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Progress on image analytics: Implications for tourism and hospitality research

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ABSTRACT

Despite the increased recognition of the importance of images as a rich data source, the full potential of images to advance tourism and hospitality knowledge, both conceptually and theoretically, has yet to be fully tapped. This study provides a critical review of image analytics, examining its broad implications for tourism and hospitality research. This paper offers the progress of image definitions, features and related theories, as well as presents a methodological framework for conducting image-related studies, complementing the dominant textual analysis used in tourism and hospitality research. The paper makes contributions to the tourism methodological literature by developing a point of reference for the application of image analytics in tourism and hospitality studies.

1. Introduction

The past decade has witnessed the increasing popularity of using images as a source of data in business research, including tourism and hospitality. This popularity is largely driven by the shift from elites and professionals to the public with the wide accessibility of cameras (Arefieva, Egger, & Yu, 2021). In its early stages of development, images were either privately stored by individuals or commercially produced in advertisements, promotional materials, or official media. With the development of the Internet and social networking applications, almost anyone can take photos and share them on social media. Images have now become the most popular user-generated content (UGC) (Taecharungroj & Mathayomchan, 2021; Wang, Luo, & Huang, 2020). Unlike textual content, an image is worth a thousand words as it conveys visual meaning by its manifest and latent content. The manifest content refers to the clear and observable features in the photograph (Van Den Berg, 2004), while the latent content describes the implicit information embedded in the picture (Holsti, 1969). The rich information embedded in images can induce people's emotional responses and influence their decision-making processes through the cognitive and affective components of the content (Moutinho, 1987).

Despite the popularity and importance of images, research on this topic in business research, particularly in tourism and hospitality, is still in its infancy (Arefieva et al., 2021; Filieri, Yen, & Yu, 2021). This is mainly due to the fact that: 1) images, as unstructured data, present technical challenges in processing and analyzing (Ma, Xiang, Du, & Fan, 2018; Vu, Li, Law, & Ye, 2015); 2) the current understanding of the image features is fragmented, which prevents researchers from effectively approaching images as data sources (Li & Xie, 2020). Through images, researchers can gain deep insights into customer behavior, habits, and moods, providing practical guidelines for practitioners to distinguish customers' needs, and more effectively improve customer experience. In fact, image analytics has much to offer when it comes to understanding tourist behavior.

In tourism, while previous reviews through traditional approaches have provided theoretical engagement with images (e.g., Park and Kim, 2018; Balomenou and Garrod (2019); Volo and Irimiás (2021)) (See Appendix 1), there present significant opportunities to develop a holistic and detailed methodological guideline for images analytics to harness its potential to generate valuable insights while ensuring its methodological rigor. Several studies have attempted to provide some initial guidelines for image analytics but they are largely context-dependent with limited ability to generalize (e.g., Steen Jacobsen (2007); Bakri, Krisjanous, and Richard (2020)). An important step to advance the current "transitional" literature is to provide a more rigorous methodological guideline for image analytics and a clear-cut representation of existing research. As suggested by Park and Kim (2018), future visual research in tourism should widen the research horizon and method selection beyond conventional practices.

Building on extant literature, the current study advances the tourism and hospitality literature both theoretically and methodologically by 1) offering a critical review of image analytics in tourism; 2) developing a

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rigorous methodological framework for image analytics; and 3) establishing a clearer research agenda for image-related studies. Different from previous studies on images, it is important to note that our study focuses on the methodological aspect of images as a data source rather than visuals or a construct that theoretically engage with images.

2. A brief introduction to image analysis

2.1. Definition and importance of image

An image depicts a visual perception that resembles a subject (Attneave, 1954). Visual perception is the primary information source when people interpret and understand the world (Cole & Balcetis, 2021). Images enable viewers to understand the details of a situation or an event in a concise, clear, and direct way (Iyer, Webster, Hornsey, & Vanman, 2014). Images possess multi-sensory effects, including metaphors that can be visual, language, mathematics, and music (Zaltman, 1997). In addition, unlike traditional textual content, which is the primary source of empirical data in tourism and hospitality research, images effectively communicate the embedded meaning through the manifest and latent content. As such, images present valuable opportunities to effectively evaluate, trace, interpret, and clarify tourist behavior (Berger et al., 2020).

2.2. Features of images

Research shows that images contain a set of fixed broad features:

1) Color-centric cues (Ferwerda, Schedl, & Tkalcic, 2016; Wang & Yu, 2005)
2) Textual characteristics (Tamura, Mori, & Yamawaki, 1978)
3) Composition (Datta, Joshi, Li, & Wang, 2006)
4) Semantic content (Machajdik & Hanbury, 2010)
5) Spatial and temporal information (Majid, Chen, Mirza, Hussain, & Chen, 2015).

The different components have distinct impacts on consumers' attitudes (Kuo & Zhang, 2021), purchase intentions (Pennings, Striano, & Oliverio, 2014), and behavioral outcomes (Lian & Yu, 2019). The following section provides a detailed review of each feature.

1) Color-centric cues

The human visual system automatically uses color to measure parts of the electromagnetic spectrum (Tkalcic & Tasic, 2003). An image is a spatial distribution of color points, where any color could be a combination of Hue-Saturation-Value (HSV) color space (Chakravorty, 2018; Ferwerda et al., 2016; Tkalcic & Tasic, 2003). Color-centric features consist of three parameters: hue, saturation, and value. Hue is the tone of an image and describes the color quality of each pixel (Ferwerda et al., 2016). Colombo, Del Bimbo, and Pala (1999) indicated that a red-orange environment produces a sense of warmth. On the contrary, green and blue convey a cold sensation. Psychological research indicates that color and its combinations can affect people's emotions (Chebat & Morrin, 2007). For example, red conveys happiness, vitality, and strength. Orange is a warm color, like the color of fire, which also indicates glory. Yellow represents wisdom and expansive thinking (Takahashi & Kawabata, 2018). Green conveys calm and relaxation and is the color of hope, whereas blue suggests gentleness, fairness, loyalty, and virtue. Purple, a gloomy color, can express fear. Typical examples of the

Table 1
Image features, possible theories, and impacts on viewers.

Focal object		Possible theories	Impact on the viewer
Image features	Color	Color Psychology (Whitfield & Whiltshire, 1990): People naturally produce perceptions and various feelings, thoughts, emotions and psychological behaviors related to color.	Red represents happiness, vitality and strength (Akcay, Dalgin, & Bhatnagar, 2011). Orange is the warmest color, similar to the color of fire, glory (Wagner, 1985). Yellow is related to wisdom and expansive thinking (Wagner, 1985). Green delivers calm and relaxation, the color of hope (Cyr, Head, & Larios, 2010). Blue indicates gentleness, fairness, loyalty, and virtue (Yu, Xie, & Wen, 2020) Purple reflects fear, richness, and creativity.
	Texture	Sensory Physiology (Guinard & Mazzucchelli, 1996): Texture affects human emotions and triggers tactile associations (Sartori et al., 2015).	A less rough texture conveys the most positive emotions, while a rough texture conveys the most negative (Ebe & Umemuro, 2015).
	Composition	Visual Balance (Obrador, Schmidt-Hackenberg, & Oliver, 2010): Certain layouts of the inner objects in an image are more aesthetically pleasing than others.	An aesthetic image with visual balance can reduce designers' workload and improve the quality of works and public acceptance (Jahanian, 2016).
	Semantic content	Self-presentation (Goffman, 1959): People show themselves mainly to please their audience and form an idealized self. Signal theory (Spence, 1978): under the premise of information asymmetry, recipients infer unobservable product quality based on their judgment of the signal transmitted by the signaler.	Image content as a travel inspiration source can trigger the viewer's travel desire and visit intention and can be used as a heuristic method for subsequent decision-making (Dai, Wang, & Kirillova, 2022)
	Spatial and temporal information	Theory of mobility (Sheller & Urry, 2006): travel is not just a question of getting to the destination, but a process of people's temporary mobility within the destination.	Spatial information: The activities of tourists and the attractiveness of travel places can be discovered by clustering their geo-tagged photos (Kisilevich, Krstajic, Keim, Andrienko, & Andrienko, 2010). Temporal information: The length and order of activities that a person performs over the course of a certain amount of time utilizing the so-called time-budget method, which can be used to further determine the space-time patterns of tourists (Cooper, 1981; Zhang, Zhang, & Kuwano, 2012).
Overall Image	Image itself	The Tourist Gaze (Crawshaw & Urry, 2002): Photographs as the product of the physical elements can mirror the photographer's own mental images. Uses and gratification theory (Katz, Blumler, & Gurevitch, 1973): Images that can satisfy recipient's needs as positive motivation and active media content use (Smock, Ellison, Lampe, & Wohn, 2011).	Photographic images have an influence on tourists' perceptions of a place (Pan, Lee, & Tsai, 2014).

