ISSN: 2710-0170

Post-covid China's Tourism Image Projection through Instagram: A Mixed Method Based on Image Tagging

Yuqi Liu

College of Foreign Languages, Guilin University of Technology, Guilin, Guangxi, 541000, China

Abstract

This study addresses the post-pandemic challenges faced by China's tourism industry, particularly focusing on the international image projected through Instagram. Utilizing machine learning-based image tagging techniques combined with Peircean semiotic theory, the study conducts a comprehensive quantitative and qualitative analysis of Instagram photos. The research identifies four key themes in China's tourism imagery: Urban Life, Natural Landscapes, Defense and Technology, and Cultural Activities. The theme of Urban Life highlights the dynamic and resilient nature of Chinese cities, with a particular emphasis on Shanghai. Natural Landscapes showcase China's commitment to ecological conservation and sustainable tourism. Defense and Technology focus on advancements in infrastructure, aerospace, and defense, reflecting national pride and technological prowess. Cultural Activities portray the rich cultural tapestry of China, emphasizing festivals and traditional attire. The findings underscore the critical role of visual content in shaping public perceptions of tourism destinations. By systematically analyzing and interpreting large-scale visual data, this study provides DMOs with valuable insights into effective image projection strategies. This research not only contributes to the theoretical understanding of tourism image construction but also offers practical implications for enhancing the global competitiveness of tourism destinations in the post-pandemic era. The innovative combination of machine learning and semiotic analysis represents a significant advancement in the methodological approaches to tourism image research.

Keywords

Semiotics; image tagging; Instagram; destination-country image; projected image.

1. Introduction

The outbreak of sudden crises, such as the COVID-19 pandemic, has had a profound impact on the tourism images of affected regions [1]. As the initial epicenter, China suffered disproportionately greater losses due to negative global media coverage, stringent lockdown measures, and the stigma associated with being the source of the virus, which together significantly hindered the recovery of its tourism sector. In 2019, China was a major player in the global tourism market, with inbound tourists surpassing 145 million and contributing $131.3 billion in revenue. However, the pandemic caused a sharp decline in tourism activities. In 2020, according to the report by The State Council of the People's Republic of China [2], domestic tourist numbers fell by 52.1% compared to 2019, and domestic tourism revenue decreased by 61.1% to 2.23 trillion yuan. The pandemic's impact was exacerbated by travel restrictions and lockdown measures, which halted both domestic and international tourism. During the early stages of the pandemic, all domestic and outbound tour groups were suspended to curb the spread of the virus. As noted by the State Council [3], the resultant economic losses were profound, with the tourism sector directly and indirectly employing nearly 108 million people, thus affecting a significant portion of the population. Despite these challenges, China has shown resilience and adaptability in its tourism sector. China's robust

ISSN: 2710-0170

vaccination campaign has also played a critical role in reviving the tourism industry. By administering over 1.5 billion vaccine doses by mid-2021, China has managed to control the spread of the virus, allowing for the gradual resumption of travel activities. The vaccine has been essential in providing a sense of safety and confidence among tourists, thereby aiding the sector's recovery [2]. By mid-2021, the number of domestic tourists had rebounded to 1.87 billion, with domestic tourism revenue reaching 1.63 trillion yuan, a 157.9% increase from the previous year [4]. In this context, the management of tourism image, especially post-covid image, has become increasingly vital.

Currently, in the era of big data, information sources and communication methods have radically evolved, with internet becoming the predominant source of information, significantly shaping people’s overall perceptions of destinations [5]. The Internet has not only revolutionized how tourism information is disseminated but also transformed travel planning behaviors [6-7], making it a critical determinant of destination image. Besides, the tourism industry heavily relies on the information age and electronic commerce, profoundly influenced by the Internet [8]. Particularly influenced by the information age and electronic commerce, social media platforms like Pinterest, Instagram, and Flickr, which meet people’s need for image cultivation, real-time communication, and creative self-realization [9], play pivotal roles in information dissemination, influencing travel decisions, and facilitating electronic word-of-mouth dissemination [10] as well as providing an ultimate space for user participation, open communication, dialogue, community-building, and connection [11]. The proliferation and diversity of websites offer online platforms for both tourism authorities and tourists to share information. Therefore, selecting the appropriate platform and content to promote the destination is vital, especially given the significant impact of crises such as the COVID-19 outbreak on tourism images. Among all types of content, such as text, audio, and figure, videos are more engaging, and they might have a stronger impact on the potential demand of tourists [12].

On the one hand, nevertheless, visual analysis on Instagram remains underexplored compared to platforms like Flickr and Pinterest [13]. On the other hand, with the development of deep learning and big data mining technology, CNNs (a deep learning model) were used to identify the contents of numerous tourist photos, overcoming the limitations of manual identification of visual information from photos [14]. Therefore, the development of computer vision technology lends substantive technical assistance to interpret the contents of big photographic data within tourism studies [15]. Given this context, we chose to combine machine learning-based image tagging techniques for large-scale quantitative processing of images with Peircean semiotic theory for qualitative interpretation. Previous research predominantly focused on tourists' perceptions of destination images [16], yet there is a growing emphasis on how Destination Marketing Organizations (DMOs) project images to influence the global tourism market. This approach allows for an analysis of both the denotative and connotative meanings in the projected images.

In sum, this study investigates the Destination Country Image (DCI) of China within the specific context of the post-pandemic era, focusing on the representation of China's international tourism image through Instagram imagery. The research aims to explore how the portrayal of China on social media platforms correlates with the management of destination country image by Destination Management Organizations (DMOs). By analyzing visual representations on Instagram through semiotic theory and examining the signifier and signified elements within the photos, this research aims to elucidate China's post-pandemic image projection strategies. Furthermore, the practical significance lies in facilitating DMOs to enhance their online projection on social media and other digital platforms. By leveraging visual data effectively, this study aims to assist DMOs in shaping positive destination perceptions, thereby expediting the recovery of the global tourism market post-COVID-19 pandemic. Ultimately, this research seeks

ISSN: 2710-0170

to contribute to the acceleration of global tourism market recovery following the COVID-19 pandemic.

2. Literature review

2.1. Destination image and destination-Country Image

The concept of "tourism destination image" was initially introduced by Hunt [17] in his doctoral dissertation at Colorado State University, where he defined it as perceptions of non-residential places. Subsequently, Echtner and Ritchie [18] characterized it as both the perception of individual attributes and the overall impression of a destination. Josiassen and Kock et al. [19] further conceptualized it as individuals' mental representations of a place, often termed 'destination image', viewed as a general appraisal of a specific location or region. Baloglu & McCleary [20] commonly define destination image as the beliefs, ideas, and impressions people hold of a place. Lian & Yu [21] add that online images of tourist destinations can be defined as tourists' holistic impressions and perceptions formed by acquiring multimedia information from various online sources. Although definitions vary, scholars like Afshardoost & Eshaghi [22] universally acknowledge its critical importance to destination marketing management. More importantly, A strong destination image is crucial for the tourism industry, as evidenced by Zhang, Fu, Cai, and Lu [23], who emphasized its significant impact on tourism loyalty. Augustyn [24] asserts that a country's management of its own destination-country image reflects strategic intentions and overall efforts in shaping and promoting its tourism identity. Recent studies, such as those by Afshardoost & Eshaghi [22] , who believe that DCI is regarded as fundamental to the development of the tourism industry, crucial for destination competitiveness, and significantly influences tourists' purchasing decisions. All of these perspectives underscore the multifaceted influence of destination image on the tourism experience, highlighting the importance of accurately projecting destination images to visitors.

