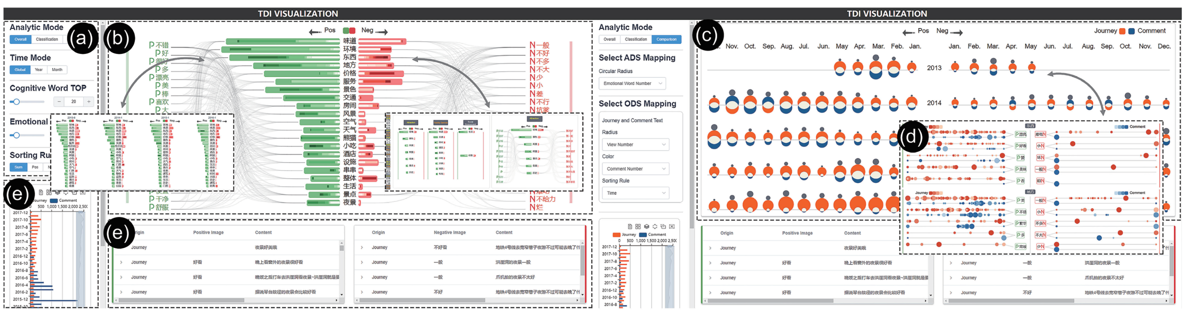

Fig. 1 User interface of TDIVis: (a) the control panel allows users to filter the data and update other views; (b) the overall view shows the cognitive and emotional images of the destination, which can switch between classification analysis and sequence evolution analysis modes; (c) the association double sequence view provides summary information for each attribute of text aggregated over time; (d) based on the selection of view (c), the original double sequence view shows the image distribution of the travel blog sequence and the comment sequence of a certain time node; (e) auxiliary views help users better understand the destination image, including a bar chart for viewing the amount of text over time and an original text view. References to color refer to the online version of this figure

5.1.1 Keyword-based sentiment visualization

The destination image contains two aspects: one is the cognitive image; the other is the emotional image, which can be divided into the positive image and the negative image. Inspired by Huang et al. (2019), the keyword-based sentiment visualization method is proposed, which combines the cognitive image and emotional image to construct an overall destination image. The detailed design includes visual encoding, basic layout, and interaction design.

1. Visual encoding

As shown in Fig. 1b, this design contains three groups of image words (i.e., cognitive image, positive image, and negative image), which are grouped data mapped by color and position markers. Three color-encoded visuals are used for the corresponding groups, with black for cognitive group words, green for positive group words, and red for negative group words. Different word groups are placed in different areas of the plane position, in which the cognitive group words are placed in the middle area, the positive emotion group words in the left area, and the negative emotion group words in the right area. Four sorting rules for cognitive words are provided, including the total frequency order (sum), the positive words frequency order (positive), the negative words frequency order (negative), and the proportion of negative words in the total frequency (negative ratio). Cognitive groups are sorted in sum by default. On both sides of the cognitive image, nested rectangular sequences are used to represent the distribution quantity of different emotional words in the current cognitive words, which are quantitative data, mapped mainly by shape, length, position, and color. The nested rectangle includes a large outer rectangle and a small inner rectangle, in which the former encodes the emotions associated with the current cognitive words, and the latter encodes the single emotion presented by the current view. The length of the outer large rectangle encodes the emotional word attribute value associated with the current cognitive word (e.g., the total number of texts of the emotional words associated with the cognitive words or the number of emotional words), and the length of the inner small rectangle encodes a single emotional word attribute value. The outer large rectangle is consistent with the cognitive word position coding method, and the inner small rectangle is encoded in a horizontal position. Nested rectangles of different colors encode different categories of emotions consistent with the image words. The shade of color of the inner small rectangle encodes different emotional words in the same cognitive word.

2. Basic layout

As shown in Fig. 1b, the image word is vertically placed according to the sorting condition selected by the user, and the relationship between the image words is represented by a line. This layout method can solve the problem that sorting results cannot be well distinguished due to the similarity of text size in the traditional tag cloud layout, and it can correlate emotional image words with corresponding cognitive image words to make the view clearer and more beautiful. We adopt the line-drawing method based on the Bézier curve and B-spline curve (Prautzsch et al., 2002). The results of the smoothing process are shown in Fig. 2. Line occlusion is alleviated in the method based on the B-spline curve, which is finally selected in this study.

3. Interaction design

Interaction design includes filtering, associating, and adding layer.

The tourism text involves a large number of image words. If all the results are presented in a single view, users cannot extract the key points from the huge amount of information. Therefore, the image data can be filtered by setting certain constraints, such as displaying the TOP-20 image words according to the word frequency, which can help users filter data according to their requirements and efficiently analyze the overall image of the tourism destination studied.

The base view provides an overview of the overall information. To further explore the relationship between the different images, users can select an image word to highlight all related words (Fig. 3b). This interaction applies to cognitive image words and emotional image words.

The adding layer operation refers to adding another layer of view to present the details, which is a common "focus+context" design method (Baloglu and McCleary, 1999). The nested rectangle sequence represents only the quantitative nature of the word; users can view more detailed information about the frequency of each emotional word mapped by each inner small rectangle through the adding layer interaction model (Fig. 4b).

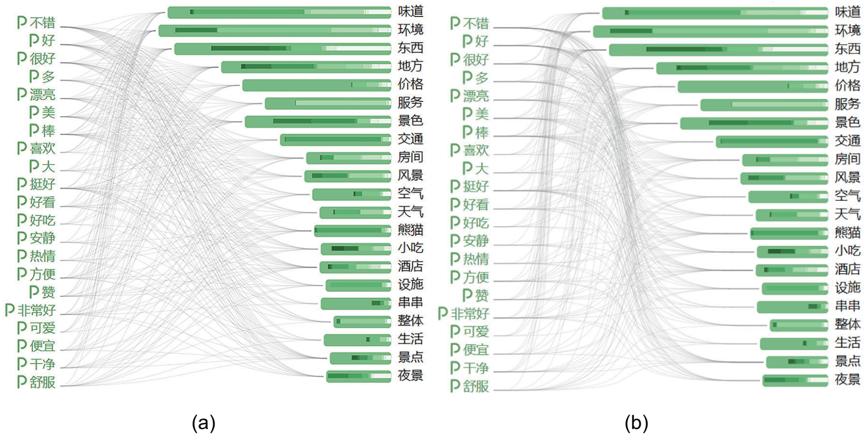

Fig. 2 Results using Bézier curve (a) and B-spline curve (b) based line-drawing methods

Fig. 3 Analysis of the overall tourism destination image: (a) the overall image of the destination; (b) positively sorted emotional images that allow users to hover the mouse to visually display relevant emotional words on the cognitive word; (c) positive emotional image (original text); (d) negative emotional image (original text); (e) negatively sorted emotional image; (f) negative emotional image of the original text associated with the ticket

4. Function

In the basic layout of the keyword-based emotional visualization method, the cognitive and emotional images of the tourism destination are combined to carry out visual exploration of the overall image of the tourism destination through filtering, correlation, and layered interaction.