psychological effects of the above six colors on consumers are in Table 1.

The second parameter is saturation. Saturation is the amount of pigment in the color (Kuo & Zhang, 2021). Saturated colors are pure and vivid. Saturation directly influences three axes of human emotion: Pleasure, Arousal, and Dominance (Valdez & Mehrabian, 1994). The Pleasure scale represents how pleasant one feels about images. The Arousal scale measures how energized one feels. The Dominance scale measures the control degree one feels. Valdez and Mehrabian (1994) highlighted that the more saturated the colors are, the more pleasant, arousing, and dominant they tend to be. The last parameter is the value that indicates the lightness of a color. The colors of high value are lighter, and those of lower value are darker (Chung & Saini, 2021). According to the Pleasure-Arousal-Dominance model, the value of a color has a strong positive effect on pleasure reactions and has a negative effect on arousal and dominance responses.

2) Texture characteristics

The texture is the innate input of human senses, affecting perception and emotions. It gives the viewer a "visual sense" of artwork and triggers tactile associations (Sartori, Şenyazar, Salah, Salah, & Sebe, 2015). Texture – like color - can influence people's emotions. For example, intentionally blurred images often appear in art photography to express fear (Machajdik & Hanbury, 2010). A less rough texture conveys positive emotions, while a rough texture conveys the most negative emotions (Ebe & Umemuro, 2015).

3) Composition

The composition of an image represents the spatial relations among its various parts. Harmonious design, for example, is essential in artworks (Machajdik & Hanbury, 2010), as the balanced space distribution conveys a sense of stability and happiness. There are four rules related to spatial composition including the Golden Section Ratio, the Rule of Thirds, the Gestalt Theory, and the Depth of Field. First, the Golden Section Ratio is an irrational mathematical constant, approximately 0.618. The balance of the smaller segment to the larger part is the same as the larger segment to the sum of both segments (Padovan, 2002). Nikolic, Cosic, Pecujlija, and Miletic (2013) showed that people generally prefer shapes with the golden ratio. Second, the Rule of Thirds represents a principle for good composition, which divides an image into three average parts. For instance, Li et al. (2019) found that when posters or game icons are designed, designers will consider the composition of each object to achieve a visual balance. Everyone sees balance as beauty (Jahanian, 2016). Third, the Gestalt Theory proposed by Arnheim (1957), suggests that lines in an image can induce emotional effects. Previous research (Arnheim, 1957; Colombo et al., 1999; Datta et al., 2006; Machajdik & Hanbury, 2010) has shown that the horizontal line is associated with the static horizon, conveying calm, tranquility, and relaxation; the vertical line is clear and direct, representing dignity and eternity; the diagonal line is unstable and conveys vitality. Lastly, the Depth of Field (DOF) is the distance from the camera that has acceptable sharpness in the image. Specifically, the Depth of the Field area is significantly more apparent. Professional photographers use low Depth of Field to blur the background, thereby simplifying the image, reducing "business", and drawing the observer's attention to sharp objects of interest (Machajdik & Hanbury, 2010).

4) Semantic content

Research shows that the content of an image has the most significant impacts on emotions (Afshardoost & Eshaghi, 2020; ; Lian & Yu, 2019). The appearance of a human face is one of the critical content parts of an image. Facial expression can provide clues about feelings, intentions, and the personalities of person(s) featured in the picture (De la Torre & Cohn, 2011). Facial features (i.e., facial aesthetic, gender, age, ethnicity, smiling expression and face proximity) in images directly influence consumer intentions (i.e., trustworthiness, attractiveness, sociability, competence) and lead to a price premium (Peng, Cui, Chung, & Zheng, 2020). Barnes and Kirshner (2021), for example, examined the relationship between Airbnb host facial features and their pricing and found that host trustworthiness and attractiveness conveyed by facial images lead to a price premium for Airbnb listings.

"Object" is another critical semantic content embedded in images. Landscape content has been frequently used to classify images in tourism (Le Busque, Mingoia, & Litchfield, 2021). Sheng, Zhang, Shi, Qiu, and Yao (2020) found out that magnificent architecture, scenic spots, and beautiful landscapes are the tourists' favorite content in online images. Research also found that the presence of more concrete images (i.e., products or services) contributed to increasing consumer purchase intentions (Walters, Sparks, & Herington, 2012). Kuhzady and Ghasemi (2019) found that food and drink were Portugal's most engaging image content for Instagram's followers. In addition, images of animals are featured as cute content commonly shared on social media platforms, which makes people feel adorable (Meese, 2014).

Besides manifest semantic content (e.g., face, object) in images, a considerable number of models in computer vision have been developed to extract latent semantic content (e.g., emotions) in images (He, Deng, Li, & Gu, 2022; Li, Ji, Liu, Cai, & Gao, 2022).The latent content of images can reflect individuals' sentiment at the moment when the images were taken. In tourism, for example, using the deep convolutional neural network model - DeepSentiBank, He et al. (2022) identified the latent content in the user-generated destination images, such as "lonely city", "lovely beach" and "excited crowd". Similarly, Li, Ji, Liu, Cai, and Gao (2022) used a deep learning network - GooLeNet to extract review image features and denoted each image with a sentiment score between 0 (the most negative) and 1 (the most positive).

5) Spatial and temporal information

Spatial and temporal information refers to the geographical location where and when an image is taken (Bermingham & Lee, 2014). The prevalence of images shared on social media provides researchers with valuable opportunities to investigate formerly unidentified and worthwhile routes from spatial-temporal photo-taker tracks. As such, spatial-temporal data is powerful in uncovering tourists' trajectories and points of interest (Bermingham & Lee, 2014). For example, Yuan and Medel (2016) utilized geotagged photos to model individual travel routes. They found that the tourism destination interests are evenly spread among European residents. Satellite images also provide large-scale spatial and temporal information which can better monitor tourism activities (Almer & Stelzl, 2002; Wu & Chen, 2016). For example, Wu and Chen (2016) utilized satellite images of Kenting National Park in Taiwan to examine the ecological environmental changesand found that the main attractions vary to different degrees on spatial-temporal scales.

Studies employing practical data-driven methodologies on the image have increased significantly as a result of the increased availability of image data in tourism (Kar & Dwivedi, 2020b). While extant studies have succeeded in identifying scenes, objects, and places from big image data sets, their engagement with theory is rather limited (Kar & Dwivedi, 2020a). Thus, linking the image features with possible theories present valuable opportunities to unpack the nuance of images and its impacts on user behavior in tourism. Table 1 presents the relevant theories related to the five image features and their impacts on viewers.