The concept of Destination-Country Image (DCI) represents a nuanced crossover between tourism and international marketing, as outlined by Zhang et al. [25]. DCI is not merely a simple amalgamation of destination image and country image. Scholars like Campo & Alvarez [26] and Mossberg & Kleppe [27] have theoretically and empirically examined the relationships between the two, recognizing that while they are interlinked, they remain distinct constructs. Nadeau et al. [28] suggest that destination and country images, though closely related, belong to different disciplines and are not directly integrable. Zhang et al. [25] proposed DCI as a restructuring of the dimensions and measurements of both images, considering destination image at various spatial scales such as scenic spots, regions, cities, and countries. Dedeoğlu [29] notes that DCI, particularly at the country level, differs from general destination images as it is influenced not only by individual consumer factors but also by broader macro factors such as geography, history, culture, and foreign policy of the country. Thus, DCI can be seen as an impression of a country as a tourist destination that stems from but is distinct from "product-country image".

2.2. Projected image and the perceived image

Gartner [30] was the first to differentiate between projected and perceived images, providing insights into how marketing strategies influence tourists' cognitive perceptions. Projected and perceived images play pivotal roles [31], and Projected image represent destinations' intentional portrayal that emphasizes scenery, culture, activities, service quality, and other distinctive features [32]. Conversely, perceived image is shaped by factors such as previous visits, expectations, personal values, and information about the destination [33]. Existing academic literature categorizes tourism destination image into projected and perceived images, distinguishing the projected image, managed by Destination Marketing Organizations (DMOs) and commercial entrepreneurs, from the perceived image formed within tourists' minds. Pappu

ISSN: 2710-0170

and Quester [34]. have examined specific country evaluations in relation to product evaluations, deconstructing country image into macro and micro components. Zhang et al. [25] further refined these concepts into macro-DCI, encompassing political, economic, technological, cultural, and human characteristics, and micro-DCI, focusing on core tourism product images such as attractions, infrastructure, and activities.

Projected and perceived images are intricately linked and are integral components of the "hermeneutic circle of representation," a pivotal concept in tourism marketing [35]. Understanding this distinction is crucial for comprehending tourist decision-making processes and enhancing destination competitiveness [30]. Projected destination images serve as primary sources of information for potential tourists researching destinations [36]. Recently, the measurement of destination images has garnered considerable interest among tourism scholars due to its profound implications for destination marketing and management. Numerous studies have extensively explored the destination image from the perspective of tourist perceptions, often integrating advanced data science methods such as sentiment analysis and text mining. Mak [37] analyzed the cognitive and affective attributes of destination images using international tourists' blogs about Taiwan and National Tourism Organizations' photos to construct an online destination image, which highlights a research gap in understanding both projected and perceived destination images from the perspective of the general public. Mirzaalian [38] utilizes social media analytics to examine destination loyalty in nature-based tourism. Through sentiment analysis and text clustering of TripAdvisor reviews, it identifies four key loyalty factors: glaciers, waterfalls, lakes/islands, and hiking/trails. His insights offer valuable guidance for enhancing visitor experiences and loyalty, emphasizing the importance of tailored marketing strategies for tourism providers and organizations. However, current research on DCI primarily explores perceived images from tourists' perspectives, indicating a need for a broader examination that includes the measurement of projected image from DMOs and the general public's perceptions.

2.3. Photograph-based analysis of destination image

With the advent of social media's widespread adoption, the use of visual content such as photographs, videos, and textual narratives has become indispensable for both destination marketers and tourists alike [39]. Photographs, particularly, serve as dynamic tools across various platforms including travel brochures, guidebooks, commercials, and webpages, playing a pivotal role in conveying the essence of a destination's culture, identity, and unique attractions [40]. They not only attract but also influence tourists' perceptions, contributing significantly to the construction and promotion of destination images in the competitive global tourism landscape [41]. This underscores the emerging paradigm in tourism destination image research, where visual content, particularly photographs, plays a pivotal role [7].

Destination Marketing Organizations (DMOs) and tour operators have increasingly recognized the strategic value of photographic representations in shaping and reinforcing destination images [42-43]. These visual narratives not only enhance tourists' cognitive understanding of a destination but also evoke emotional connections and aspirations, crucial for effective destination marketing [13]. Despite the prevalence of user-generated content, there remains a notable gap in research focusing on how official entities strategically deploy photographic representations to project destination images [13]. Apart from that, the measurement of a country’s destination image through visual elements mainly based on qualitative method including grounded theory approach and frame theory [44]. In the era of cross-media big data, however, deep learning models in computer vision offer unique advantages for processing vast amounts of image data. Recent studies increasingly integrate artificial intelligence technologies to quantitatively analyze large-scale image datasets. Zhang and other scholars [45] use deep learning models to analyze 39,117 tourist photos from Beijing, exploring how positive emotions

ISSN: 2710-0170

in user-generated images influence viewer perceptions. It suggests practical strategies for destination marketing by selecting emotionally resonant and contextually fitting images, thus advancing theoretical understanding of user-generated content in shaping destination images. Nanne [46] examines the use of computer vision models—YOLOV2, Google Cloud Vision, and Clarifai—to analyze visual brand-related User Generated Content (UGC) from 21,738 Instagram images across 24 brands. The results showed that Google Cloud Vision proves highly accurate in object detection. The research highlights computer vision's potential for marketers to glean valuable insights from visual UGC, enhancing brand performance monitoring and trend analysis.

On the whole, previous research on destination image predominantly focuses on utilizing tourists' perceptual images for destination image assessment and studies on DCI destination-country image also largely analyze from its product image. Importantly, there is limited integration of quantitative analyses such as advanced natural language processing tools or other data science analytics, with qualitative analysis prevailing [42]. This paper aims to fill these gaps. Firstly, it requires large-scale quantitative analysis through big data mining, deep learning-based image tagging as the computer vision technology AWS recognition provided by Amazon company, and natural language processing methods to mitigate subjectivity inherent in qualitative analysis. Secondly, it aims to conduct a deeper semiotic interpretation of tourism destination images projected by national organizations on social media and investigate how tour operators utilize photographs to project destination images, emphasizing their role in creating compelling first impressions and attracting specific tourist demographics [7,47]. Thirdly, China is chosen as the post-COVID-19 era destination image measurement site because it was one of the world's largest international tourist destinations before COVID-19. Analyzing its international tourism image strategy post-COVID-19 will assist other DMOs in making relevant decisions. This study is significant as it not only contributes to advancing methodological approaches in destination image research but also provides practical insights for destination marketing organizations in adapting strategies to post-pandemic tourism environments, thereby enhancing global tourism resilience and competitiveness.

3. Theoretical background Semiotics theory

Semiotics, an academic discipline exploring the theory of symbols, investigates the essence, characteristics, meaning, and their relationship with humans [48]. This field's theoretical foundation was primarily established by Swiss linguist Saussure and American philosopher Peirce [49]. Saussure proposed the theory of the binary structure of symbols, where a symbol comprises a signifier and a signified [50]. Saussure emphasizes that in semiotics, the signifier represents the symbol's external form—such as sound, image, shape, color, or material—while the signified refers to its cultural meaning, constituting its internal content. He underscores their inseparability in forming linguistic symbols, where the symbol's significance derives not from the signifier alone but from the arbitrary relationship between the signifier and the signified, shaped by social conventions and linguistic habits.

Semiotic analysis is pivotal in interpreting photography by transforming literal reality into signs and symbols and these markers, or signs, play a crucial role in distinguishing a place and capturing tourists' attention [42]. Cameras encode these markers, selecting elements that convey explicit and implied meanings interpreted by viewers. Semiotics distinguishes between denotative and connotative meanings of sign elements in photographs, a method extensively utilized in tourism to analyze their content and significance [51]. Rodriguez [52] emphasizes that visual grammar and stylistic conventions in photography, such as composition, eye contact, expressions, and angles, subtly shape viewer perceptions of images and depicted characters. In tourism research, Echtner [53] proposes a triangle where the destination is the signified, tourism advertisements serve as signs or signifiers, and potential tourists act as interpretants.