5.1.2 Comparison analysis visualization

The basic design of the keyword-based sentiment visualization method provides the overall destination image constructed by the travel blogs and comments. Based on the visualization tasks T1.2, T2.2, and T3, users need to view the image based on different dimensions (sequential evolution and classification), so two new layouts are provided to complete the comparative analysis of cognition and emotion.

1. Sequential evolution layout

As shown in Fig. 5d, the evolution of an image in the time dimension is displayed in a horizontal arrangement on the basis of the basic layout. This design uses "flow" to map the appearance, development, and disappearance of the same image at different time points. Users can click on the image word to dynamically display the "flow." In addition, two kinds of time granularity are provided for users to select, i.e., annual granularity and monthly granularity, which are convenient for users to analyze the destination image evolution in different years or months.

2. Classification comparison layout

As shown in Fig. 1b, the classification comparison layout aims to add the destination cognitive image category dimension to the basic layout. The left area of the view shows the overall cognitive image

Fig. 4 Analysis of the tourist attraction image: (a) the overall image of tourist attraction; (b) analysis of the emotional image of tourist attraction, taking the scenery as an example; (c) negatively sorting the tourist attraction image; (d) negative ratio sorting of the tourist attraction image

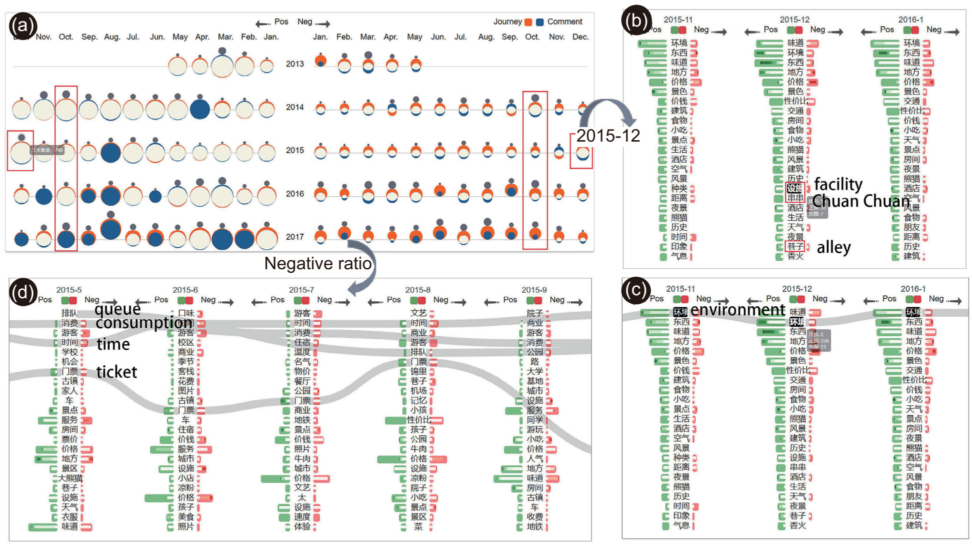

Fig. 5 Analysis of the destination image evolution under monthly granularity mode: (a) multi-attribute association double sequence analysis; (b, c) analysis of the evolution of time sequence in December 2015; (d) time sequence evolution of monthly granularity of the emotion image based on the negative ratio

words, and the right area displays the destination images of different categories in a horizontal or vertical arrangement. As for the interaction design, it provides a method to add category labels, select colors, and dynamically update the results in real time, so that users can obtain more in-depth information.

3. Function

In the temporal layout of the keyword-based emotion visualization method, two time granularities are selected to analyze the temporal evolution of the destination image. In the classification layout, users can define the categories of destination images and accomplish a detailed as well as comparative analysis of the images under different categories.

5.2 Double sequence view

We visually map text data in two sequences, which include a pattern of travel blogs and a sequence of comments. Existing sequence visualization methods cannot satisfy the association and comparison analysis of double sequence data (T4). We propose a visualization method for the multi-attribute association double sequence, which associates multiple attributes of text sequences and provides a dynamic visual encoding interaction to fulfill the task of association and analysis of double sequences.

5.2.1 Visual encoding

According to the visualization task, we divide the data into time-aggregated text sequences and original text sequences. For the former, we implement the ADS view (Fig. 1c), and for the latter, we propose the ODS view (Fig. 1d). The time-aggregated text sequences are composed of text units with several aggregation attributes under different time nodes. For example, all the travel blogs in May 2017 including the numbers of cognitive words and emotional words are a text unit. The original text sequence is composed of text units containing several attributes, such as publication time, the number of views, and the number of comments, as a text unit. Each text unit is encoded using a circle, and the text unit is primarily encoded by position, color, and area markers. Fig. 6e shows a time-aggregated text sequence unit, which associates a travel text unit with a comment text unit to form an associated double-sequence text unit. One double-sequence text unit consists of four areas made up of three circles. Area 1

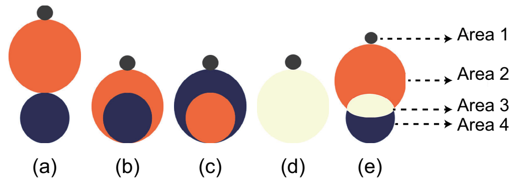

Fig. 6 Multi-attribute association double sequence text unit: (a) no intersection; (b, c) inclusion relationship; (d) ample overlap; (e) general time-aggregated text sequence unit. References to color refer to the online version of this figure

encodes the sum of the attribute values of the current node double sequence, such as the sum of the numbers of travel blogs and comments, expressed in gray. Area 2 encodes a text unit corresponding to a larger attribute value in travel or comment, and the remaining one is encoded with area 4. Area 3 is the intersection of areas 1 and 4, encoding the common attributes of the two parts. The area encodes the attribute value size in the unit, with the horizontal position encoding a text sequence. For example, the selected text unit attribute is the number of cognitive words; the number of cognitive words in the travel blogs is greater than that in the comments; areas 2–4 refer to the numbers of cognitive words of the travel text unit, commonly included part, and comment text unit, respectively. Orange and blue represent the travel text unit and the comment text unit, respectively. Area 3 is encoded in beige. In addition to the general form, the unit has four other forms (Fig. 6). The original text sequence is also encoded in the horizontal position, with the upper circular sequence representing the travel text and the lower circular sequence representing the comment text. The color mapping of the travel text and the comment text is the same as that for the time-aggregated text sequence, with color lightness mapping the attribute value. To distinguish similar attribute values more clearly, we implement three color-mapping methods, traditional linearization, box plot equalization, and histogram equalization. Fig. 7 shows that the latter two methods yield better results, and that the histogram equalization method is more granular in data partitioning. The mapping method of histogram equalization is selected to deal with the original text sequence.