3. Procedures, algorithms, and tools for image analytics

3.1. Image analytics framework

A close examination of extant literature using images as a source of data has revealed two challenges 1) applicability and 2) consistency.

The applicability issue is that extant studies have developed their image analytics approach largely based on one type of image data with the majority on social media images . For example, Lin, Liang, Xue, Pan, and Schroeder (2021) analyzed images from Flicker to examine tourism destination image and discovered that image content offers crucial information on ambiance and emotions. While social media images are informative and insightful, other sources of images, such as satellite images, can provide a more precise location for tourism destinations and more detailed information (Wati & Narieswari, 2011). Satellite images are ultrahigh-resolution and can be used to obtain information on the amount of green space, sloping shores, local topography, changes over time, and the sunlight received by a beach to assess the environmental degradation caused by the development of the tourism (Hou, Bai, Li, Shang, & Shen, 2021). This information would not be available through social media images, thus presenting methodological challenges for using social media data-based image analytics framework to analyze satellite images; 2) consistency refers to the fact that the methodological approaches to image analytics in extant studies vary. For example, Yu et al. (2020) used content analysis and linear regression analyses to investigate how an Instagram post's pictorial features (e.g., colors) influence its popularity. Arefieva et al. (2021) adopted machine learning approaches to uncover destination images. Confronted with the increasingly big data set, the methodological approaches to image analytics are diverse, failing to make a methodological taxonomy to systemize the research processes. For example, Li, Xu, Tang, Wang, and Li (2018) provided a three-step framework for online image analysis in tourism research: (1) data pre-processing, (2) metadata clustering, and (3) trajectory discovery with a mere focus on clustering methods for tourist trajectories. Our framework differs in that we overcome the two challenges by providing various data sources for image collection and generalizing extant approaches from a macro-perspective, which offers a useful procedural guideline for researchers seeking to perform image analytics.

As such, based on the review of extant studies, a methodological framework for image analytics has been developed that neither requires a specific image source nor relies on specific domains (Fig. 1). Our framework consists of four steps: (1) data collection, (2) data transformation, (3) mapping data to image analytics, and (4) visual representation. In step 1, researchers identify the data source and collect the images. For example, researchers may use scrapping algorithms to harvest social media images (Andreotta et al., 2019). In step 2, image data need to be transformed including cleaning (e.g., deduplication) and pre-processing (Bow, 2002). In step 3, pre-processed image metadata are mapped into computational models for further analysis. Specifically, images are first processed through computer vision techniques (i.e., feature extraction and classification) and then the outputs (e.g., labels) are analyzed by using advanced statistical analysis (i.e., clustering, pattern mining and regression). For example, Arefieva et al. (2021) used machine learning algorithms called k-means to cluster Austria's destination images on Instagram. In step 4, the results of image analytics are reasoned and reported by researchers with an effective narrative called visual representation (Edwards, Cheng, Wong, Zhang, & Wu, 2017). Deep insights into the image data can be gleaned from the interactive and iterative process between the human mind and computers. Often, the data processing algorithm works iteratively in the first three steps as each step would require some degree of processing to ensure that the mega data of images can be extracted and used for further analysis (Brusch, 2022; Li et al., 2018).

Step 1: Identify the data source and collect images, e.g., scraping the images from social media.
Step 2: Check the quality of image data, e.g., the pixels of images. Then, apply algorithm to transform images.
Step 3: 1) Choose computer vision techniques to recognize images.
2) Select the appropriate statistical tools and methods for image analytics, e.g., Python packages for clustering.
Step 4: Report the results by visual representation.

3.2. Data collection

As the famous saying goes, "an image is worth a thousand words". When images are used as a data source, the process starts with image generation and acquisition. Image data adopted in tourism and hospitality can be divided into four categories (Li et al., 2018). These include official release images (e.g., official websites, brochures, postcards), volunteered-employed images, user-generated images (e.g., social media platforms) and professional images (e.g., Google Street view) (Table 2). Images also contain rich and useful metadata information, including user-related information (users ID), locations (latitude and longitude), temporal information (the time taken and uploaded time), textual information (title, description, hashtags), and the image itself

Table 2
Image collection Tool.

Image Data Source	Commonly data collection approach
Official release images	Data scraping tools (e.g., Instamancer)
Volunteered-generated images	N/A
User-generated images	Platform API (e.g., Flicker API)
Professional images	Database (e.g., Google Earth)

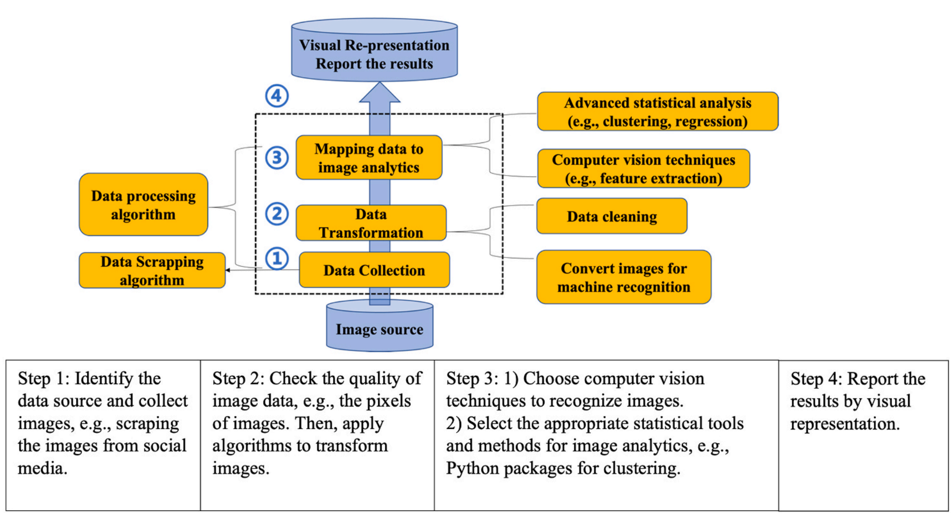

Fig. 1. A methodological framework for image analytics.

(numbers and content) (Go, Kang, & Nam, 2020).

The official release images refer to photographs released by destination marketing organizations or service providers on their official websites, social media channels, and brochures or postcards. These images are critical for brands and destinations as they influence viewers' attitudes and behavioral outcomes towards the business and destination (Lian & Yu, 2019; Majid et al., 2015). For example, Luo, Tang, and Kim (2021) collected the cover images on an online travel agency website – HomeAway and found that images containing façade and property amenities can positively influence customers' attention. Instamancer is a data scraping tool to support such image research projects (Norman et al., 2021).

Volunteered-employed images characterize the participants' tourist experience, which can help researchers to gain insights into their motives, preferences, and tastes. Researchers invite tourists or residents to take images related to the research topic and to write a photo blog. The volunteered-employed data collection methods are primarily adopted in studies concerning the assessment of tourism destination images (Garrod, 2007), pinpointing basic properties of tourism route design (Go et al., 2020), and tourist behavior (Li et al., 2018).

User-generated images are among the most popular data sources in tourism due to their wide availability. User-generated images are usually collected from three image-oriented platforms: Flickr, Panoramio, and Instagram (Li, Zhang, et al., 2019). Researchers can obtain user-generated images through the Application Programming Interface (API) provided by these platforms. User-generated images also convey rich metadata information, such as locations and other associated data points, which provide powerful insights into tourists' behaviors. For instance, Önder (2017) used API to collect geotagged images on Flicker to classify multi-destination trips in Austria.