ISSN: 2710-0170

MacCannell [54] discusses semiotic meanings in tourism, highlighting cultural icons and symbolic signs within tourist attraction systems. Peircean semiotics, as noted by Zhang & Sheng [55], investigates signs and their role in producing meaning through interpretation, particularly suited for analyzing visual representations of tourism destinations [56]. Several studies have investigated the intersection of semiotics and tourism. Hunter [43] applied a semiotic approach to analyze the visual representations of Seoul's tourist destination image online, comparing it with its traditional portrayal in printed media. Many of these studies draw on philosopher Charles Peirce's semiotic theory to examine tourism phenomena and representations. Lian & Yu [21] focused on the critical role of online imagery in shaping the perception of tourist destinations, using Huangshan as a case study. Employing semiotic theory, content analysis, and visual analysis, it examined how different media sources present and emphasize elements such as tourism resources, facilities, and services to construct Huangshan's online destination image with consistency across various platforms. Mele [57] combined semiotics to investigate how Destination Marketing Organizations in Milan and Paris utilized Instagram before and during the COVID-19 pandemic, highlighting shifts in communication strategies and user engagement. It emphasizes the promotion of cultural themes and pro-social behaviors amidst global health challenges.

4. Methodology and data

This section details the methodology for data collection and analysis, as illustrated in Fig. 1. Initially, we collected all Instagram posts from China Daily News containing images along with their textual descriptions. Subsequently, the collected data underwent preprocessing. During this stage, we utilized Amazon's AWS Rekognition service to annotate the images, followed by computing the frequency of all tags in the corpus. Next, we applied Latent Dirichlet Allocation (LDA) for topic clustering. Finally, using this processed data, we conducted semiotic qualitative analysis for each cluster themes.

4.1. Content analysis

Adopting a mixed qualitative and quantitative content analysis approach, this study examines the portrayal of China's destination country image through Instagram photos, aiming to explore the underlying themes and patterns in the visual representation of China's tourism image on this platform. Content analysis, a popular quantitative method, is chosen to delve into both the explicit and implicit meanings conveyed by visual images. It systematically and objectively describes the content of mass communication, such as books, magazines, movies, and television (Hsieh & Shannon, 2005), allowing for the classification of content units into distinct categories [58]. In tourism research, content analysis involves systematic procedures for categorizing various elements including words, phrases, symbols, and pictures [59]. This approach facilitates the quantitative exploration of key themes and measurement of variables, thereby providing insights into the representation and perception of destination images in digital media.

4.2. Deep learning-based image labelling

The AWS Rekognition API, provided by Amazon, is an image analysis service leveraging state-of-the-art machine learning and deep learning technologies to recognize content and context within images. Trained on millions of images, its robust algorithms can classify content into thousands of categories ranging from traffic to animals, and detect objects, logos, landmarks, and faces. The label detection feature identifies objects or concepts (including scenes and actions) in images or videos, such as identifying objects like palm trees, scenes like beaches, actions like running, and concepts like outdoors. The metadata provided by the celebrity recognition API significantly reduces manual efforts in tagging content, enhancing its searchability. Some scholars utilize similar tools such as Google Cloud Vision for image tagging, which enhances its utility in marketing research and other applications involving image data processing [60]. According to AWS

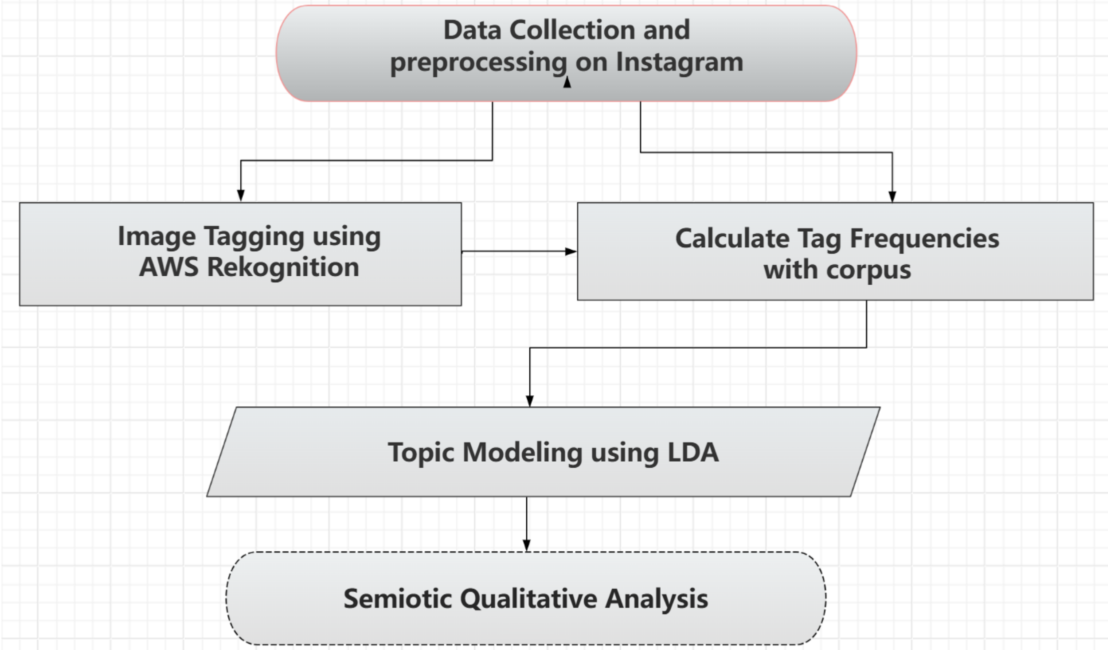

Figure 1. Methodology Flowchart

Rekognition's official pricing structure, the free tier allows users to annotate one image per session. Upon registration, users become eligible for the free tier, enabling them to annotate up to 5,000 images without charge; beyond this limit, each subsequent image incurs a fee of $0.008 USD. This service is customizable, leveraging its machine learning capabilities to train on image collections based on customized annotation tags, without requiring programming skills. In our assessment of its potential as a ready-made annotation tool, we primarily utilized default annotation categories.

4.3. Topic modeling

In the realm of natural language processing, Latent Dirichlet Allocation (LDA) stands out as an unsupervised clustering algorithm capable of categorizing vast repositories of unstructured text and extracting underlying thematic information [61]. Topic models encompass a suite of algorithms designed to uncover latent patterns within extensive collections of unstructured text. LDA analysis generates two primary probability distributions: text-topic and topic-word. The latter distribution delineates key words and their probabilities within each topic, where higher probabilities indicate stronger associations and contributions to the respective topic [62]. Since its introduction by Blei [63], LDA has proven instrumental in unveiling multidimensional themes (referred to as "topics") from large datasets, leveraging the co-occurrence of labels to infer these dimensions in photo analysis [64]. Utilizing unsupervised machine learning algorithms, LDA effectively discerns patterns from unstructured textual data, particularly beneficial in scenarios with sparse observations where qualitative analysis alone might falter [65] Moreover, the efficiency of the LDA model in processing textual big data enables the identification of latent attributes, typically manifested as nouns or noun phrases, thereby elucidating relationships embedded within textual content.

5. Data collection and analysis

5.1. Image collection

The first step in image collection was to define the scope and target DMO (Destination Marketing Organization) accounts. We restricted our search scope to the period from May 5,

ISSN: 2710-0170

2023, to May 5, 2024. The choice of May 5th as the starting point for data collection was due to the World Health Organization Director-General Tedros Adhanom Ghebreyesus announcing in Geneva that COVID-19 was no longer considered an international public health emergency. May 5, 2024, marks exactly one year into the post-pandemic era. After conducting our search, no official DMO posts from China were found on Instagram for promotion. Consequently, we selected China Daily News as the DMO organization because it boasts a significant global following (1.67million) on Instagram, making it an influential platform for promoting China's cultural and developmental narratives. The account's focused content on traditional Chinese culture and modern advancements provides a reliable and varied source of images that accurately reflect China's diverse appeal to international tourists. Most of its posted images and videos revolve around traditional Chinese culture and development, making it an ideal source for collection. Finally, we utilized the instaloader Python package, chosen for its simplicity and up-to-date API, to capture all posts and images from the China Daily account posted within the specified dates, along with their respective URLs, image URLs, and titles. Through this method, we collected 4,891 images and their associated captions in July 2024.

