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Color and engagement in touristic Instagram pictures: A machine learning approach☆

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Color plays a critical role in recognizing tourist experiences and influencing their emotions. By classifying tourism photos on Instagram using machine learning, this study uncovers the relationship between color and user engagement based on pictures with different features. The findings show that the presence of the color blue in photos featuring natural scenery, high-end gastronomy, and sacral architectures contributes to user engagement. A red/orange color scheme enhances pictures regarding local delicacies and ambience, while the coexistence of violet and warm colors is crucial for photographs featuring cityscapes and interior design. By taking a broader lens from aesthetic philosophy and narrowing down to color psychology, this study offers guidelines for marketers to promote tourism activities through the application of color.

Introduction

Travel photography goes beyond capturing the beauty of destinations. Pictures can be influential (Paül i Agustí, 2018) in that they convey tourism experiences (Yu & Ko, 2017), shape cognitive and affective image of a destination (Lee, 2020), serve as memorabilia (Yu & Ko, 2017), and inspire traveling (Joyner et al., 2018). As visual content continues to rise in popularity, tourism aesthetics has been highlighted by modern philosophers (Kirillova & Wassler, 2019). Distinct from mass consumer products having generic appeal (Lund et al., 2018), tourism aesthetics is unique in that it delivers multisensory, engaging and lived experiences (Kirillova et al., 2014). Hence, the field of tourism stands out as it is premised upon selling an emotional journey (Gao & Kerstetter, 2018) by evoking feelings (Lund et al., 2018) and promoting a certain lifestyle (Salazar, 2012).

However, while acknowledging that visual content goes hand in hand with aesthetic judgments (Kirillova et al., 2014), the aesthetic aspect has been largely overlooked in tourism literature (Kirillova & Wassler, 2019; Scott et al., 2020). To name but a few, tourists evaluate aesthetics based on the intensity of color, the degree of crowdedness, and the spatial characteristics related to destinations (Scott et al., 2020). Among which, color is not only the most relevant aspect to tourism aesthetics (Kirillova &

Wassler, 2019), but is one of the subliminal yet profound factors associated with emotional experiences (Poels & Dewitte, 2019). Likewise, color in tourism settings has been conceptualized in the psychophysical paradigm of landscape studies as a proxy of tourist experiences (Lee, 2020). Other scholars underpinned that color offers a premise to the servicescape literature in tourism and marketing as it plays a critical role in directing one's emotional and behavioral responses (Ozkul et al., 2019).

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In fact, appealing to emotions lays the groundwork for raising advertising awareness (Datta & Kaushik, 2019) and influences consumers' subsequent behaviors on social media (Aramendia-Muneta et al., 2020). As we are amidst the age of digitalization, social media content provides compelling impact in influencing tourists' planning and decision-making process (Ma & Kirilenko, 2020; Narangajavana et al., 2017). Particularly, visually-centered social media platforms, such as Instagram, have been receiving an increasing amount of attention by tourists and marketers, especially among the younger generation (Varkaris & Neuhofer, 2017). Pictures presented on Instagram unconsciously affect tourists' rational thinking and behaviors (Poels & Dewitte, 2019) and influence how they engage with posts (Yu et al., 2020). Note that Instagram differs from other conventional media as it pools together shared experiences among tourists, where all users co-create the destination image (Jansson, 2018). Since these visual appeals are the key to attracting attention, marketers can benefit from natural human responses to images (Rietveld et al., 2020). However, seeing that tourism marketers are often struggling to design effective visual materials/tools (Swani et al., 2017) for image-based social media (Yu et al., 2020), Instagram is valuable in that it offers marketers tourist trends and preferences (Mata et al., 2018) so as to best leverage potential tourists' emotions and influence subsequent decisions.