Satellites and drones are often used to take professional images, including high-resolution aerial images, remote sensing images, street scene images, and 3D city modeling images. These professional images are usually stored on government websites or image provider websites (Turner et al., 2015). Static street view images, for example, can be downloaded for free through the API interface provided by map providers. If these images are not publicly available, they normally need providers' permission to access.

3.3. Data transformation

Data transformation is critical to processing an image by transforming the raw image data and its valuable features for further analysis, which involves data cleaning and pre-processing.

3.3.1. Data cleaning

Data cleaning involves the removal of extraneous noises that do not fit the research purpose or result in image de-duplication. For example, using user-generated content from travel web pages in studying Barcelona's destination image, Marine-Roig and Clavé (2015) found that a web page contains numerous noises, such as advertisements, which are not related to the study aim. As such, they eliminated the irrelevant content in the raw data.

3.3.2. Data pre-processing

Data pre-processing transforms the raw data into graphs or matrixes so that the image data can be recognized and processed for relevant analysis. For instance, Chang, XING, ZHANG, HAN, and Kim (2020) used a python package - OpenCV-Python to preprocess images in a 299×299 matrix. The processed images were then normalized and stored in arrays of python files.

3.4. Mapping data to image analytics

Manual coding of images is possible on a small scale (Joo, Bucy, & Seidel, 2019). However, manual coding is limited in scope and cumbersome to apply consistently across different settings (Bucy, Gong, & Browning, 2016, p. 63). Research evidence suggests that automated coding (computer vision and machine learning techniques) is useful for scaling up manual coding, particularly when dealing with a large amount of image data (Sitnikov, Gubinskiy, Ivaschenko, & Nikiforova, 2021). Computer vision techniques are part of artificial intelligence that uses computers to extract, analyze and understand visual data like human visual systems (e.g., images), which includes feature extraction and classification (Xu et al., 2021). The next step is to adopt advanced statistical analysis (e.g., clustering, pattern mining, and regression) to process the output from feature extraction to gain deeper insights. Advanced statistical analysis offers substantial benefits over the standard method (e.g., mean, standard deviation) by providing more robust results and yielding more smooth meaningful probability densities (Pollard, Chang, Haran, Applegate, & DeConto, 2016). There are primarily five computer-assisted analytics methods for analyzing images: feature extraction, classification, clustering, pattern mining, and regression (Table 3).

3.4.1. Computer vision techniques

3.4.1.1. Feature extraction. Feature extraction focuses on three main perspectives: image object recognition (El-Gayar & Soliman, 2013; Lowe, 2004); semantic content analysis (Rao, Xu, Liu, Wang, & Burnett, 2016;); and emotion recognition (Borth, Ji, Chen, Breuel, & Chang, 2013;). This method can be divided into low features and high features extraction. Low features relate to the color, texture, composition, spatial and temporal information of images, while high features refer to the semantic content and emotion of images. For instance, color-based algorithms (color histogram) can efficiently detect the color distribution features of any given image (El-Gayar & Soliman, 2013). A color histogram cannot match pictures with complex texture backgrounds. To overcome the limitations, texture-based algorithms were developed. Lowe (2004) for example, began by extracting the invariant features and presenting the Scale Invariant Feature Transform (SIFT). This feature extraction is broadly applied to image mosaic, recognition, and retrieval. To unpack the semantic content of images by viewers, researchers have begun to extract the high features to recognize the semantic content (Zhao et al., 2021). For instance, Rao et al. (2016) employed bag-of-visual-words (BoVW) to detect any object or images.

Another popular research stream is related to the emotion feature extracted from images. Currently, the self-report questionnaire method is the most common measure of emotion in tourism (Li, Scott, & Walters, 2015). However, the self-report measure is subject to various biases in reliability and validity since it often depends on participants' recall of their experiences after travel, which can result in socially desirable responses (Braun, Jackson, & Wiley, 2001). With the development of computer vision techniques, data scientists develop machine learning algorithms to extract the emotion of images to meet the high need for high-level understanding without cognitive intervention (Zhao et al., 2014). For example, Borth et al. (2013) laid the foundation work in the visual sentiment ontology, which detects the emotion, affect, and sentiment from visual content through the development of the Sentibank, which contains 1200 adjective and noun pairs to fulfill the emotive gap between image semantic content and provoked emotions. Convolutional Neural Networks (CNN) have gained great attention in affective image content analysis in recent years. DeepSenti Bank, an analysis tool developed by Chen et al. (2014) based on CNN, can effectively extract the content and emotional keywords in images. He et al. (2022) used DeepSenti Bank to detect emotions and objects from Los Angeles' destination images on Flicker. They found that the most frequently detected cognitive keywords were "city," "food," "view," "beach," and "street", and the most frequent affective keywords were "great," "beautiful," "famous," "amazing," and "lovely". The other related applications of emotion features include opinion mining,

Table 3
A taxonomy of image data analysis.

Pipeline	Approach	Method	Tool	Outcomes	Specific application
Feature extraction	Low-level feature extraction (El-Gayar & Soliman, 2013)	● Computer vision • Color histogram • SIFT detector	Programming	● Represent the color or texture distribution ● Extract distinctive invariant features from images.	● Image mosaic ● Image recognition ● Image retrieval
	High-level feature extraction	● Computer vison • BoVW (Rao et al., 2016) • ANPs (Borth et al., 2013)	Sentibank	● Extract and encode the multi-scale blocks of images. ● Reveal the latent semantic meaning	● Sentiment prediction ● Object detection
	Emotion feature extraction (Zhao et al., 2021)	● Computer vision • CNN(Zhao et al., 2021)	DeepSentibank	Investigate the relationship between visual stimuli and emotions.	● Opinion mining ● Psychological health ● Business intelligence ● Entertainment assistant
Image data analysis	Classification (William, Ware, Basaza-Ejiri, & Obungoloch, 2018)	● Machine learning • Bayesian networks • Support vector machines • Decision tree • K-nearest neighbor ● Computer vision • CNN • Vision transformer (Dosovitskiy et al., 2020)	● Manual class labels ● Online tools • Google Cloud Vision API • Baidu Cloud • Microsoft Project Oxford • Clarifai (Jaakonmäki et al., 2017)	Label and classify the images to better understand them.	Tourists' photo classification
	Clustering (William et al., 2018)	● Machine Learning • K-means • DBSCAN • Hierarchical	Programming	Partition image data into clusters on the basis of similarities.	● Medical imaging ● 3D imaging ● Remote sensing ● Tourism destination
	Pattern mining	● Machine Learning • Spatial analysis • Markov Chain	● Google trends ● Weka (Hall et al., 2009)	Detect valuable knowledge from huge datasets, such as patterns, trends, and rules	● Movement prediction ● Classical travel sequences ● Personality prediction
	Regression (Jaakonmäki et al., 2017)	● Machine Learning • LASSO	● R ● Stata	Statistically model the image content with other variables (i.e., likes)	Social media engagement

psychological health, business intelligence and entertainment assistant (Schwenzow, Hartmann, Schikowsky, & Heitmann, 2021; Sitnikov, Gubinskiy, Ivaschenko, & Nikiforova, 2021; Vendemia, DeAndrea, & Brathwaite, 2021; Zhao et al., 2021).