5.2. Image labeling and frequency calculation

As mentioned above, in this paper we utilized the AWS Rekognition API (Detecting labels in an image - Amazon Rekognition, accessed on 10 July 2024) to label our images based on their context and subsequently categorize them into relevant groups, such as animals, logos, landmarks, and faces. The response from DetectLabels is an array of labels detected in the image and the level of confidence by which they were detected, usually containing following attributes. For the analysis, detection results were assessed based on their confidence levels, categorized as follows: "Very Unlikely" (less than 25%), "Unlikely" (less than 50%), "Possible" (greater than 50%), "Likely" (greater than 65%), "Very Likely" (greater than 80%), and "Highly Likely" (greater than 95%). To ensure rigor, only elements categorized as "Possible," "Likely," or "Very Likely" were included in our dataset. Additionally, each label was recorded only once, disregarding information with confidence scores below 50%.

Name - The name of the detected label.

Confidence - Each label has an associated level of confidence.

Parents - The ancestor labels for a detected label.

Aliases - Information about possible Aliases for the label.

Categories - The label category that the detected label belongs to.

In addition to that, Recognize Celebrities API program returns an array of recognized celebrities and an array of unrecognized faces. In the example, note the following:

Recognized celebrities – is an array of recognized celebrities. Each Celebrity object in the array contains the celebrity name and a list of URLs pointing to related content—for example, the celebrity's IMDB or Wikidata link. Amazon Rekognition returns an ComparedFace object that your application can use to determine where the celebrity's face is on the image and a unique identifier for the celebrity. Use the unique identifier to retrieve celebrity information later with the GetCelebrityInfo API operation. Celebrities

Unrecognized faces – is an array of faces that didn't match any known celebrities. Each ComparedFace object in the array contains a bounding box (as well as other information) that you can use to locate the face in the image.

For example, AWS Rekognition identified the following labels for Fig. 2, which detected the following labels: Land (100.00%), Nature (100.00%), Outdoors (100.00%), Vegetation (100.00%), Tree (99.99%), Woodland (99.99%), Water (99.58%), Lake (98.85%), Aerial View (97.87%), and Sea (90.04%). For Fig. 3, which features a photo of China's highest leadership shaking hands with another president, AWS Rekognition detected the celebrities Xi Jinping and

ISSN: 2710-0170

Andrés Manuel López with confidences of 99.978% and 99.923%, respectively. Across the dataset, all 4,891 photos were processed for label detection. The maximum number of labels per photo, set at 10 by AWS Rekognition API, culminated in a total of 43,288 labels being identified (see table1).

Figure 2. Natural Landscape Example

Table 1. Image Labeling Statistics

Source data	Collected photos	Detected labels	Detected celebrity labels	Detected national leader labels
China daily news	4891	43288	1710	1465

5.3. Label clustering with topic modeling

In this step, we firstly utilized the corpus tool AntConc to perform a frequency analysis of all tags and then visualized the frequency data with a word cloud in figure.4 to provide an initial overview of China's post-covid international image. The word cloud reveals that human subjects, particularly adult males and females, are the primary focus in these images, indicated by prominent tags such as "person," "adult," "male," and "female." Additionally, natural landscapes and outdoor scenes are highly prevalent, as evidenced by tags like "outdoors," "nature," "man," "woman," "flower," "tree," and "plant." Urban landscapes and architectural structures also feature prominently, with tags like "building," "city," "urban," and "architecture." The presence of tags such as "animal," "mammal," "bird," and "wildlife" demonstrates that animals and wildlife are important elements. Furthermore, detailed features of human subjects, including their faces, heads, and clothing, are frequently highlighted, as indicated by tags like "face," "head," "jacket," and "coat." Overall, the images associated with China's international tourism image on Instagram primarily focus on people and natural landscapes, with significant representation of urban settings and wildlife, showcasing a diverse range of tourist attractions and cultural aspects.

Furthermore, the celebrity recognition results indicate that out of 9,878 personal tags, 1,710 were identified as celebrities, accounting for 17.3% of the total. Among these, the frequency of national leaders appearing in the visual content is notably high at 85.7%. This suggests that China is strategically using the image of its leaders to convey specific national values and an

ISSN: 2710-0170

international image. Such a practice aims to enhance the country's authority, credibility, and international standing. The presence of leaders often coincides with major national events, policy announcements, and international exchanges, highlighting China's achievements in politics, economics, and technology, thereby shaping a positive international image. When images depict leaders interacting with ordinary citizens, they project an approachable and caring image, demonstrating the government's commitment to public welfare, which enhances recognition both domestically and internationally. By showcasing the leaders' international engagements, China emphasizes its active participation and influence in global affairs, thereby boosting its soft power and international image.

Figure 3. Word Cloud of Image Tags

In this study, Latent Dirichlet Allocation (LDA) was employed for topic modeling to cluster a series of themes from all tags. The key to applying the LDA topic model is determining the optimal number of topics, as the effectiveness of topic extraction in the LDA model is directly related to the number of latent topics. The two most common evaluation methods for determining the number of topics are based on coherence [66] or perplexity. In this study, we chose coherence scores as the standard for determining the number of topics, which quantitatively measures the semantic relatedness of words within the topics generated by LDA. The LDA model identified 4 topics for this dataset as it had the highest coherence score. Figure 1 shows the coherence scores for different numbers of topics returned by the LDA model. However, since the LDA model operates as an unsupervised learning method, researchers needed to manually assign labels to each topic based on the top ten highest probability words for each topic [67]. The labeling of each topic was manually performed by one researcher and then confirmed by another researcher. We used pyLDAvis (https:// pypi.org/ project/ pyLDAvis/; accessed July 10, 2024) to create an interactive visualization where the top 30 most relevant terms are displayed by frequency after selecting a topic. Figure 5 shows the selected first topic of the four topics and table 2 displays the twenty most relevant terms for each topic.

6. Results and discussion

Through the thematic analysis of Instagram image tags, China's post-pandemic international tourism image emerges as a richly diverse tapestry of life scenes. According to the results of table 2, we manually labeled these four themes which include Urban Life, Natural Landscapes, Defense and Technology, Cultural Activities. The first theme, Urban Life, represents tags like "Person," "Male," "Building," "Urban," "Plant," "Food," and "Rural" that depict a variety of

ISSN: 2710-0170

human activities, highlighting the cultural and everyday aspects of life. The second theme, Natural Landscapes, emphasizes the harmonious coexistence of natural beauty and human presence. With tags such as "Nature," "Bird," "Tree," "Sea," "View," and "Countryside," it showcases China's diverse natural attractions that captivate international tourists. The third theme, Defense and Technology, focuses on China's advancements in infrastructure, defense, and technology. Terms like "Architecture," "Airplane," "Weapon," "Car," "Produce," and "Farm" illustrate the nation's progress in critical fields, emphasizing its role as a leader in technological innovation and captures the essence of modern China's achievements in creating advanced transportation systems, cutting-edge architectural marvels, and state-of-the-art defense mechanisms. The final theme, Cultural Activities, highlights the aesthetic appeal of floral elements and their integration into cultural and outdoor activities. Tags such as "Adult," "Outdoors," "Woman," "Art," "Flower," "Festival," and "Scenery" reveal China's appreciation for natural beauty and cultural vibrancy. Collectively, these themes reflect China's multifaceted appeal as a travel destination, showcasing its cultural richness, technological progress, natural beauty, and vibrant urban life. The analysis reveals a country that balances modernity with tradition, urban sophistication with natural splendor, and technological prowess with cultural depth. China's post-pandemic tourism image is one of a nation that not only values its heritage and natural landscapes but also embraces innovation and progress.