5.2.2 Basic layout

The basic layout consists of the time-aggregated text sequence layout and the original text sequence

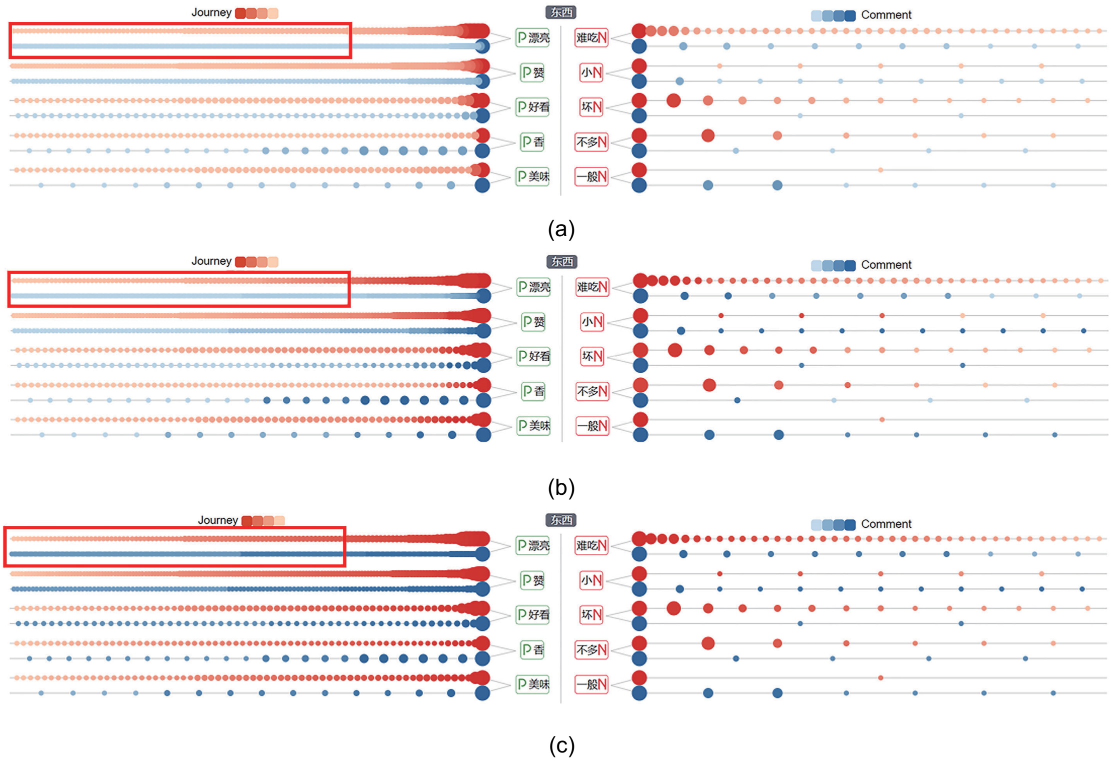

Fig. 7 Schematic diagrams of the traditional linear color-mapping method (a), the color-mapping method based on box plot equalization (b), and the color-mapping method based on histogram equalization (c)

layout. Both layouts divide the view into three areas, with the left and right sides showing positively and negatively related sequence units respectively, and the middle area displaying textual information vertically. The difference is that the middle area of the former shows the year in a row, while the latter shows cognitive words, positive emotional words, and negative emotional words in a vertical arrangement.

5.2.3 Interaction design

We view information of the various attributes of the circular text unit through the interactive mode of "levitation+highlighting." In the aggregate layout view, users can enter the original sequence layout view to complete the progressive exploration by clicking on the upper circle of the associated double-sequence text unit; in the original sequence layout view, users can view the corresponding original text information by clicking on a circular text unit.

No matter whether the images are ADS text units or ODS text units, they contain several attributes, and the circle also has a series of encoding methods such as color lightness, area, and position on the X axis. In the ADS view, the radius of the circle can be encoded as the number of cognitive words or emotional words. In the ODS view, each circle represents a travel blog or comment, and the color lightness, area, and position on the X axis of the circle can dynamically encode the number of views, comments, favorites, and publication time of the travel article or comment. Thus, there is no fixed encoding mode, but users are allowed to complete the exploration of text data by dynamic encoding according to their requirements.

5.2.4 Function

Both ADS and ODS views analyze the impact of different types of text on the construction of the destination image. The ADS view achieves the image comparison analysis of different types of text at different time nodes and provides the overall analysis. On clicking on the text unit of the ADS view, the ODS view implements the detailed text comparison analysis. Users can customize the coding for the ADS and ODS views to achieve multi-angle exploration and analysis.

5.3 Auxiliary view

The auxiliary view includes a text quantity bar chart and an original content view (Fig. 1e).

The text quantity bar chart shows mainly how the numbers of travel blogs and comments change at different time points. It also provides interactive operations for hovering, zooming, and frame selection. The zooming operation can adjust the time granularity (for example, switching from annual granularity to a more detailed monthly granularity). The frame selection interaction is linked with keyword-based sentiment visualization, enabling the display of the image of the tourism destination in the selected period time.

For text data, the original content is an essential part of destination image analysis. The original content view is used to display the original text content of a travel blog or comment. On clicking on the cognitive word in the keyword-based sentiment visualization view, the original content view presents the emotional image words (positive or negative) and the original textual content (travel blogs or comments) associated with the cognitive word.

6 Case studies

We assess the effectiveness and usefulness of TDIVis by designing and performing several case studies for various analysis tasks, taking Chengdu (Sichuan Province, China) as an example. The correspondence between cases and visualization tasks is shown in Table 1.

6.1 Overall image analysis

In the correlation analysis of the tourism destination image, the cognitive image is usually used as an entry point. Therefore, we first analyze the overall cognitive image of the tourism destination through the text bar chart and the cognitive part of the destination's overall image view. We frame the data from 2013 to 2017 in the bar chart and analyze the overall image view (Fig. 3a). Words including "taste," "environment," "thing," and "place" are often mentioned. "Taste" ranks first, reflecting that tourists are experiencing food as one of the indispensable contents of Chengdu tourism, and the words related to food such as "hot pot" and "Chuan Chuan" are mentioned $\geq$1000 times. The "environment" is used mainly to describe the social environment and atmosphere of Chengdu. Because Chengdu is known as "leisure," it can be found that most tourists travel to feel "Chengdu's environment." Chengdu is the birthplace of ancient civilizations in terms of history; it has tourist attractions such as "Wuhou Shrine," "Wenshu Monastery," and "Du Fu Thatched Cottage." Therefore, "scenery" and "landscape" are also ranked high in words related to the scenic area.

After analysis of the destination's overall cognitive image, the emotional image is analyzed in combination with the emotional part of the overall image view. Multi-angle emotional images are obtained by switching the sorting of cognitive words. As shown in Fig. 3b, most of the cognitive vocabulary has more positive evaluations than negative evaluations under the "positive" ranking. When the mouse hovers over one cognitive word, relevant emotional words are highlighted. For example, positive descriptions such as "good," "quiet," "beautiful," and "tidy" are used to describe the term "environment." Tourists mentioned that the urban environment in Chengdu is very clean and tidy, and there are also good reviews describing the accommodation and catering environment (Fig. 3c), but negative evaluations also exist. Many negative comments on the "environment" involve the catering environment in Chengdu, mainly for the "greasy spoon." As shown in Fig. 3d, most of the descriptions of the restaurant are not good, but the taste is good, for instance, "I have to go to a greasy spoon for lunch, the restaurant environment is not good, but the business is good ... Taste and cost performance can be said to be the best one for our three-day trip" and "The food was not bad. The

Table 1 Correspondence between visualization tasks and case analysis

Case name	Experiment detail	Visualization task
Overall image analysis	Cognitive and emotional images	T1.1, T2.1, and T5
Classification comparison image analysis	Attraction, facility service, and social environment	T1.2 and T2.2
Time sequence image analysis	Annual granularity and monthly granularity	T3.1, T3.2, and T5
Text comparison image analysis	Comparative analysis of travel blogs and comments	T4 and T5

shop owner was nice, letting us charge our cellphones for free. However, the restaurant was not good in terms of cleanliness and quietness."