3.4.1.2. Classification. Classification is the process to obtain a set of human-given or machine-identified labels (Al-Doski, Mansor, & Shafri, 2013). Various classification approaches can be put into two general categories: machine learning and deep learning. The common machine learning techniques contain Bayesian networks, Support Vector Machines (SVM), Decision tree, and K-Nearest Neighbor (KNN). Machine learning requires extracting features manually, while deep learning shifts the burden from humans to computers (Shen, Wu, & Suk, 2017). The limitation of traditional data analysis is that attribute categories need to be manually formulated, which is inefficient when analyzing big data (Taecharungroj & Mathayomchan, 2021). Google Cloud Vision is a user-friendly API tool that helps researchers to interpret the semantic content and features of an image. Ferwerda et al. (2016) employed this easy-to-use tool to relate the content characteristics of Instagram profiles to the personality features of the posters. Similarly, Jaakonmäki, Müller, and Vom Brocke (2017) used Clarifai image recognition API to capture the visual features and classify images. In addition, deep learning Applicant Program Interfaces (APIs) are provided by some cloud service suppliers (e.g., Baidu, Alibaba, Azure) to help consumers accomplish computer vision classification tasks (Li, Ji, et al., 2019). Image classification has been broadly applied to tourists' photo classification (Cho, Kang, Yoon, Park, & Kim, 2022).

3.4.2. Advanced statistical analysis

3.4.2.1. Cluster analysis. Cluster analysis is designed to identify the intrinsic attributes, structure, and information. Three basic algorithms: K-Means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and Hierarchical clustering, are frequently used. Using the K-Means technique can quickly group image pixels based on given feature vectors and original centroids (Burney & Tariq, 2014). However, this method needs to set cluster numbers before analysis. In contrast, DBSCAN is a non-parametric clustering tool based on density without the need to know the number of clusters initially (Tran, Drab, & Daszykowski, 2013). Hierarchical Clustering starts with each point being considered a cluster and recursively combining pairs of clusters until all issues are part of one hierarchically constructed cluster (Olson, 1995). Önder (2017) conducted an image cluster analysis to categorize the same regions and cities based on tourists who had been to the related destinations. Similarly, applying big data analysis to a tourism marketing context, Arefieva et al. (2021) identified certain destination image clusters for experiencing alpine wilderness and spirituality.

3.4.2.2. Pattern mining. Pattern mining aims to identify the association between the data, which contains spatial analysis and Markov Chain. Pattern mining has been used to examine tourist movement prediction, classical travel sequences and personality prediction. For example, Pan et al. (2014) searched for the association rules between image attributes, travel motives and tourists' emotional attitudes toward destinations to help marketers choose the most attractive images for tourists. In addition, researchers can predict the next tourist attraction a tourist might visit based on their current location (Kurashima, Iwata, Irie, & Fujimura, 2013). Ferwerda et al. (2016) used the visual features of Instagram profiles consisting of helpful information to predict users' personalities.

3.4.2.3. Regression. Regression analysis is used to examine the impacts of image features on other variables, such as social media engagement. Jaakonmäki et al. (2017) used an at least absolute shrinkage and selection operator (LASSO) regression analysis on Instagram images to identify the most influential characteristics associated with social media engagement. Their results indicate that people's engagement can be increased by those images with landscapes and several emojis because they provoke people's positive emotions (e.g., relief, love, joy). Table 3 outlines the taxonomy of image data analytics, including the approaches, methods, tools, outcomes and specific applications.

4. Ethical considerations

Tourism and images are inseparable as tourists often venture off to destinations with cameras or smartphones to capture their moments using images (Fennell, 2020). While tourism researchers have given growing attention to the ethics of images in recent years (Fennell, 2020; Höckert, Lüthje, Ilola, & Stewart, 2018), the ethical consideration of images in tourism research has been rather limited.

In line with Wiles et al. (2008)'s visual ethics, publicity, privacy, anonymity, confidentiality, consent, and dissemination or potential re-use of data are needed to be taken into consideration when analyzing images in tourism.

According to the Data Protection Act 2018 (Cornock, 2018), the processing of personal data is permitted when the data subject is made public. For example, social media platforms, such as Instagram, have privacy settings that allow platform users to determine what posts they want to make publicly available. Thus, researchers have agreed that when the images are publicly available, it is not necessary to obtain users' consent when analyzing them (Bishop & Gray, 2017; Ravn, Barnwell, & Barbosa Neves, 2020).

However, when the images contain information that can identify individuals, anonymity and de-identification of the people in the images are required (Ravn et al., 2020; Wiles et al., 2008). For instance, despite having used publicly available image data, Caruso and Roberts (2018) have suggested some practical ethical practices, including the removal of the features that can identify users such as placing a black box across the eyes in images, and replacing usernames with pseudonyms to protect the privacy and security of users. In addition, Finn and Wright (2016) suggested that images of people captured by drones can have privacy implications as images captured by drones can identify people's geographical data and body features.

If the data are not judged to be publicly available, informed consent is needed to protect the privacy of participants (Michaelidou, Micevski, & Cadogan, 2021). For example, the volunteered-employed photography technique requires the informed consent of participants to participate. Meanwhile, the principle of minimizing harm and risks involved for subjects or participants in each step of the image research process needs to be considered (Varela-Rodríguez & Vicente-Mariño, 2020).

Furthermore, Joo and Steinert-Threlkeld (2022) indicated that image analytics that employs computer vision techniques has the "model biases" ethical challenge in the pre-trained data, especially in automatic facial analysis (e.g., facial detection, recognition, and classification). For example, three commercial gender classification APIs respectively released by Microsoft, IBM, and Face++ have been criticized due to the worst classification performance of darker-skin females (Buolamwini & Gebru, 2018). Xu, White, Kalkan, and Gunes (2020) suggest that mitigating model bias is required to ensure the accuracy and fairness of image analytics results.

5. Current status of tourism and hospitality research using image analytics

The present study employed a snowballing approach to select relevant journal articles that have used images as the data source. A snowballing approach is to use the reference list of a paper to identify additional papers, including start set, backward snowballing and forward snowballing (Wohlin, 2014). This approach is particularly powerful in identifying important sources published in obscure journals (Greenhalgh & Peacock, 2005). The first step of the snowballing procedure is to identify the tentative start set of articles, which exists in the research topic. That is, image analytics in tourism and hospitality in our study. "Image(s)", "image analytics" "visual(s)" "photo(s)" "picture(s)" and "photography" were used as the keywords in Google Scholar and Scopus. All the journal articles on images/visuals without using image analytics or not using images as the data source were excluded. As a result, 27 journal articles are the start set. Then, backward snowballing was applied to recursively assess each journal article's references manually as potential review candidates. Hundreds of results that largely deal with destination image studies and do not use actual images have been excluded from the first step. Hence, the 27 journal articles are included in the full-text review. Finally, forward snowballing was conducted to identify additional journal articles based on the journal articles who cited our star set. While there are a number of cited papers, we are unable to identify additional journal articles that fit our selection criteria. Thus, the final review contains 27 journal articles in tourism and hospitality for further analysis (see Appendix 2).

Specifically, a very small number ($N = 4$) of articles published prior to 2010 mainly used questionnaires to investigate tourists' perceptions of given images. The period between 2011 and 2020 ($N = 14$) saw significant growth in the number of articles due to the rise of image-oriented social media platforms (e.g., Instagram, Facebook, Flickr, Pinterest) and the use of visual-based methodologies (Nanne et al., 2020). It was found that the articles published as of 2021 ($N = 9$) used advanced image analytics methods such as machine learning (e.g., Support vector machines, K-nearest neighbor) and deep learning methods (e.g., CNN, Vision transformer) (Luo et al., 2021). Our review only identified five articles in hospitality, highlighting the fact that hospitality research is in its infancy in tapping into the potential of image analytics and offers enormous theoretical and practical opportunities to advance the hospitality field using image analytics, which our study directly contributes to fulfilling this research gap.