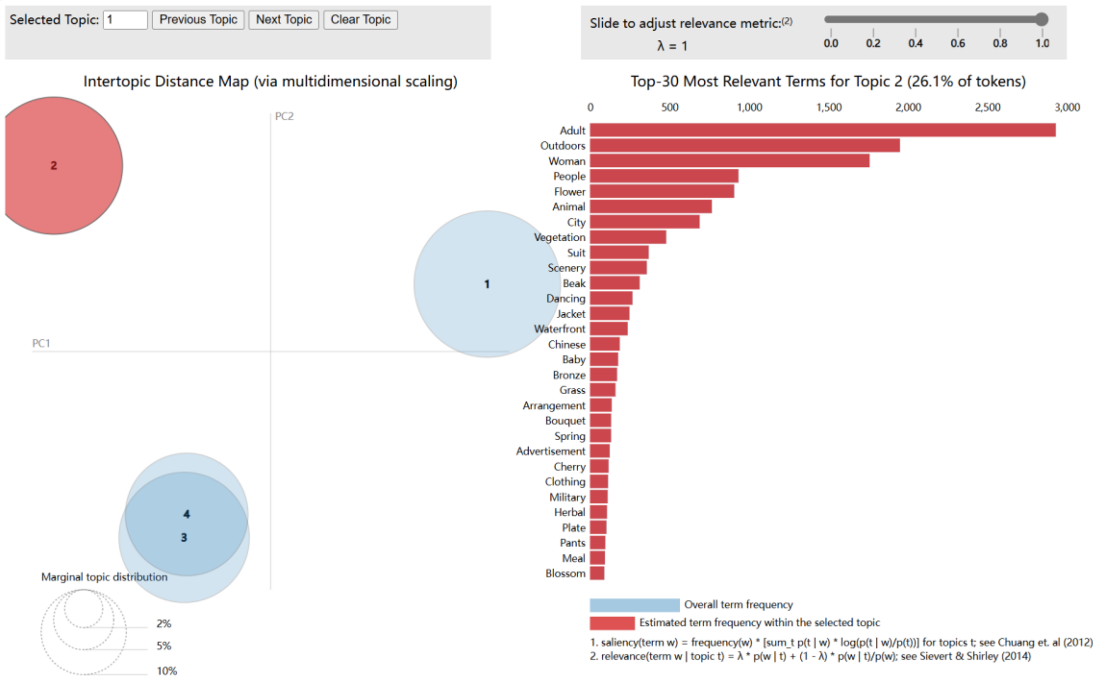

Figure 4. LDA Topic Visualization

The theme “Urban Life” vividly portrays individuals in their daily routines and special occasions, capturing the essence of human presence in bustling cities and reflecting the dynamic urban culture. In figure 6, the juxtaposition of Shanghai's iconic high-rise buildings, including the Oriental Pearl Tower and the Shanghai Tower, against a bustling waterfront filled with diverse groups of people, underscores the city's economic prosperity and international character. The presence of both tourists and locals engaging in leisure activities, some wearing masks, reflects the city's adaptability and resilience in the face of global health challenges, illustrating the continuity of social interaction amid new norms. Apart from that, the image captures pedestrians and cyclists navigating the urban space, symbolizing the seamless blend of tradition and progress. The evening sunlight casting a warm glow on the buildings not only enhances the aesthetic appeal but also signifies the harmonious transition from day to night,

ISSN: 2710-0170

paralleling the city's blend of old and new. The use of mobile phones by some pedestrians' points to the pervasive influence of digital technology in maintaining social connectivity and personal engagement in contemporary urban life.

In figure 7, the street scene is dominated by towering historical buildings juxtaposed with modern skyscrapers in the background, framed by a serene sunset. This visual metaphor of historical continuity and forward-looking development encapsulates Shanghai's dual identity as a guardian of cultural legacy and a beacon of modernity. The varied activities of people in the street—walking, cycling, and using smartphones—emphasize the multifaceted nature of urban life, where personal routines and public interactions coexist fluidly. The presence of masks on some individuals serves as a poignant reminder of the ongoing impact of the pandemic, highlighting a collective vigilance that underpins the city's return to normalcy. In sum, the careful balance of historical architecture and contemporary infrastructure, coupled with the vibrant daily activities of its inhabitants, paints a comprehensive picture of a resilient, adaptive, and culturally rich metropolis. This semiotic analysis underscores the importance of visual elements in conveying complex socio-cultural narratives, making Shanghai a compelling subject in the study of post-pandemic urban dynamics and international tourism imagery.

Table 2. Top Terms for Each Topic

Topic1	Weight	Topic2	Weight	Topic3	Weight	Topic4	Weight
Person	0.22508	Female	0.13079	Architecture	0.09729	Adult	0.15839
Male	0.09782	Tree	0.02232	Cityscape	0.03903	Outdoors	0.10541
Head	0.04477	Bird	0.02231	Coat	0.03295	Woman	0.09508
Building	0.03575	Nature	0.02040	Indoors	0.02558	Art	0.05047
Water	0.03549	Sea	0.02037	People	0.02327	Flower	0.04903
Urban	0.03364	View	0.01962	City	0.02127	Animal	0.04143
Plant	0.02793	Aerial	0.01962	Landmark	0.01725	Festival	0.03728
Food	0.02676	Photography	0.01943	Arrangement	0.01624	Vegetation	0.02590
Bride	0.02459	Crowd	0.01927	Airplane	0.01550	Suit	0.01996
Shoe	0.02389	Boy	0.01899	Dress	0.01510	Scenery	0.01931
Vehicle	0.02271	Glove	0.01743	Car	0.01490	Beak	0.01689
Petal	0.02040	Produce	0.01724	Leaf	0.01474	Dancing	0.01444
Child	0.01965	Blazer	0.01616	Hat	0.01470	Jacket	0.01341
Mammal	0.01550	Wildlife	0.01602	Formal	0.01299	Waterfront	0.01281
Handbag	0.01444	Performance	0.01498	Weapon	0.01299	Chinese	0.01010
Fruit	0.01255	Sky	0.01455	Transportation	0.01190	Baby	0.00955
Boat	0.01201	Garden	0.01427	Finch	0.01046	Bronze	0.00919
Road	0.01118	Solo	0.01335	Train	0.00972	Grass	0.00865
Portrait	0.01092	Ice	0.01255	Phone	0.00951	Girl	0.00737
Land	0.01036	Waterfowl	0.01157	Night	0.00938	Bouquet	0.00716

The second theme "Natural Landscapes" emphasizing natural settings and wildlife, these images reflect China's commitment to ecological conservation and sustainable tourism, attracting international visitors interested in environmental protection and natural ecology. In figure 8, the scene of caretakers feeding two giant pandas in a lush, green environment highlights the country's commitment to wildlife conservation and the harmonious relationship between humans and nature. The presence of bamboo baskets and the naturalistic setting symbolize efforts to replicate the pandas' natural habitat, reflecting the importance of ecological preservation. In figure 9, the image captures

ISSN: 2710-0170

a tranquil scene of a bamboo raft floating on a mist-covered river, surrounded by verdant mountains.

Figure 5. Shanghai Urban Life

Figure 6. Historical and Modern Shanghai

This photograph illustrates the profound connection between traditional lifestyles and the serene beauty of nature, with the bamboo raft and traditional attire symbolizing the harmonious relationship between humans and their natural environment. The mist and the river create a sense of mystique and tranquility, emphasizing the purity and serenity of the natural world. The visual elements in these photographs convey complex socio-cultural narratives, showcasing the profound respect for nature and the integration of cultural traditions within these landscapes. This semiotic analysis underscores the significance of natural settings as vital components of cultural identity and heritage, offering deep insights into the post-pandemic representation of China's natural and cultural tourism imagery.