It can be seen that although tourists are willing to go to the greasy spoon for delicious food, the catering environment will have some negative impact on tourists.

Switching the sorting mode to "negative," we find that there are more negative descriptions of the term "tickets" in the cognitive vocabulary, this number being smaller than the number of positive descriptions (Fig. 3e). By looking at the specific emotional vocabulary and the original text, there are 318 texts to evaluate "expensive tickets," most referring to "Du Fu Thatched Cottage" (Fig. 3f). For example, "Du Fu Thatched Cottage a ticket for 60 yuan is too expensive, not as good as Wangjiang Tower."

Therefore, the relevant staff can make appropriate adjustments based on the feedback from the tourists.

In this case, we combine the overall image view and the original content view to understand the overall cognitive image and emotional image of Chengdu in a comprehensive and detailed manner (T1.1, T2.1, and T5).

6.2 Classification comparison image analysis

According to the ranking of cognitive words, in this case the classification comparison view is used to classify the destination image of Chengdu, mainly into three categories, tourist attraction, tourist facility service, and social environment atmosphere.

6.2.1 Attraction

Tourist attractions refer to all kinds of tourist resources that attract tourists, including mainly scenic spots of natural scenery and cultural landscape. As shown in Fig. 4a, the tourist attraction destination image is presented. The main words are "scenery," "landscape," "panda," "night scene," "history," "park," "alley," and so on. According to the analysis of lexical distribution, because Chengdu has a famous giant panda breeding base, "panda" is the first specific scenic spot mentioned in the tourist attraction. Chengdu has natural tourist attractions such as Qingcheng Mountain, Du Fu Thatched Cottage, Wuhou Shrine, and Huanhuaxi Park. Therefore, many texts describe these natural scenic spots. For example, "The scenery in Wuhou Shrine is also very beautiful, and the most attractive to me is the green forest red wall."

In terms of the emotional image, the positive description is mainly for words such as "scenery," "panda," and "night scene." By clicking on the word "scenery", the front and negative words, as well as the frequency information of the word, are presented in a layered manner (Fig. 4b), where the positive words include "beauty" (2091 times), "good" (1407 times), and "spectacular" (202 times); specific text descriptions include descriptions such as "Ginkgo tree at the entrance of Jinli is particularly beautiful, the next door from Jinli is Wuhou Shrine, and the scenery inside is really beautiful." To analyze the negative image, the ranking mode is switched to "negative" and "negative ratio." It can be found that in addition to the "environment" and "ticket" mentioned above, "park," "alley," and "ancient town" have more negative comments (Fig. 4c). The total number of negative words on "Kuanzhai Alley" is 86, and most of the tourists think that Kuanzhai Alley is too commercialized. For example, "Kuanzhai Alley is a well-known attraction in Chengdu. It was also famous for its reputation. The result is disappointing ... The commercial atmosphere is very strong and the people are super." Moreover, the negative evaluation of tourists on the ancient towns around Chengdu involves mainly the terms "no characteristics," "small area," and "commercial atmosphere" (Fig. 4d). For example, "the so-called ancient towns are all general," "the streets of the ancient town at noon are too crowded," and "the ancient town of Tai'an at the foot of Mount Qingcheng has not had many features."

6.2.2 Facility service

Tourist facility services are targeted mainly at tourism-related infrastructure and services such as food, transportation, accommodation, and entertainment.

Food is an indispensable aspect of Chengdu tourism. By observing the ranking of food-related words in the overall cognitive image, it is known that tasting the food is one of the motives for tourists to choose Chengdu for tourism. The words related to food include mainly "taste," "hot pot," "Chuan Chuan," "snack," "beef," "beancurd," and "rabbit head." As shown in Fig. 8a, in addition to the highest frequency of "taste," as mentioned earlier, “snack” is the most frequently mentioned food, being mentioned a total of 1680 times. At the same time, words such as “beancurd” and “rabbit head” are snacks, ranked higher in the overall cognitive words. Moreover, hot pot and Chuan Chuan are the most famous food in Chengdu. They are the first meals that many tourists choose to eat in Chengdu. For example, “The most important thing to come to Chengdu is the hot pot” and “The first meal, of course. It is a hot pot.” It is found in the food-related destination image that the frequency of Sichuan cuisine is significantly behind those of the above words, which can help tourism planning researchers find the weakness of Chengdu tourism development.

For the emotional image description of the food, similar to the tourist attraction, most of the descriptions are biased toward the positive (Figs. 8b and 8c). In terms of the negative image, we find that “taste,” “snack,” and “hot pot” rank high. Fig. 8b shows the negative image results related to “snacks”: tourists believe that snacks are expensive and tasteless, and most of them are aimed at “Jinli” and “Kuanzhai Alley,” such as “Jinli snacks are many, but there are too many people; we tasted a few, which were expensive and bad, and more importantly, they were not enough and they let us feel uncomfortable after eating.” It can be found that the taste and price of the snacks in the scenic spot have left a lot of negative impressions on the tourists, which affects the overall feeling of the tourists to Chengdu. Switching the sorting method to “negative” (Fig. 8c), although “beef” is not mentioned as much as the “hot pot,” “Chuan Chuan,” and other food, it has a higher negative proportion. Further analysis finds that some tourists believe that beef is too expensive, mainly regarding “Zhang Fei Beef” and the beef in Sichuan cuisine; for instance, “Jinli snacks are not expensive, but Zhang Fei Beef is very expensive. I will not buy it next time” and “Stir-fried beef is expensive and unpalatable.”

6.2.3 Social environment atmosphere

Social environment atmosphere refers to the feelings of tourists about the overall environment of the tourism destination and the perception of the friendliness of the residents. As shown in Fig. 9, tourists’ perceptions of Chengdu’s social environment are reflected in the terms “life,” “impression,” “people,” “city,” and “ambience.” People of Chengdu is one of the most frequently mentioned aspects of tourists. As shown in Fig. 9a, many people use the words “gentle,” “enthusiasm,” and “friendly” to describe the people of Chengdu, such as “From the taxi master, I feel the enthusiasm of the Chengdu people.”