5.1. Research approaches from 2001 to 2010

There are only four articles in this period. The research themes and theories employed in these articles mainly revolve around destination image. For example, Baloglu and Mangaloglu (2001) focus on the visual representation of travel intermediaries' images. Similarly, Choi, Lehto, and Morrison (2007) and Hunter (2008) concentrated on destination image representation. Grosspietsch (2006) focused on the comparison between projected and perceived images. The images analyzed were mainly collected from promotional tourist brochures and guidebooks. Questionnaires were the main approach used during this period, leading to the analysis being mainly exploratory and relying on subjective judgment, which overlooks the semantic content of images.

5.2. Research approaches from 2011 to 2020

The period from 2011 to 2020 saw rapid growth in research on tourism images due to the increased accessibility and availability of image data, with a total of 14 articles. Research topics include tourist attitudes toward destinations, tourist trajectories and preferences, and hotel images. Theories in this period have diversified. They include projected and perceived images, the manifest and latent content of images, self-objectification, and complex network theory. The main research focus of this period was still largely on the analysis of tourist-perceived images. For example, Kim and Stepchenkova (2015) examined the effect of tourists' images on their perceptions of the destination. They suggested that images contained not only manifest content but also latent content. This period also saw growth in the different types of images that researchers were now examining. Chaplin and Brabyn (2013) analyzed satellite images to investigate the impacts of tourism on forest cover. In addition, Zach, Ma, and Fox (2019) used online hotel image reviews to investigate the concerns of customers. These studies led to the advancement of the analytic approach to images, including spatial analysis, cluster analysis, eye tracking techniques, and deep learning techniques. For instance, Zhang, Chen, and Li (2019) investigated user-generated photos and geotagged images to conduct cluster and spatial analysis. Through this analysis, the authors were able to identify the travel trajectory and preferences of tourists. Li, Huang, and Christianson (2016) employed eye-tracking to record consumers' visual attention toward tourism images. However, little research over this period explored how travel images affect tourist behaviors, overlooking the cognitive and affective effects of image content.

5.3. Research approaches from 2021 to 2022

The last two years saw the publication of 9 journal articles from 2021 to 2022. Five journal articles focused on hospitality images to understand the importance of host profiles in the accommodation industry. For example, Luo et al. (2021) examined the impact of hosts' images on the process of consumers' decision-making, while Barnes and Kirshner (2021) examined trust and attractiveness based on the facial features of the hosts on Airbnb pricing. The theoretical frameworks employed during this period include color psychology (e.g., Yu et al., 2020). For example, Barnes (2022) used color psychology to interpret US accommodation's massive image data sets to test the small palette principle and the visual coherence perspective. This period has also seen the popularity of interdisciplinary research using more advanced methods such as machine learning and deep learning. The reason for this is that the sheer scale of images available makes it impossible to use traditional manual coding. However, these recent studies only focus on a single feature of the image, which fails to explore the richness of images in their color, texture, composition, and semantic content. These limitations highlight the future opportunities now available to gain extended insights by using image analytics in tourism and hospitality and to broaden its engagement with the theories and practices that this extension represents.

5.4. Critical reflections

While we have seen progress in the use of image analytics in tourism and hospitality research, the literature in this area is still limited. Firstly, the extant studies have progressed in terms of their use of big data and GIS tools to explain what tourists do and/or where they go (McKercher, Filep, & Moyle, 2021). However, they fail to fully explain why people make these decisions. Future research using traditional methods, such as interviews, can offer insights into why. Secondly, the current studies on this topic focuses largely on the semantic content of the images, thereby overlooking the impact of the image content on behavioral outcomes (Kiper & Ulema, 2021; Kuhzady & Ghasemi, 2019; Li et al., 2018). Little is known about how images affect user engagement (i.e., reviews help votes, likes, comments), subsequent travel intentions, and destination choice. Thirdly, the current research tends to pay most of its attention to the specific feature of images (Deng & Li, 2018; Nikolic et al., 2013; Yu et al., 2020), overlooking many of the other rich features they contain. Fourthly, the accessibility and availability of image datasets have created a data-driven research focus for tourism and hospitality research without in-depth conceptual and theoretical engagement.

6. Implications for tourism and hospitality research

The study contributes to our theoretical and methodological knowledge of image analytics in the tourism and hospitality literature. Given the growing availability of image data and a dearth of guidance on how to analyze these in tourism and hospitality, this paper provides a taxonomy for performing image analytics guided by a set of theoretical underpinnings. It also details the main methodological approaches and tools that researchers can use when conducting research in this area. A set of research propositions for future research is discussed to pave the way for further research endeavors using images as the main data source.

Given the novelty of image analytics in tourism and hospitality, there are ample opportunities for future research to extend this approach, including 1) expanding research topics, 2) exploring the dyads between image producers and image receivers, 3) expanding data sources, and 4) methodological challenges and opportunities. Table 4 outlines the image content involved in the communication between image producers and receivers.

6.1. Expand research topics

6.1.1. Service robots' visual design in hospitality

Service robots are now commonly used in hospitality to perform basic tasks (Ivanov & Webster, 2021) and its images have been widely used to showcase hospitality business's technological distinction. For example, hotels usually use images of "robot reception" to convey the their innovation for check-in, room services, and concierge services (Ivanov, Webster, & Berezina, 2017). The first impression of a service robot image depends on the robot's appearance and visual design, such as human-like traits and emotions (Tung & Au, 2018). While extensive research has explored the influence of human-like traits and emotions, the visual design of robots as shown in the images is overlooked (Hanson et al., 2005; Ivanov & Webster, 2021). Previous research in images has shown that visual features, including color, texture, composition, and facial expressions, can have a significant influence on viewers' perceptions (Barnes, 2022; Ebe & Umemuro, 2015; Obrador et al., 2010; Peng et al., 2020). However, how robotics' visual design in images can leverage these features remains untapped in hospitality research.

6.1.2. Animated GIFs and tourism

The animated Graphics Interchange Format (GIF) refers to a moving image data format that has a simple animation (Juzar & Munir, 2016).

Table 4
Image producers and receivers.

Image Producers	Image Receivers		
	Consumers	Brands	Institutions
Consumers	Social media travel content Online image in hotel reviews (Guo, Pesonen, & Komppula, 2021; Tran, 2020)	Tourists perceived images (Beerli & Martín, 2004) Consumer complaints (Aguiar et al., 2018)	Social media movement (Allen, Chen, & Ferrara, 2021)
Brands	Influencer marketing in tourism (Argyris et al., 2020) Celebrities Advertising images (Lim & Childs, 2020)	Business-to-Business communication (Singh, Marinova, & Singh, 2020)	Satellite images (Duan, Cao, Shen, Liu, & Xiao, 2019)
Institutions	News coverage (Hsu & Song, 2013) Travel guidebooks and magazines (Bieger & Laesser, 2004)	N/A	N/A

Animated GIFs have high platform portability and vivid emotional expression, which are more expressive than still images (Liao, Peng, & Cao, 2021). Animated GIFs can convey and depict certain information when introducing a new product or showcasing a new product feature (Bashirzadeh, Mai, & Faure, 2022). Thus, animated GIFs are increasingly being utilized in tourism to amplify text messages and convey emotions in online communication (Highfield & Leaver, 2016). Nematizadeh, Atayee, and Mirabi (2021) designed and presented the internet advertising model with the GIF marketing method in Iran's tourism hubsand found that GIF attractiveness and content are important components of the model to improve the competitiveness of e-tourism. As such, it presents significant opportunities to explore how animated GIFs manifest both theoretically and practically in tourism literature.