Grounded in color psychology, color affects one's emotions (Zailskaitė-Jakštė et al., 2017), perceived product evaluation (Labrecque et al., 2013), and purchase intentions (Zailskaitė-Jakštė et al., 2017). Its influence has an even stronger impact on online marketing (Zailskaitė-Jakštė et al., 2017). For instance, because of the differences in users' psychological responses towards color (Amsteus et al., 2015), red and cyan negatively correlate with the click-through rate, whereas green has a positive effect (Jalali & Papatla, 2016). However, scholars have only recently started to link pictorial content and user engagement on Instagram (Rietveld et al., 2020; Schreiner & Riedl, 2019) within tourism contexts (Yu et al., 2020; Yu & Sun, 2019). Despite a rise in visual tourism research (Balomenou et al., 2017; Lee, 2020), literature investigating the effects of color in digital marketing is scarce (Jalali & Papatla, 2016). Existing studies often classify travel photographs based on the dominant landscape attributes, while overlooking color, as an objective and quantifiable measurement, in recognizing tourist experiences (Lee, 2020). Additionally, the adopted measurements are normally based on a single color (e.g., red) (Bakhshi & Gilbert, 2015) or broader categories (e.g., warm/cool colors) (Labrecque et al., 2013), which limit the knowledge on how multicolored pictures influence tourist behaviors.

Nonetheless, while admitting the potentials of visual content marketing (Rietveld et al., 2020), a significant methodological gap exists within the disciplines of marketing and data science. Existing research has focused on the volume and valence of data (Wedel & Kannan, 2016) rather than disclosing the hidden messages behind user-generated content (Bharadwaj et al., 2020). Previously, one could have spent several months cleaning and analyzing a large dataset (Balomenou et al., 2017); now, however, the big data revolution has brought new life into marketing by highlighting the interplay between advanced techniques (e.g., machine learning, visual analytics) and consumer experiences on social media (Dekimpe, 2020; Rietveld et al., 2020).

Thus, this study uses machine learning approaches and incorporates color psychology as a theoretical lens to investigate the effectiveness of engagement rate regarding tourism photographs on Instagram. Specifically, the main objective is to identify the interplay between color and user engagement on Instagram based on tourism pictures with different features. Grounded in aesthetics, as a modern branch of philosophy, this study is novel in that it infuses the effects of color into tourism marketing on Instagram and adds knowledge to emerging visual tourism research. Methodologically, not only does the machine learning approach present a new way of identifying pictorial content in user-generated content for marketers, but it also allows replication of the study's methods within other disciplines. Practically, this study offers guidelines and suggestions for optimizing and manipulating the dominant color in a photo when advertising a certain tourism activity.

Literature review

Color psychology and its influences

Derived from the discipline of psychology, different colors connote various meanings (Cyr et al., 2010) and impact human perception (AL-Ayash et al., 2016). For instance, red expresses excitement and passion (Labrecque & Milne, 2012). Blue is connected to openness and peacefulness (Hsieh et al., 2018). Yellow implies cheerfulness and happiness, while green relates to security and environmental consciousness (Labrecque et al., 2013). Among all the colors, blue and black depict more universal associations (Amsteus et al., 2015). Blue, in particular, is the most preferable color and barely receives negative reactions from viewers, regardless of their cultural background (Amsteus et al., 2015; Singh, 2006). In contemporary tourism contexts, color impacts website design (Cyr et al., 2010), brand identity (Tasci et al., 2018), and destination image (Yu et al., 2020). The manipulation of color in a product's appearance can trigger curiosity, subsequently increasing purchase probability (Garaus & Halkias, 2019). When it comes to influencing impulse buying, for example, red is recommended for in-store displays owing to its high arousing effects (Labrecque et al., 2013). In tourism branding, on the other hand, using a country's representative color improves consumers' familiarity with the products (Tasci et al., 2018).

The effects of color have also been examined in various online contexts (Jalali & Papatla, 2016). For instance, a website with good color design influences users' perceived trustworthiness towards sellers and enhances their loyalty and satisfaction (Cyr et al., 2010). Additionally, consumers are more likely to pay a higher price on a retail website with a blue background, compared to a red one, since blue suggests superior quality (Hsieh et al., 2018). On social media, red has negative effects on Instagram's click-through rates due to its intrinsic meaning of danger and stress (Jalali & Papatla, 2016). However, pictures dominated by red, purple, and pink have a higher likelihood of being shared on Pinterest, whereas blue and green reduce these chances (Bakhshi & Gilbert, 2015). Nevertheless, the role of color in digital environments is still underexplored (Poels & Dewitte, 2019), especially in the case of how consumers engage with pictorial content (Valentini et al., 2018). Overall, color significantly influences human physiological responses (AL-Ayash et al., 2016), resulting in changes regarding online behavioral reactions (Cyr et al., 2010). Seeing as the growing popularity of visual content marketing increased by 10.5% between 2018 and 2019 (Khoja, 2020), an urgent need for marketers to effectively develop engaging content through the manipulation of color is apparent.