The third theme “Defense and Technology” showcasing China's cityscapes, modern architecture, and technological prowess in defense, these visuals highlight China's cultural charm and modern development as a tourism destination. The figure 10, showcasing a towering rocket poised for launch, encapsulates the nation's technological prowess and ambitious strides in the aerospace sector. The rocket, adorned with the "China Aerospace" emblem and flanked by red flags, symbolizes national pride and technological achievement. The presence of uniformed personnel underscores the importance of teamwork and human resources in executing high-stakes technological missions. In figure 11, it captures the triumphant return of an astronaut, who, while seated on a simple chair amidst a desolate landscape, salutes with a smile, epitomizing the heroism and success of space exploration. The astronaut's suit, festooned with

ISSN: 2710-0170

mission patches and insignia, highlights the sophisticated technology enabling human exploration of extreme environments. The red flag in the background reaffirms national pride and recognition of individual contributions to the country's space endeavors. These images convey a narrative of technological advancement, national pride, and the human element in scientific exploration. They reflect China's significant achievements in aerospace, emphasizing the integration of advanced technology with national identity and the valorization of individual contributions to collective progress. This semiotic analysis elucidates the profound implications of visual elements in representing complex socio-technological narratives, underscoring the role of defense and technology in shaping contemporary national imagery.

Figure 7. Panda Conservation Scene

Figure 8. Bamboo Raft on Misty River

The final theme "Cultural Activities" brings to life the country's rich cultural tapestry, with festivals, artistic expressions, and outdoor celebrations that feature prominently as well as promoting understanding and participation in Chinese culture and festivals among international tourists. The figure 12 captures the lively atmosphere of a festive celebration, with red lanterns symbolizing joy and prosperity. The bustling crowd reflects the post-pandemic revival of public life, where people gather to celebrate and welcome visitors, creating a warm and inviting ambiance. This scene underscores the resilience of social traditions and the collective spirit of celebration that endures even in challenging times. The next photograph

ISSN: 2710-0170

(figure 13), featuring a foreign woman dressed in traditional Chinese Hanfu, emphasizes the global appeal and influence of Chinese culture. Her attire and confident smile in a modern indoor setting suggest a context of cultural exchange, illustrating the harmonious blend of tradition and modernity. This juxtaposition of ancient attire against a contemporary backdrop highlights the timeless elegance of Hanfu, making it a powerful symbol of cultural continuity and adaptation. The woman's enthusiastic participation in wearing traditional Chinese clothing signifies not only a respect for the culture but also an active engagement in its preservation and celebration. Furthermore, the photograph can be seen as a testament to the global diaspora of Chinese cultural practices, where elements such as Hanfu are celebrated not just within China, but by diverse populations around the world. This phenomenon is indicative of a broader trend where traditional cultural elements gain new life and relevance in the global arena, contributing to a richer, more diverse cultural tapestry. Thus, the image serves as a visual narrative of cultural hybridity and the globalized journey of Chinese traditions, reflecting both the resilience of cultural heritage and its evolving nature in the modern world.

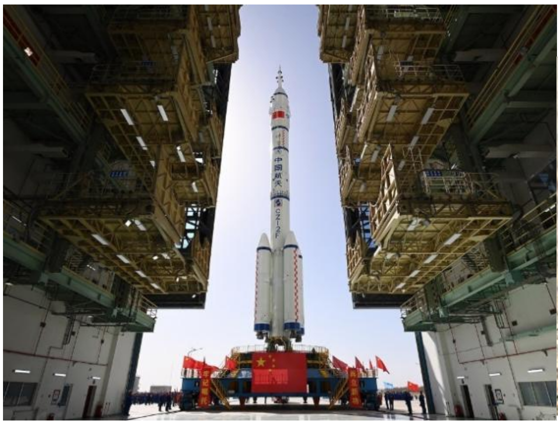

Figure 3. Rocket Launch

Figure 4. Astronaut Return

Figure 5.Festival Celebration

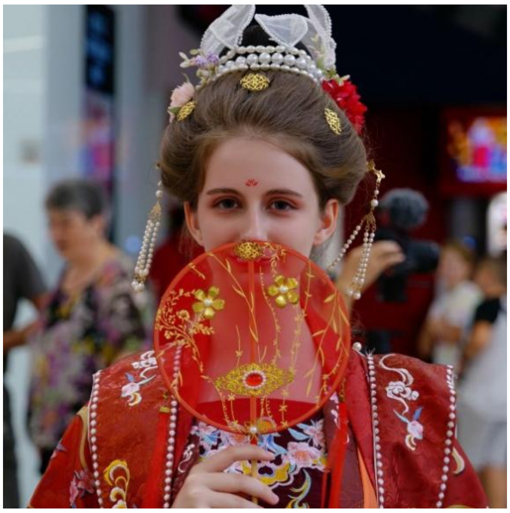

Figure 6.Foreign Woman in Hanfu

The semiotic analysis of photographs across four distinct themes—urban life, natural landscapes, defense and technology, and cultural activities—reveals a multifaceted portrayal of contemporary China. In the theme Urban Life, images of Shanghai's bustling streets and waterfronts highlight the city's blend of historical heritage and modernity, showcasing its economic vitality and social dynamism in the post-pandemic era. The Natural Landscapes theme, illustrated by serene scenes of pandas, mist-covered rivers, and vibrant cultural displays in natural settings, underscores the harmonious coexistence of cultural heritage and environmental beauty, emphasizing conservation efforts and traditional practices. In the theme of Defense and Technology, photographs of rocket launches and astronauts capture China's significant advancements in aerospace, symbolizing technological prowess, national pride, and the human spirit of exploration. These images reflect the country's commitment to scientific progress and its position in the global arena. The theme Cultural Activities, featuring lively festival celebrations and a foreign woman dressed in traditional Hanfu, demonstrate cultural resilience, the revival of social life post-pandemic, and the dynamic interplay between cultural preservation and globalization. "These images collectively narrate China's contemporary identity, blending tradition with modernization and embracing cultural exchange, conveying nuanced socio-cultural narratives that reflect China's historical legacy and future aspirations."

7. Conclusion and limitation

In conclusion, this research provides a comprehensive analysis of China's Destination Country Image (DCI) in the post-pandemic era, particularly focusing on the role of Instagram imagery in shaping international perceptions of China's tourism image. The study's results emphasize the potential role of visual media in shaping public beliefs and perceptions of the world. The theme of Urban Life captures the dynamic and resilient nature of China's cities, particularly highlighting Shanghai's blend of historical heritage and modernity. Natural Landscapes emphasize China's commitment to ecological conservation and sustainable tourism, with images showcasing tranquil settings and wildlife. Defense and Technology focus on China's advancements in infrastructure, aerospace, and defense, reflecting the nation's technological prowess and national pride. Cultural Activities portray the rich cultural tapestry of China through festivals, artistic expressions, and traditional attire, highlighting the global appeal of Chinese culture.

In sum, the study's findings underscore the critical importance of visual content in modern tourism marketing, revealing that China's DMO (Destination Management Organization) has effectively utilized Instagram to project a multifaceted image of the nation. Furthermore, this paper makes several innovative contributions to the field. By integrating both qualitative and quantitative methods, it offers a robust analysis framework. The combination of Latent Dirichlet Allocation (LDA) for topic modeling and image tagging facilitated a large-scale identification and categorization of themes from Instagram images. The practical implications of this research are significant for destination management and marketing. Firstly, the proposed LDA and image tagging methodology can be utilized by DMOs to systematically identify and interpret themes from vast sets of visual data, thereby informing policy-making and strategic planning. Secondly, the integration of qualitative and quantitative analyses provides a more nuanced understanding of destination images, bridging the gap left by earlier research methodologies that were either solely qualitative or quantitative frameworks such as encoding, framing theories and content analysis for photo analysis. In essence, this study demonstrates the effectiveness of using advanced data analysis techniques to understand and manage destination images. The findings not only enhance our theoretical understanding of tourism image construction but also provide practical insights for DMOs aiming to leverage visual media in their marketing strategies, ultimately contributing to the recovery and competitiveness of the global tourism market post-pandemic.