6.1.3. Thumbnail image in tourism

The phrase "thumbnail" originally referred to the thumb's nail. It led to the development of the now-commonly used definition: "a little picture on a computer screen that displays the appearance of a larger picture or videos". The thumbnail of a video on YouTube is a picture that, coupled with the title, provides a summary of the video (Shimono, Kakui, & Yamasaki, 2020). A single video thumbnail image has a significant impact on a user's browsing behavior, and studies have shown that having more representative thumbnails significantly boosts both user satisfaction and the effectiveness of video search activities (Christel, 2006; Gao, Zhang, & Xiao, 2009). Namely, a superb thumbnail makes a tourism promotional video more enticing to click and watch since it is usually regarded as the most representative snapshot of the video and gives viewers their first impression (Song, Redi, Vallmitjana, & Jaimes, 2016). As such, research into how to create meaningful and attractive thumbnails for tourism videos is promising.

6.1.4. Image in social movement in tourism

Images have become a critical tool in tourism social movements such as the 'over tourism' and 'degrowth' phenomenon in large European cities (e.g., Barcelona, Venice) as they convey information in the shortest amount of time (Paivio, 2013) and are influential in building trust towards the information (Park, Sutherland, & Lee, 2021). As a result, activists have leveraged image-oriented social media platforms to spread their messages, such as the anti-tourism campaign under the hashtag #touristgohome (Karyotakis, Antonopoulos, Veglis, & Kiourexidou, 2018) and the global cyber movement against wild animal trophy hunting under the hashtag #CecilTheLion (Mkono, 2018a). Although several studies examined the information dissemination of above mentioned social movements in tourism, they only focused on the events themselves, ignoring the role that images play in terms of information dissemination of tourism social movements (Karyotakis et al., 2018; Mkono, 2018a). Casas and Williams (2019) theorized that enthusiasm, anger, and fear evoked by images are powerful means for mobilizing social movements, whereas images that portray sadness are demobilizing by studying Twitter activity related to a #BlackLivesMatter protest. As these various social movements attest, images are a powerful means for inspiring groups to come together to achieve a particular social or political goal. Therefore, there is much to be gained by employing image analytics into future tourism research.

6.1.5. Cultural difference

Different cultural groups may interpret the messages delivered by the same image differently, such as the color of the image (Barber & Badre, 1998). Color connotes different meanings in different cultures. For example, red represents joy in China but danger in the United States (Cyr et al., 2010). As such, employing color psychology can provide an understanding of cultural differences in the way that images influence tourist behavior and the way that images are produced and received (Zavodna & Zavodny Pospisil, 2018). Future research is recommended to study the characteristics of user-generated images of different cultural groups to understand how the dynamics of cultural differences influence both image receivers and producers.

6.1.6. Theory building

The greater availability of image data in tourism has seen the growth of research using big data-driven approaches (Kar & Dwivedi, 2020a). While these studies have successfully identified scenes, objects, and places describing tourists' activities and experiences, it is argued that the theoretical perspectives they draw on are limited. Employing more varied (interdisciplinary) and sophisticated theories can go some way to explaining "what" is implicit (hidden) in the image as well as "how" these factors are interrelated and "why" they behave in such a manner. As noted by Kar and Dwivedi (2020a, p. 4), "these studies may lack a strongly defined dependent variable, an explanation as to why findings are so, how visual elements relate to each other, and how they explain the focal phenomenon objectively through model specification". Therefore, future research is encouraged to leverage the insights generated through big data sets of images to develop inferential research models linking the findings to tourists' and business outcomes. A mixed-methods approach combining big data image analytics and statistical and inferential methodologies is encouraged for subsequent model validation.

6.2. Exploring the dyads between image producers and image receivers

Several dyads deserve additional research attention, including tourist-tourist and tourist-firm interactions. How user-generated images influence tourist decision-making and engagement presents several opportunities. Consumers share images about brands, tourism products, experiences, or specific destinations on social media and online reviews, and these images and reviews, in turn, influence tourists' decision-making (Kaiser, Ahuvia, Rauschnabel, & Wimble, 2020). While research has shown how textual descriptions drive user engagement, little is known about how images influence users' engagement (i.e., review helpfulness vote, likes, comments) and subsequent behavioral intentions.

Another opportunity for tourist-tourist interactions is to explore the interactions between travel social media influencers and viewers. Influencer marketing has become a critical marketing tool for destination marketers (Fedeli & Cheng, 2022). Shin and Lee (2021) have observed that images in posts are important in examining whether viewers adopt the information influencers' suggestions. There is existing literature exploring the impact of travel social influencers' characteristics on viewers' travel intentions and attitudes toward the destination (Jang et al., 2021). However, they did not consider images of destinations posted by tourism social meida influencers. Recent research by Femenia-Serra, Gretzel, and Alzua-Sorzabal (2022) included images posted by influencers; however, it failed to look into how viewers and potential tourists perceived the information embedded in images. There is ample opportunity for future research to investigate specific factors in travel influencers' posts that can successfully lead to positive attitudinal and behavioral outcomes.

Turning to tourist-firm interactions, a large portion of existing work has focused on firms' or destinations' communication with tourists, including how viewers perceived a business's cover images or peer-to-peer accommodation hosts' facial expressions, neglecting the role of tourists in the value co-creation process. Vargo and Lusch (2004) argued that the tourist is always an active value creator, not a passive pre-existing value recipient. Future research is recommended to leverage the rich messages embedded in user-generated images to explore the role of tourists in value co-creation. One potential avenue for future research is to study how tourists react to tourism companies and destination campaigns and 'express destination love' using user-generated images on social media. Meanwhile, connecting user-generated images to common marketing outcomes (i.e., brand performance and consumer engagement) seems promising.

6.3. Expand data resources

Social media platforms (i.e., Instagram) are the dominant image data sources for most studies, raising issues such as constrained research questions and continuously repeated methodological practices. Conducting research on user-generated images extends these studies by providing an opportunity to complement online texual reviews (Li, Ji, et al., 2022). Review images convey rich information on numerous aspects and a more holistic rendering of the hospitality experience, hotel products and services (Ma et al., 2018). Visual cues are provided by these images to show certain product information from the users, reflecting their preferences and experiences. Future research is encouraged to combine textual reviews and review images to provide a more comprehensive view of the customer experience. In addition, review images help identify fake reviews as they aim to verify that the place/destination has been physically visited by the reviewer.

Street image is another promising and growing source of data for tourism studies, such as Google Street View (GSV). GSV enables researchers to identify travel modes and capture street activity, which complements traditional data (Hankey, Zhang, Le, Hystad, & James, 2021). Doersch, Singh, Gupta, Sivic, and Efros (2015) use the extensive database of street-level images to investigate why tourists regarded Paris as a charming destination and found that the "look and feel" of a city is not only based on well-known landmarks (e.g., the Eiffel Tower) but on smaller, more modest details such as doors, balconies, windows with railings, and street signs. The potential of street view images in assessing the level of environmental disturbance in urban neighborhoods and the relationship between facility construction and personal safety at intersections can also provide a more comprehensive evaluation of the destination environment.

As satellite images can show the actual geographical appearance, they can be used to assess the environmental suitability of natural habitats (Gosteva, Matuzko, & Yakubailik, 2019). For example, Irrgang, Lantuit, Gordon, Piskor, and Manson (2019) used the Yukon coast air- and satellite-borne images to derive shoreline change rates and assess the impact of these on travel routes. In addition, satellite image data can be used to investigate the ecological environment and its dynamic changes. By utilizing satellite images and a geographic information system (GIS), Wu and Chen (2016) examined the ecological environment in Kenting National Park in Taiwan. Their results show that ecological environment changes at the main attractions are related to the number of artificial facilities and tourists. However, satellite images are still rarely used in tourism, which could complement the traditional methodological approaches on sustainable tourism research. Future studies may consider using satellite images to examine the effects of tourism on natural resources such as forests.