User-generated content and consumer engagement

The ubiquity of social media and mobile devices enables anyone to create or share content online. This form of user-generated content includes pictures, videos, texts, or audio messages (Narangajavana et al., 2017), and have impacts on a consumer's decision-making process and purchase intentions (Filieri, 2016). In the tourism industry, user-generated content plays a significant role in influencing travel plans and destination choices (Matikiti-Manyevere & Kruger, 2019). Even during a trip, tourists use social media (e.g., Facebook and Instagram) to share their experiences and look for information about a specific attraction (Matikiti-Manyevere & Kruger, 2019). Thus, user-generated content can potentially enhance or worsen tourists' destination-related perceptions (Liang et al., 2020) based on pictorial features (e.g., color) (Yu et al., 2020). In order for marketers to evaluate the destination image and advertising efficiency, looking at engagement rate provides an essential indicator of performance (Schreiner et al., 2019).

Users can engage with social media content through liking and commenting (Aramendia-Muneta et al., 2020; Yu & Sun, 2019). Essentially, engagement rate, calculated based on the number of likes and comments and users' follower numbers, refers to the popularity of a post (Swani et al., 2017). Popular posts increase purchase intentions (Lin et al., 2017), lead to a high level of brand awareness (Swani et al., 2017), and boost business revenue (Aramendia-Muneta et al., 2020). Thus, marketers have been striving to achieve higher engagement rates by changing the captions (e.g., length and content) and the vividness of visual elements (Lin et al., 2017). One way to improve the degree of vividness is to change the color of the visual stimuli (Valentini et al., 2018). However, research has yet to focus specifically on the effects of pictures as visual elements on social media (Schreiner et al., 2019; Valentini et al., 2018). Given that the tourism industry strongly relies on digital pictures (Joyner et al., 2018), analyzing the effectiveness of online photographs is still in its infancy (Lee, 2020; Li & Xie, 2020). Although a recent study has started addressing the knowledge gap regarding how the color of digital photos influence tourist reactions (Yu et al., 2020), the results are limited to certain geographical areas and cannot be generalized to the global tourism industry.

Travel photos and data science

Essentially, pictures deliver messages about a destination (Yu & Ko, 2017), create a sense of fantasy, and shape expectations prior to a trip (Narangajavana et al., 2017). With the increasing popularity of visual tourism research (Balomenou et al., 2017), the application of data science has advanced the current knowledge derived from traditional methodological approaches (e.g., surveys and interviews) (Mazanec, 2020). Several studies have investigated the visual elements of tourism pictures (Picazo & Moreno-Gil, 2019). For instance, Kim and Stepchenkova (2015) identified several attributes such as heritage, nature landscape, architecture, and transport in which architectural heritage-related pictures seemed to strengthen tourists' intentions and desire to visit Russia. Recently, Yu et al. (2020) classified Instagram travel pictures of China into eight different categories (e.g., food, cityscape, and man-made attractions). Furthermore, Paül i Agustí (2018) affirmed that tourism marketers should pay close attention to user-generated content so as to tailor to tourists' preferences in marketing campaigns. For instance, Mata et al. (2018) reported that the Norwegian destination marketers focus on adventure and outdoor images, while the characteristics of user-generated content relate more to culture and natural landscapes. The incongruence between marketers and tourists thus underpins the significance of analyzing user-generated content to uncover tourist trends and preferences that might not have been previously recognized (Mata et al., 2018).