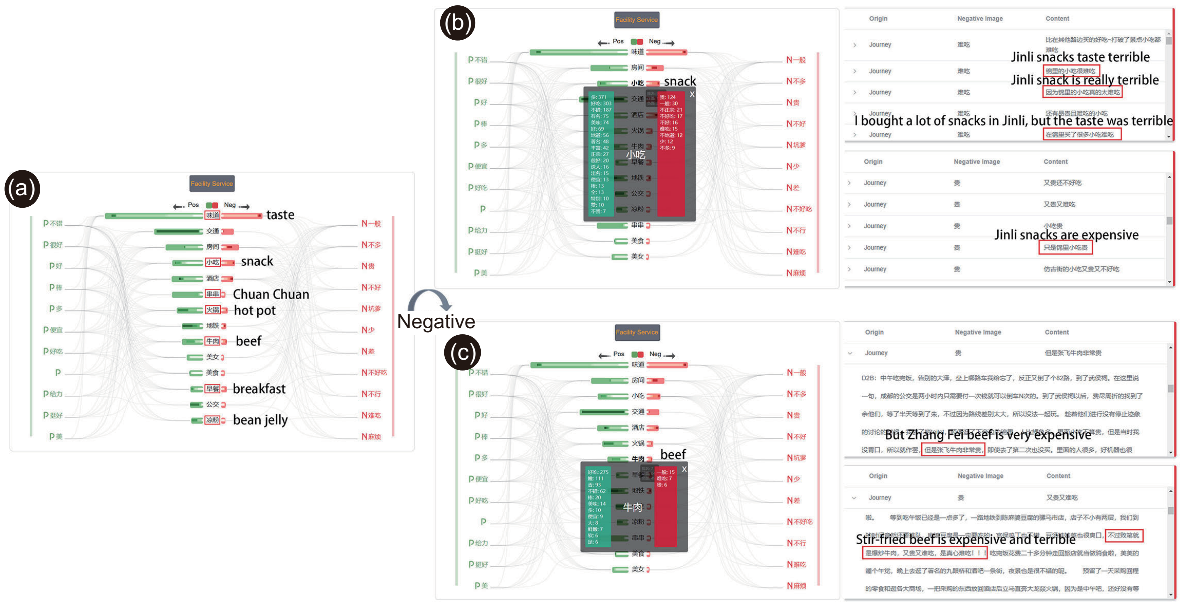

Fig. 8 Analysis of the tourist facility service image: (a) tourist facility service (overall destination image); (b) “snack” emotional image based on negative sorting; (c) “beef” emotional image based on negative sorting

Furthermore, tourists describe the city's cleanliness, city management, and city appearance using such terms as "city," "street," and "square." In the word "city," 65 texts describe "clean" in Chengdu (Fig. 9b). For the streets in Chengdu, there are also 119 texts using the description "clean," in addition to the positive words such as "spacious" and "good" (Fig. 9c). In addition, ≤10 texts describe the streets of Chengdu using negative words such as "general" and "chaotic." It can be seen that the overall appearance of Chengdu is relatively satisfactory for tourists.

Through the above image classification analysis, the analyst can use interactive operations to define and classify the cognitive image. At the same time, different categories of the cognitive image and emotional image are analyzed to find similarities and differences between categories (T1.2 and T2.2).

6.3 Time sequence image analysis

Time is the most basic and important attribute of tourism UGC. The changes in the tourism destination image can be reflected as the combination of time and cognitive/emotional words.

Two time-related granularities are provided in the overall image view of the tourism destination, annual granularity and monthly granularity. First, we select the annual granularity time mode and the "sum" sorting mode (Fig. 10a). It is found that the cognitive words mentioned by tourists every year are mostly the same, such as "environment," "something," "taste," and "price," and the top six cognitive words from 2013 to 2015 have similar ones. After clicking on one cognitive word, the corresponding evolution is visually displayed in a "flow." Note that the number of words related to scenic spots such as "scenery" and "landscape" is on the decline. However, words related to food, such as "taste," "price," and "service," show the reverse trend. Since 2013, "taste" has gradually increased from the third to the first, and the frequency has increased year by year. The change in the word "hot pot" is also obvious, ranging from 30 to 14. This shows that Chengdu cuisine is getting increasing attention from tourists. Food is a very important part of the traveler's itinerary. It can be speculated that some tourists may plan a trip to Chengdu specifically for experiencing Chengdu cuisine.

Next, the focus of the analysis is shifted to the emotional image at the annual granularity. First, we select the "positive" sorting method (Fig. 10b). Similar to the cognitive image, the top cognitive words are mostly the same. Words related to scenic spots such as "scenery" and "landscape" are gradually replaced by gourmet words. Next, we choose to sort cognitive words by the "negative" impression (Fig. 10c). On the whole, there are many words related to food in the cognitive words that negatively describe the top-20 cognitive words every year, including words such as "taste," "price," and "snack." We click to view the emotional words related to "taste" each year. As shown in Fig. 10d, the negative words are mainly "general" and "poor," which show an increasing trend in the frequency. To further analyze the negative emotional image of cuisine, the ranking mode is switched to the "negative ratio" (Fig. 10e). The ranking of "taste" in the negative ratio is basically after the TOP-50, but the fluctuation is more severe. It is found that Chengdu cuisine has been paid increasing attention by people and it has received many positive evaluations; however, the negative emotional image presented by Chengdu cuisine cannot be ignored.

In the monthly granularity mode, to reduce the information load, the overview information is first viewed through the ADS view, and then the overall image view is switched to the monthly granularity

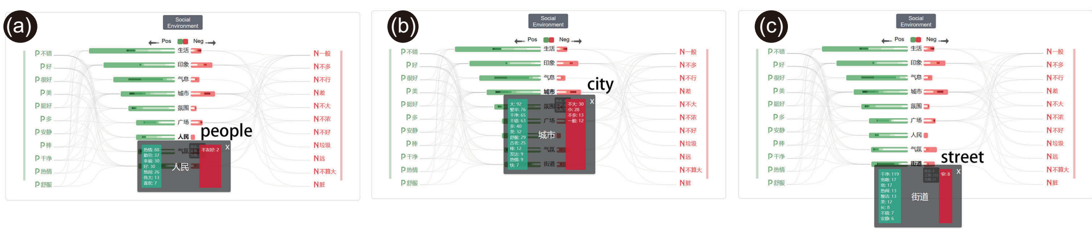

Fig. 9 Analysis of the image of social environment atmosphere: (a) "People" overview of the emotional image; (b) "City" overview of the emotional image; (c) "Street" overview of the emotional image