6.4. Methodological challenges and opportunities

Despite the many advantages of using image analytics, mining images is not always a straightforward task. The process of image analytics can be divided into four stages including data collection, data preprocessing, mapping data to image analytics and visual presentation. The main limitation lies in the capability of the commonly adopted methodological practices. Considering the multifaceted nature of tourism images, the widely adopted approach of classifying images into a single category can miss critical information. Thus, more sophisticated approaches to analyzing images are encouraged (Park & Kim, 2018).

Recent studies show that there are increasing applications of self-configured models or APIs for feature extraction and label annotation. Image appreciation is a holistic experience. So how do researchers focus on selected features without yielding missed variable biases? For subjective technical features (e.g., object detection, face detection, emotion detection), different algorithms generate different types of errors related to the substantive problem of interest. Existing research findings rest on the accuracy of their annotator labels, which presents both challenges and opportunities for future research. Even though there are numerous commercial and open-source APIs for researchers to use. However, these APIs are trained by different datasets, which will affect their performance and challenge their performance evaluation (Kubany et al., 2020). Also, the existing models might not necessarily be appropriate or configured for tourism images. Future studies may compare the best-of-breed performance of the most efficient deep learning label classification APIs and choose one that is state-of-art that performs better than others to more accuratelly understand tourism images accurately.

Fake images also present significant challenges. With broad public accessibility, image editing tools (e.g., Adobe Photoshop) allow users to revise images without leaving traces, which evades the scrutiny of human observers (Chai, Bau, Lim, & Isola, 2020). Recent research indicates that the propagation of fake images can mislead and create complications at the individual, organization, and societal levels (Kwok & Koh, 2021; Shen et al., 2019; Xia & Hua, 2021). For instance, Kasra, Shen, and O'Brien (2018) suggested that some people may strategically use fake images to control public awareness, arouse psychological reactions, imitate ideology, and shape individual and collective memory. For tourism and hospitality businesses, some have criticized and prosecuted review sites, such as TripAdvisor and Yelp, because certain reviewers of these platforms have created unverified and malicious images in their reviews, which greatly damage a tourism business reputation, tourists' online experience, and information search efforts (Mkono, 2018b).

7. Conclusion

The multi-sensory dimensions of images offer an abundant amount of implicit and explicit information that tourism researchers can use to gain deeper insights into the contemporary tourism phenomenon (Spencer, 2010). Images can significantly enhance the objectivity and rigor of tourism research findings, which are traditionally generated from a text-centric approach (Balomenou & Garrod, 2019). With the increasing computing capability and diversification of advanced machine learning, the analysis of images becomes possible. Automated image analytics now enable researchers to generate valuable insights from these raw materials, bridging the gap between words and visual depictions that were not possible in the past.

This paper critically assesses the progress of image analytic research in tourism and hospitality and paves the way for future research. Existing knowledge using images as data sources is fragmented, and the generalizability to other contexts is highly limited. By developing a step-by-step methodological framework for tourism researchers and practitioners to conduct image analytics, this research helps ensure the scientific rigor of research findings using images. The insights from our critical review not only lie in providing a holistic view of image analytic research but also in identifying pertinent research gaps. These novel directions discussed in this study provide a starting point for investigating the important but understudied areas of images in tourism and hospitality. With the wide use of images in tourism and hospitality, we envision this work would encourage more studies to advance tourism and hospitality knowledge, both conceptual and theoretical, through the lens of images.

8. Limitation

Notwithstanding this study's significant contributions, it is not without limitations. First, this study only reviews journal publications in English and within tourism and hospitality. A review of image analytics in tourism studies in other languages and outside tourism would offer more insights into the traditions of image analytics. Second, this study only examines the literature review of academic journal publications, and further investigation into the grey literature would provide another level of insight.

Impact statement

This paper provides important implications for tourism and hospitality researchers and practitioners by offering a clear-cut representation of research topics and image analytics approaches in tourism and hospitality. This article has also developed a rigorous step-by-step image analytics framework, serving as a blueprint for understanding and conducting image analytics. This detailed knowledge of various discussions on image definitions, features and its wide implications in tourism and hospitality will greatly assist tourism researchers, students and practitioners in gaining deep insights into images by positioning themselves in the literature to set future research agendas.

Author contribution

Lingxue Zhan: Conceptualization, Data curation, Formal analysis, Methodology, and Writing – original draft. Mingming Cheng: Conceptualization, Investigation, Validation, and Writing – original draft, review, and editing, and Supervision. Jingjie Zhu: Data collection, Methodology, Revising,and editing the draft.

Declaration of competing interest

We declare that there is no potential conflict of interest.

Appendix 1. Comparison between this study and existing review/conceptual studies on images

Author	Object	Aims
Current paper	Images	● Provide a critical review of image analytics in tourism ● Provide a methodological framework for conducting image analytics
Urry (1992, 2002)	Photographs	Examine the fundamentally visual nature of the tourist experience
Rakić and Chambers (2012)	Images and videos	The first book discussing the use of visual methods in tourism studies.
Balomenou and Garrod (2019)	Photographs	The prejudice, power and performance of photography in tourism
Park and Kim (2018)	Photographic images	● Provide a critical literature review on tourism photography ● Provide key issues and challenges of visual research in tourism research.
Pike (2002)	N/A	Provide a review of 142 destination image papers during 1973–2000
Steen Jacobsen (2007)	Landscape images	Provide a review of photo-based landscape perception and assessment approaches
Volo and Irimiás (2021)	Instagram images	Advocate for rigorous visual analysis of Instagram

Appendix 2. List of Journal Articles in Tourism and Hospitality Using Images as the Data Sources

[1]. Baloglu, S., & Mangaloglu, M. (2001). Tourism destination images of Turkey, Egypt, Greece, and Italy as perceived by US-based tour operators and travel agents. Tourism management, *22*(1), 1–9.
[2]. Grosspietsch, M. (2006). Perceived and projected images of Rwanda: visitor and international tour operator perspectives. Tourism management, 27(2), 225–234.
[3]. Choi, S., Lehto, X. Y., & Morrison, A. M. (2007). Destination image representation on the web: Content analysis of Macau travel related websites. Tourism management, 28(1), 118–129.
[4]. Hunter, W. C. (2008). A typology of photographic representations for tourism: Depictions of groomed spaces. Tourism management, 29(2), 354–365.
[5]. Castley, J. G., Bennett, A., & Pickering, C. M. (2013). Wildlife Visual Imagery: Do Pictures Used to Promote Destinations Online Match On-site Species Visibility at Two Geographic Destinations? Geographical Research, 51(1), 59–70.
[6]. Chaplin, J., & Brabyn, L. (2013). Using remote sensing and GIS to investigate the impacts of tourism on forest cover in the Annapurna Conservation Area, Nepal. Applied Geography, 43, 159–168.
[7]. Hunter, W. C. (2013). China's Chairman Mao: A visual analysis of Hunan Province online destination image. Tourism management, 34, 101–111.
[8]. Matteucci, X. (2013). Photo elicitation: Exploring tourist experiences with researcher-found images. Tourism management, 35, 190–197.
[9]. Stepchenkova, S., & Zhan, F. (2013). Visual destination images of Peru: Comparative content analysis of DMO and user-generated photography. Tourism management, 36, 590–601.
[10]. Camprubi, R., Guia, J., & Comas, J. (2014). Analyzing image fragmentation in promotional brochures: A case study of two urban destinations. Journal of Hospitality & Tourism Research, 38(2), 135–161.
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