Despite the comprehensive approach, this study acknowledges certain limitations. Firstly, the reliance on Instagram as the sole source of visual data may limit the generalizability of the findings, as other social media platforms might offer different perspectives. Additionally, the manual interpretation of themes, while validated by multiple researchers, may still introduce subjective biases. Secondly, the analysis of photo tagging might contain errors; future studies could utilize customized machine learning models for tagging to improve accuracy. Finally, this research only analyzes the post-pandemic image presentation. Future studies could include a comparative analysis of images from both pre- and post-pandemic periods to further explore the shifts in China's international image strategies.

8. Reference:

[1] Hunter, W.C. Semiotic fieldwork on chaordic tourism destination image management in Seoul during COVID-19. Tour. Manag. 2022, 93, 104565. https:// doi.org/ 10.1016 /j. tourman. 2022.104565

[2] State Council of the People's Republic of China. (2021, February 19). China's domestic tourism shrinks in 2020 amid COVID-19 epidemic https:// english.www.gov.cn/ archive/ statistics/ 202102/ 19/content_WS602f6da1c6d0719374af9129.html

[3] State Council of the People's Republic of China. (2022, December 29). China's COVID measures to facilitate cross-border travel, int'l exchanges: spokesperson https:// english.www.gov.cn /archive/statistics/202102/19/content_WS602f6da1c6d0719374af9129.html

[4] State Council of the People's Republic of China. (2023, December 15). China's cultural, tourism sectors see robust recovery, expect higher-quality development https://english. www.gov.cn/ archive/statistics/202102/19/content_WS602f6da1c6d0719374af9129.html

[5] Iordanova, E.; Stainton, H. Cognition, emotion and trust: A comparative analysis of Cambodia's perceived and projected online image. Tour. Stud. 2019, 19, 496–519. https:// doi.org/ 10.1177/1468797619829152

[6] Zeng, B., & Gerritsen, R. (2014). What do we know about social media in tourism? A review. Tourism Management Perspectives, 10, 27–36. https://doi.org/10.1016/j.tmp.2014. 01.001

[7] Leung, D., Law, R., Van Hoof, H., & Buhalis, D. (2013). Social media in tourism and hospitality: A literature review. Journal of Travel & Tourism Marketing, 30(1–2), 3–22. https:// doi.org/ 10.1080/10548408.2013.750919

[8] Hung, Y. C., Yang, Y. L., Yang, H. E., & Yahsueh, C. (2011). Factors affecting the adoption of e-commerce for the tourism industry in Taiwan. Asia Pacific Journal of Tourism Research, 16(1), 105–119. https://doi.org/10.1080/10941665.2011.539391

[9] Beyvers, E.M.A.; Herbrich, T. Social media and the European fundamental rights to privacy and data protection. In Proceedings of the 3rd European Conference on Social Media Research EM Normandie, Caen, France, 12–13 June 2016; pp. 33–39.

[10] Zeng, B., & Gerritsen, R. (2014). What do we know about social media in tourism? A review. Tourism Management Perspectives, 10, 27–36. https://doi.org/10.1016/j.tmp.2014. 01.001

[11] Cao, B. (2011). Social media: Definition, history of development, features and future. Journal of Hunan Radio and Television University, 3,65–69.

[12] Song, L., Li, R. Y. M., & Wareewanich, T. (2023). The Cultivation Effect of Architectural Heritage YouTube Videos on Perceived Destination Image. Buildings, 13(2), 508. https:// doi.org/ 10.3390/buildings13020508

[13] Picazo, P., & Moreno-Gil, S. (2019). Analysis of the projected image of tourism destinations on photographs: A literature review to prepare for the future. Journal of Vacation Marketing, 25(1), 3–24. https://doi.org/10.1177/1356766717736350

[14] Xiao, X., Fang, C., & Lin, H. (2020). Characterizing tourism destination image using photos' visual content. ISPRS International Journal of Geo-Information, 9. https://doi.org/10.3390/ijgi9040262

[15] Dong, J. and Li, L. (2022), "Customer visual perception of indoor environments: computer vision analysis of social media photos of cafes in China", Leisure Sciences, Vol. 9, pp. 1-21.

[16] Li, J., Weng, G., & Pan, Y. (2021). Projected Destination-Country Image in documentaries: Taking wild China and aerial China for example. Journal of Destination Marketing & Management, 20, 100609. https://doi.org/10.1016/j.jdmm.2021.100609

[17] Hunt J D. Image As a Factor in Tourism Development[D]. Colorado State University, 1971.

[18] Echtner, C. M., & Ritchie, J. R. B. (1991). The meaning and measurement of destination image. Journal of Tourism Studies, 2(2), 2–12.

[19] Florian Kock, Alexander Josiassen, A. George Assaf, Advancing destination image: The destination content model, Annals of Tourism Research, Volume 61,2016, Pages 28-44, ISSN 0160-7383, https://doi.org/10.1016/j.annals.2016.07.003.

[20] Baloglu, S., & McCleary, K.W. A model of destination image formation. Ann. Tour. Res. 1999, 26, 868–897. https://doi.org/10.1016/S0160-7383(99)00031-1

[21] Lian, T., & Yu, C. (2017). Representation of online image of tourist destination: A content analysis of Huangshan. Asia Pacific Journal of Tourism Research, 22(10), 1063–1082. https:// doi.org/ 10.1080/10941665.2017.1368678

[22] Afshardoost, M., & Eshaghi, M. S. (2020). Destination image and tourist behavioral intentions: A meta-analysis. Tourism Management, 81, Article 104154. https:// doi.org/ 10.1016/ j.tourman. 2020.104154

[23] Zhang, H., Fu, X., Cai, L. A., & Lu, L. (2014). Destination image and tourist loyalty: A meta-analysis. Tourism Management, 40, 213 – 223. https://doi.org/10.1016/j.tourman.2013.06.006

[24] Augustyn, M. (1998). National strategies for rural tourism development and sustainability: The polish experience. Journal of Sustainable Tourism, 6(3), 191–209. https:// doi.org/ 10.1080/ 09669589808667311

[25] Zhang, H., Xu, F., Leung, H. H., & Cai, L. A. (2016). The influence of destination-country image on prospective tourists' visit intention: Testing three competing models. Asia Pacific Journal of Tourism Research, 21(7), 811–835. https://doi.org/10.1080/10941665.2015.1075566

[26] Campo, S., & Alvarez, M. D. (2010). Country versus destination image in a developing country. Journal of Travel and Tourism Marketing, 27(7), 749–765. https:// doi.org/ 10.1080/ 10548408. 2010.519679

[27] Mossberg, L., & Kleppe, I. A. (2005). Country and destination image – different or similar image concepts? The Service Industries Journal, 25 (4), 493 - 503. https:// doi.org/ 10.1080/ 02642060500092147

[28] Nadeau, J., Heslop, L., O'Reilly, N., & Luk, P. (2008). Destination in a country image context. Annals of Tourism Research, 35(1), 84–106. https://doi.org/10.1016/j.annals.2007.06.012

[29] Dedeoğlu, B. B. (2019). Shaping tourists' destination quality perception and loyalty through destination country image: The importance of involvement and perceived value. Tourism Management Perspectives, 29, 105–117. https://doi.org/10.1016/j.tmp.2018.11.005

[30] Gartner, W. C. (1993). Image formation process. Journal of Travel Research, 31(4), 10–15. https://doi.org/10.1177/004728759303100402

[31] Ji, S., & Wall, G. (2015). Understanding supply- and demand-side destination image relationships: The case of Qingdao, China. Journal of Vacation Marketing, 21(2), 205–222. https:// doi.org /10.1177/1356766714542189

[32] Beerli, A., & Martin, J. D. (2004). Factors influencing destination images. Annals of Tourism Research, 31, 657–681. https://doi.org/10.1016/j.annals.2004.01.010