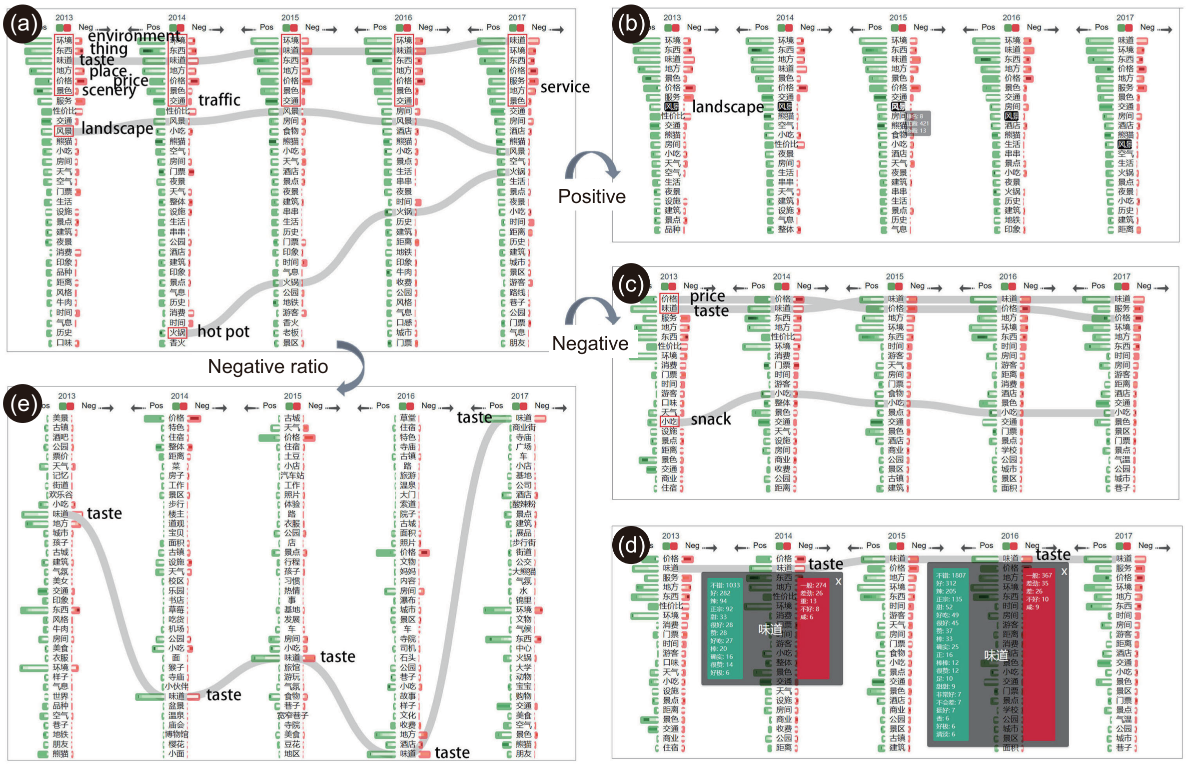

Fig. 10 Analysis of destination image evolution under annual granularity mode: (a) time sequence evolution of annual granularity of the cognitive image; (b) time sequence evolution of annual granularity of the emotional image based on positive sorting; (c) time sequence evolution of annual granularity of the emotional image based on negative sorting; (d) "Taste" emotional image based on negative sorting; (e) time sequence evolution of annual granularity of the emotional image based on negative ratio sorting

to show the detailed information. In Fig. 5a, the upper circular radius is encoded to the total number of texts (travel blogs and comments), while the middle and lower circular radii are encoded to the number of cognitive words. In terms of the cognitive image, it is found that the numbers of cognitive words in April, May, July, August, and October of each year are larger than those in other months, presumably because these months are during legal holidays and summer vacations. At the same time, it is found that the number of cognitive words in December 2015 is 122, and that the total number of texts is 1026, even larger than the number in October 2015, which is the largest of all months in that year. We can see that the travelers mention some cognitive words that are not mentioned in the adjacent month, such as "facilities," "Chuan Chuan," and "alleys," and the frequency of each cognitive word is also substantially greater than that in the adjacent month. Compared with other months, tourists departing in the off-season in December 2015 have a more comprehensive experience, creating a richer destination cognition image, which helps travel researchers understand the traveler's feelings from other perspectives. In terms of the emotional image, it can be seen from Figs. 5b and 5c that the number and frequency of cognitive words in the positive area of each month are larger than those in the negative area, which is consistent with the overall destination image. We next select the sorting method according to the "negative ratio" (Fig. 5d). From May to August 2015, the negative proportion of the words "visitors," "queuing," "time," "tickets," and "consumption" increased significantly. This phenomenon indicates that the evaluation of the destination emotional image by tourists to Chengdu during the tourist season will be affected by negative reasons, such as more tourists in peak seasons, rising consumer prices, and inadequate services.

In the above time sequence evolution analysis, users find the image change process in different years or months by selecting the sorting methods and time granularities (T3.1, T3.2, and T5).

6.4 Text comparison image analysis

Travel blogs and commentary texts have relevance and consistency in the tourism destination image, but there are certain differences in length, description content, and methods. To gain a deeper understanding of the destination image presented by the tourism UGC, ADS and ODS views are combined for comparative analysis. As shown in Fig. 11a, in the ADS view, the upper circular radius is encoded to the total number of texts (travel blogs and comments), and the middle and lower circular radii are encoded to the number of emotional words. Through this view, the overlapping area between the travel blogs and comments in the negative area is significantly smaller than that in the front area because the number of positive texts is larger than that of negative texts. Compared with Fig. 5a (the lower middle circular radius is encoded to the number of cognitive words), the overlapping area of Fig. 11a is significantly reduced. This phenomenon indicates that the tourist's emotional words used in travel blogs and comments are not the same, which reflects the differences in the emotional image. Taking 2014 as an example, we switch to the ODS view of 2014 by clicking on it. As shown in Fig. 11b, the travel blogs are shown in orange, and the comments are shown in blue. The circular radius, color lightness, and sorting method in the travel and comment sequences correspond to the favorite number, view number, and time, respectively. This view enables a comparative analysis of the cognitive words that exist in the 2014 text and the corresponding positive and negative emotional images. Each emotional word corresponds to a sequence of travel blogs and comments. From the view, it is found that most cognitive words are distributed evenly in time, and the number of positive words and texts is significantly higher than that of negative texts. The travel blogs of some emotional words have the same density as the comment sequence, which usually refers to related words with high frequency, such as "things-beautiful" and "places-nice" (Fig. 11b). The length of the travel sequence of most emotional words is larger than that

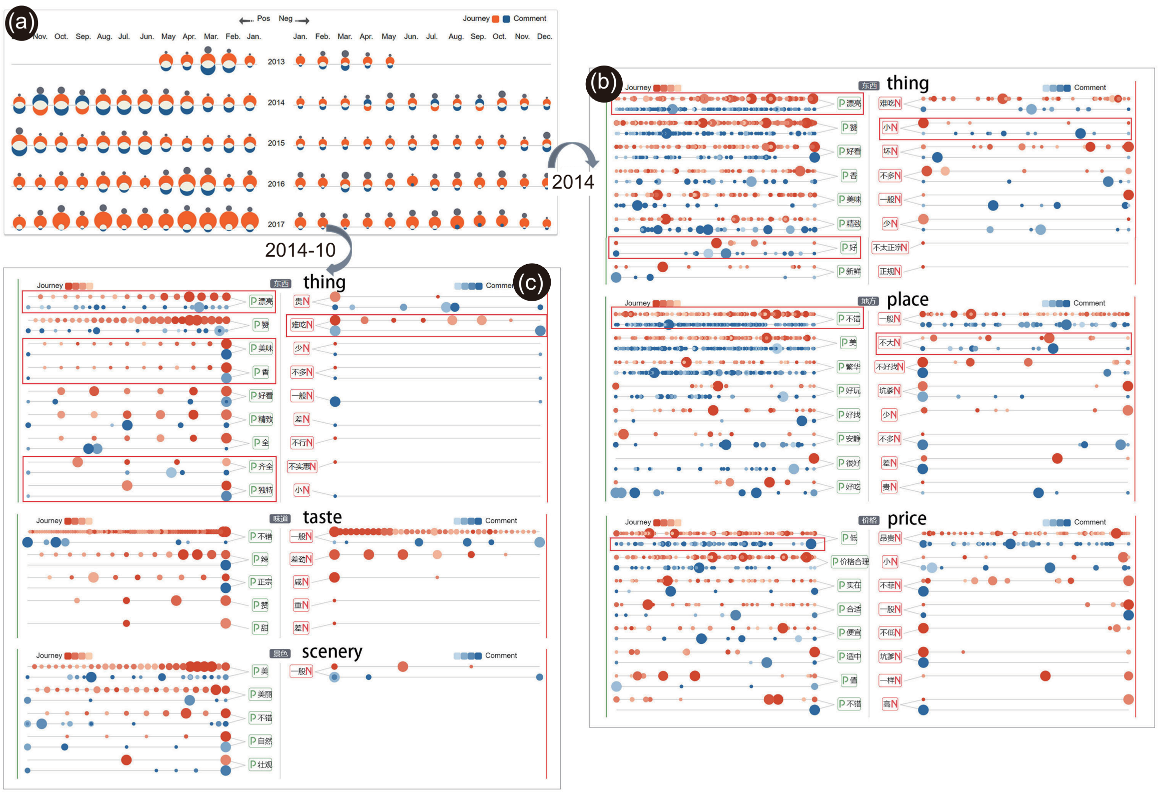

Fig. 11 Comparative analysis of the tourism destination image: (a) multi-attribute association double-sequence analysis; (b) comparative analysis of the original sequence in 2014; (c) comparative analysis of the original sequence in October 2014. References to color refer to the online version of this figure

of the sequence of comments, but there are a few exceptions, such as “things-good,” “things-small,” and “place-not big” (Fig. 11b). We switch the sorting mode to descending order according to the number of collections. In the word “price,” it is found that the distribution patterns of travel blogs and the comment sequence are similar. Only a few texts have a large collection. For a sequence of travels, the higher the number of favorites is, the more views there are; however, the number of favorites in the comment sequence does not change proportionally to the number of views, such as the ODS distribution of “price-low” (Fig. 11b).

Next, we focus on the comparative analysis of the ODS text in October 2014. As shown in Fig. 11c, for the word “thing,” the number of emotional words related to food (“delicious,” “fragrant,” and “bad taste”) is greater than the number of comments, while the number of emotional words related to scenic spots (“beautiful,” “complete,” and “unique”) is completely the opposite. The same rules are found for other words. In the cognitive words related to food, such as “taste” and “service,” the number of travel blogs is also higher, while in the cognitive words related to scenic spots, such as “scenery,” “place,” and “landscape,” the number of comments is higher.

In this case, the destination image results presented by travel blogs and comments are analyzed from both the overview and details approaches, and a more comprehensive comparative analysis (T4 and T5) is completed by combining the dynamic attribute mapping in this process.

7 User study

To further verify the effectiveness and usability of TDIVis, we conducted a user study.

7.1 Study design

We performed a user study with 11 participants (including four females and seven males) to evaluate whether our system is helpful in constructing a relatively complete destination image. The participants are researchers with a research background in tourism. First, we introduced our user interface to the participants and went through an example to explain the system functions. Then, we asked the participants to build destination images in the system. Based on the visualization tasks we proposed in Section 3.1, we defined the following four tasks that participants needed to complete using TDIVis: (t1) to explore the preliminary destination image of Chengdu from the overall image, positive, negative, and negative ratio perspectives through the keyword-based sentiment view, (t2) to find the trend of image evolution under different time granularities (yearly and monthly), (t3) to complete the definitions of attraction, facility service, and social environment atmosphere and then find the differences among the different categories, and (t4) to find the differences between travel blogs and comments in terms of describing the images.

Participants were encouraged to speak out while they were performing the tasks, so that we could gather more detailed user feedback. We constantly observed the participants’ exploration process and recorded their main operations and opinions. After the participants completed the tasks, they were asked to complete a questionnaire (Table 2) to collect detailed feedback on the effectiveness and usability of TDIVis. Participants were asked to rate each question on a five-point Likert scale (1=very difficult, 5=very easy) and to provide the main reasons for their response. To verify the effectiveness of TDIVis, we set Q1–Q5 in Table 2, where questions Q1–Q4 correspond to the four tasks completed by participants (t1–t4). Q5 involves the overall evaluation of the effectiveness of TDIVis in constructing the destination image. To verify the usability of the system, questions Q6 and Q7 were proposed.

7.2 Results

From Fig. 12, our user study demonstrates that TDIVis can effectively help users construct a relatively complete destination image and that it has good usability for users.

7.2.1 Effectiveness

The results in terms of the responses to Q1–Q5 in Table 2 verify the effectiveness of TDIVis. Fig. 12 shows that most participants can construct relatively complete destination images using TDIVis without difficulty, supporting the effectiveness of TDIVis.

For preliminary exploration, all of the participants felt that with TDIVis, they could easily and quickly combine cognition and emotion to build a

Table 2 User study questions

No.	Questions on ease of using TDIVis
Q1	Is it convenient for you to construct the image of Chengdu, including the cognitive image and emotional image?
Q2	Is it easy for you to understand the evolution of the image at different times of granularity?
Q3	By classifying images, is it easy for you to compare the images of different categories?
Q4	Is it easy for you to find the difference between the image descriptions of travel blogs and comments at different time points?
Q5	Overall, is it easy for you to construct a relatively complete destination image?
Q6	Is it easy for you to learn and use TDIVis?
Q7	Is it easy for you to understand the overall visual designs of TDIVis?

Q1–Q5 focus on assessing the effectiveness of TDIVis in the construction destination image, and Q6 and Q7 evaluate its usability