[33] Grosspietsch, M. (2006). Perceived and projected images of Rwanda: Visitor and international tour operator perspectives. Tourism Management, 27(2), 225–234. https:// doi.org/ 10.1016/ j.tourman.2004.08.005

[34] Pappu, R.; Quester, P. Country equity: Conceptualization and empirical evidence. Int. Bus. Rev. 2010, 19, 276–291. https://doi.org/10.1016/j.ibusrev.2009.12.006

[35] Bordelon, L.A., & Ferreira, S.L.A. (2017). Tourist photographs and destination imagery on social media: Reading the Stellenbosch Winelands through a tourist lens. Tourism Review International, 21(3), 317-329. https://doi.org/10.3727/154427217x15022104437765

[36] Koltringer, C.; Dickinger, A. Analyzing Destination Branding and Image from Online Sources: A Web Content Mining Approach. J. Bus. Res. 2015, 68, 1836–1843. https:// doi.org/ 10.1016 /j.jbusres.2015.01.011

[37] Mak, A.H.N. Online destination image: Comparing national tourism organization's and tourists' perspectives. Tour. Manag. 2017, 60, 280–297. https://doi.org/10.1016/j.tourman.2016.12.012

[38] Mirzaalian, F., & Halpenny, E. (2021). Exploring destination loyalty: Application of social media analytics in a nature-based tourism setting. Journal of Destination Marketing & Management, 20, 100598. https://doi.org/10.1016/j.jdmm.2021.100598

[39] Zhao, Z., Zhu, M., & Hao, X. (2018). Share the Gaze: Representation of destination image on the Chinese social platform WeChat Moments. Journal of Travel and Tourism Marketing, 35(6):726-739. https://doi.org/10.1080/10548408.2018.1432449

[40] Mull, I. R., & Lee, S. E. (2014). "PIN" pointing the motivational dimensions behind Pinterest. Computers in Human Behavior, 33, 192-200. https://doi.org/10.1016/j.chb.2014.01.011

[41] Herath, H. M. H. M., & Stanford, D. (2017). The analysis of responsible tourism photography and its influence on destination image in Sri Lanka. In Proceedings of International Conference on Hospitality and Tourism Management, Colombo, Sri Lanka, pp. 27. https:// tourismconference.co /wp-content/uploads/2018/03/Book_Abstracts_ICOHT_ 2017.pdf

[42] Park, E., & Kim, S. (2018). Are we doing enough for visual research in tourism? The past, present, and future of tourism studies using photographic images. International Journal of Tourism Research, 20(4), 433–441. https://doi.org/10.1002/jtr.2194

[43] Hunter, W. C. (2016). The social construction of tourism online destination image: A comparative semiotic analysis of the visual representation of Seoul. Tourism Management, 54, 221–229. https://doi.org/10.1016/j.tourman.2015.11.012

[44] Arefieva, V., Egger, R., & Yu, J. (2021). A machine learning approach to cluster destination image on Instagram. Tourism Management, 85, 104318. https://doi.org/10.1016/j.tourman.2021.104318

[45] Zhang, K., Zhang, J., Shang, X., Yang, J., & Li, C. (2023). Linking UGP' s affective and cognitive concepts together for tourism destination image development. Current Issues in Tourism, 1–16. https://doi.org/10.1080/13683500.2023.2288161

[46] Nanne, A. J., Antheunis, M. L., Van Der Lee, C. G., Postma, E. O., Wubben, S., & Van Noort, G. (2020). The Use of Computer Vision to Analyze Brand-Related User Generated Image Content. Journal of Interactive Marketing, 50(1), 156–167. https://doi.org/10.1016/j.intmar.2019.09.003

[47] Bell, E., & Davison, J. (2013). Visual management studies: Empirical and theoretical approaches. International Journal of Management Reviews, 15(2), 167–184. https://doi.org/10.1111/j.1468-2370.2012.00342.x

[48] Barthes, R. (1967). Elements of Semiology.

[49] ZHAO Yi-heng. Cultural Semiotics Studies: Present Situation and Future Trends. Journal of Southwest University for Nationalities (Humanities and Social Science), 2009, 30(12): 169-172.

[50] Shumaker, S.A., & Taylor, R.B. (1983). Toward a Clarification of People-Place Relationships: A Model of Attachment to Place [J]. Environmental psychology.

[51] Rose, G. (2012). Visual methodologies: An introduction to researching with visual materials. Thousand Oaks, CA: Sage Publication.

[52] Rodriguez L and Dimitrova D (2011) The levels of visual framing. Journal of Visual Literacy 30 (1): 48–65. https://doi.org/10.1080/23796529.2011.11674684

[53] Echtner, C. M. (1999) 'The Semiotic Paradigm: Implications for Tourism Research', Tourism Management 20: 47–57. https://doi.org/10.1016/S0261-5177(98)00093-2

[54] MacCannell, D. (1976). The tourist: A new theory of the leisure class. Berkeley: University of California Press.

[55] Zhang, X., & Sheng, J. (2017). A Peircean semiotic interpretation of a social sign. Annals of Tourism Research, 64, 163–173. https://doi.org/10.1016/j.annals.2017.04.002

[56] Pennington, W. J., & Thomsen, C. R. (2010). A semiotic model of destination representations applied to cultural and heritage tourism marketing. Scandinavian Journal of Hospitality and Tourism, 10(1), 33–53. https://doi.org/10.1080/ 15022250903561895

[57] Mele, E., Filieri, R., & De Carlo, M. (2023). Pictures of a crisis. Destination marketing organizations' Instagram communication before and during a global health crisis. Journal of Business Research, 163, 113931. https://doi.org/10.1016/j.jbusres.2023.113931

ISSN: 2710-0170

[58] Weber, R. P. (1990). Basic content analysis. Beverly Hills, CA: Sage.

[59] Krippendorff, B. K. (2010). Content analysis: An introduction to its methodology. Thousand Oaks, CA: Sage Publications.

[60] Hosseini, H., Xiao, B., & Poovendran, R. (2017). Google's cloud vision API is not robust to noise. Paper presented at the 2017 16th IEEE international conference on machine learning and applications (ICMLA). https://doi.org/10.1109/ICMLA.2017.0-126

[61] Jing, P., Cai, Y., Wang, B., Wang, B., Huang, J., Jiang, C., & Yang, C. (2023). Listen to social media users: Mining Chinese public perception of automated vehicles after crashes. Transportation Research Part F: Traffic Psychology and Behaviour, 93, 248–265. https://doi.org/10.1016/j.trf.2023.01.018

[62] Ghosh DD, Guha R. What are we 'tweeting' about obesity? Mapping tweets with Topic Modeling and Geographic Information System. Cartogr Geogr Inf Sci. 2013;40(2):90-102. Doi: 10.1080/ 15230406. 2013.776210. PMID: 25126022; PMCID: PMC4128420.

[63] David M. Blei, Andrew Y. Ng, and Michael I. Jordan. 2003. Latent dirichlet allocation. J. Mach. Learn. Res. 3, null (3/1/2003), 993–1022.

[64] Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using Latent Dirichlet allocation. Tourism Management, 59, 467–483. https://doi.org/10.1016/j.tourman.2016.09.009

[65] Pavlinek, M., & Podgorelec, V. (2017). Text classification method based on self-training and LDA topic models. Expert Systems with Applications , 80 ,83 – 93. https:// doi.org/ 10.1016 /j.eswa.2017.03.008

[66] Stevens, K.; Kegelmeyer, P.; Andrzejewski, D.; Buttler, D. Exploring topic coherence over many models and many topics. In Proceedings of the Empirical Methods in Natural Language Processing 2012, Jeju Island, Korea, 12–14 July 2012.

[67] Aman, J. J. C., Smith-Colin, J., & Zhang, W. (2021). Listen to E-Scooter Riders: Mining Rider Satisfaction Factors from App Store Reviews. Transportation Research Part D: Transport and Environment, 95(June), 102856. https://doi.org/10.1016/j.trd.2021.102856