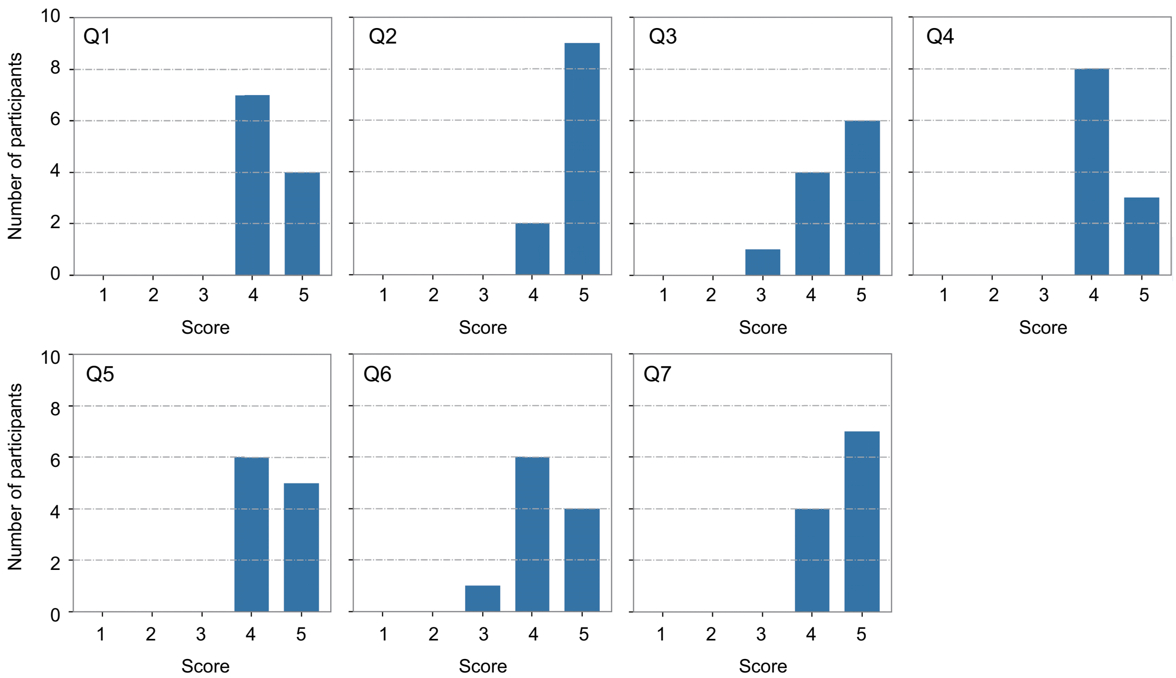

Fig. 12 Results from the user study. The users responded to questions 1–7 on a five-point Likert scale, with responses 1–5 representing the difficulty scale ranging from "very difficult" to "very easy"

preliminary destination image (Q1), because cognitive image words and associated emotional image words are intuitively encoded and interlinked by interactions. Multiple sorts provide further analysis of the destination image.

After preliminary exploration, the participants carried out a temporal evolution analysis of the image through year granularity and month granularity. Participants commented that they liked the temporal evolution analysis function of TDIVis, which enables them to directly view the evolution trend of the cognitive image (Q2 in Fig. 12). For example, participant 2 (P2) chose annual granularity and the negative ranking method and found that Chengdu's "taste" image was getting worse year by year. P2 commented that such information is hard to obtain through a questionnaire or UGC.

Participants also evaluated the classification comparison analysis, and 10 out of 11 participants agreed that they could complete the category definition and comparison analysis of the images (Q3 in Fig. 12) because it helped them analyze each category in detail and compare multiple categories.

Participants also confirmed that TDIVis provides intuitive comparative analyses of travel blogs and comments, taking the time and original text into account (Q4 in Fig. 12). The ADS view can intuitively present the differences between travel blogs and comments in describing the cognitive image and emotional image, and the ODS view encodes the original text of the relevant image. Participants liked to combine the ADS and ODS views, because this can help them explore the details from the whole to part. Taking all these factors into account, all the participants agreed that TDIVis is an excellent tool for building a destination image (Q5 of Fig. 12).

7.2.2 Usability

From Fig. 12 and questions Q6 and Q7, we find that users have no difficulty in learning to use TDIVis, and most users can easily understand the visual design. User feedback also shows that the interactions with TDIVis contribute to the exploration of destination images. In conclusion, this feedback demonstrates the good usability of TDIVis.

7.2.3 Limitations and suggestions

Despite the positive feedback above, our participants also pointed out some limitations of TDIVis and offered suggestions. For example, P2 suggested providing automatic image classification to reduce the interaction of category definitions, and P6 suggested adding time information in the comparative analysis of classification to support the comparison of the image trends of different categories. These have been left for future work. We will use relevant methods of text mining to complete the automatic classification of images and provide temporal analysis of classification.

8 Discussion and conclusions

We have compared two existing methods of destination image construction, i.e., questionnaires and surveys based on the UGC and TDIVis from four aspects, namely, the overall image, time evolution, classification, and UGC attributes of the destination image. The overall image includes the cognitive image and the emotional image of the tourism destination. The time evolution represents the time sequence of the destination image. The classification reflects the analysis of the destination in different dimensions. The UGC attributes are considered by the UGC method and TDIVis, and they reflect the impact of different UGC types on the destination image.

Table 3 compares the existing destination image studies (corresponding to Section 2.1) with TDIVis. The traditional questionnaire survey mostly constructs the overall image of the destination, ignoring the temporal evolution and classification comparison of the destination image. At present, UGC is used for destination image studies to support the overall image, but the time factor and classification comparison are not considered.

As a visual analysis system for tourism destination studies, TDIVis provides an intuitive construction of the destination image. Compared with previous works on the image of existing tourist destinations, TDIVis performs well in all aspects. TDIVis not only supports the overall image analysis of destinations but also adds the function of temporal evolution analysis and classification comparison of images. In addition, two sources of existing UGC, namely, travel blogs and comments, have been considered. Through the comparative analysis of travel blogs and comments in the process of destination image construction, the influence of different types of

Table 3 Questionnaire survey, UGC research, and TDIVis support for different dimensions of the destination image

Method	Reference	Overall image	Time evolution	Classification	UGC attribute
Questionnaire	Lu S et al. (2020)	*			
	Jeng et al. (2019)	*			
	da Silva et al. (2018)	*			
	Papadimitriou et al. (2018)	*			
UGC	Gkritzali et al. (2018)	*	*		
	Wang R and Hao (2018)			*	
	Tseng et al. (2015)	*		*	
	Sun et al. (2015)	*		*	
	Stepchenkova and Zhan (2013)	*			
TDIVis	This study	*	*	*	*

* For support

text on destination image construction can be found.

In this study, we have proposed a system to help users build a relatively complete destination image. According to the characteristics of UGC, which are crawled from mainstream travel platforms and visualization tasks of the tourism platform, a multiple visualization method and an interactive control technique are used to establish a destination image visualization model. Then, a keyword-based emotion visualization method has been proposed, which associates the cognitive image of the destination with the emotional image and then constructs the destination image from multiple aspects of the overall image, time sequence, and classification. Furthermore, a multi-attribute association double sequence visualization method has been proposed, which uses a dynamic visualization coding scheme to correlate travel blogs and comments and combines the multi-attribute characteristics of the text to explore the influence of different attributes on the destination image. Finally, we have used the UGC on Chengdu City to conduct four case studies and a user study to verify the effectiveness and usability of our visualization system. While TDIVis is a visual analysis system based on data from Chinese travel websites, the methodology can also be applied to other datasets, such as UGC in English.

The image of the tourism destination involves many aspects such as scenic spots, food, accommodation, transportation, and social environment. In the future, we plan to enrich the data sources and types to build a more comprehensive image of tourism destinations through visualization methods and technologies. Moreover, we will apply TDIVis to other cities to further examine the usability and effectiveness of TDIVis.

Contributors

Jing LIANG designed the research. Meng-qi CAO and Jing LIANG implemented the system. Meng-qi CAO drafted the manuscript. Min ZHU helped organize the manuscript. Meng-qi CAO, Ming-zhao LI, and Zheng-hao ZHOU revised and finalized the paper.

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Compliance with ethics guidelines

Meng-qi CAO, Jing LIANG, Ming-zhao LI, Zheng-hao ZHOU, and Min ZHU declare that they have no conflict of interest.

Informed consent was obtained from all individual participants included in the user study.

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