Despite the booming popularity of social media research (Matikiti-Manyevere & Kruger, 2019), studies examining image-based user-generated content (e.g., Instagram) are emerging, yet to a limited extent (Aminudin et al., 2020; Yu et al., 2020). Techniques that have been adopted to examine pictorial elements include canonical variate analysis (Balomenou et al., 2017), thematic content analysis (Aminudin et al., 2020), and visual content analysis (Tomaž & Walanchalee, 2020). Recent advances in big data analytics have additionally brought in machine learning models (Rietveld et al., 2020), deep learning technology (Zhang et al., 2019), transfer learning methods (Wang et al., 2020), and natural language processing (Ma & Kirilenko, 2020) to analyze travel photos. Take Instagram as an example; marketers can benefit from the analysis of pictures with respect to staging visual materials through filters or color tuning in an effective way (Yu et al., 2020). Nevertheless, given the importance of Instagram as an effective platform for marketing/advertising, the role of visual elements and tourism photographs in influencing the engagement rate remains unclear (Jalali & Papatla, 2016; Schreiner & Riedl, 2019). This opens up avenues of investigation regarding how the features of pictorial content act on potential tourists' engagement.

Methodology

To investigate the role of color in influencing user engagement on Instagram based on tourism pictures with different features, a detailed description of this study's six-step methodological procedure is presented below.

Step 1: picture selection

To recognize Instagram tourism photos as the data sources, several terms related to destinations were identified. This was based on the study by Picazo and Moreno-Gil (2019), where they summarized 497 destination image attributes (e.g., gastronomy, landmark, mountain) published in previous tourism literature between 1996 and 2015. Similar to the procedure in other visual tourism studies (Wang et al., 2020; Yu & Sun, 2019), the researcher developed 18 general categories since duplicated/similar attributes appeared. Thereafter, two rounds of coding, with one week in between, were performed by one researcher based on the above image attributes. For instance, "historical buildings" was classified as "heritage", and "local specialty" was classified as "gastronomy". Place-specific (e.g., Kinabalu Park) and religious (e.g., Islamic architectures) terms were excluded. Inter-rater reliability was measured by Cohen's kappa value (Zwick, 1988) in which the value was 0.92, suggesting almost perfect agreement between the two rounds (Landis & Koch, 1977).

The top destination attributes mentioned more than 20 times, including "beach", "mountain", "heritage", "forest", "gastronomy", "temple", "lake", "museum", and "cityscape", were considered. These terms were treated as hashtags to facilitate the data crawling process. However, the basis of extracting data via hashtags was chosen solely to simplify and complete the identification of the tourism pictures as comprehensively as possible. Since hashtags do not necessarily reflect the pictorial content (e.g., one might post a selfie with #mountain when hiking), this study re-assigned the extracted photographs based on image annotation, which will be explained in step three. Hence, no strict rule on the number of hashtags was applied. In fact, this is a conventional practice in visual tourism research (Wang et al., 2020; Yu & Sun, 2019). Although the existing framework can be used as guidance, ensuring that the classifications fit into the specific study context is of high importance because of the way nature photos differ (Wang et al., 2020).

Step 2: data extraction

The aforementioned nine terms/categories were treated as hashtags (e.g., #mountain) to extract Instagram photos. Data crawling was conducted in October 2019 through *Octoparse*, a web scraping tool, which has been embraced more recently within the marketing discipline (Zhou & Gupta, 2019) and tourism contexts (Yu et al., 2020). The extracted data of a post included the date, page URLs, image URLs, username, and the number of likes and comments. Note that if a post contains multiple photos, the extracted image URLs were only based on the first picture. A total of 7887 public posts published between 2017 and 2019 were crawled chronologically.

Since the Instagram algorithm is timeliness (Dimson, 2017), only the most recent posts are presented to users. Although engagement rate for posts published in earlier years may remain unchanged, the number of likes and/or comments could still increase significantly for posts published around the date of data collection. Based on the observation, this study concludes that the growth of engagement rate is logarithmic change, with an exceptional increase especially in the first three days after a post is published. The observation was conducted on a daily basis until the changes of engagement rate became minimal. Thus, data was re-collected from the page URLs after 14 days of the first data extraction. In the second round of data collection, some of the posts were removed by the users and posts with videos were excluded, resulting in a total of 4757 picture posts published by 3646 user accounts (Table 1). This implies that each user published 1–2 posts on average, resulting in a sample size similar to other recent studies using machine learning techniques (Martinez-Torres & Toral, 2019; Zhang et al., 2020). Notably, this study did not differentiate between pictures published by tourists, locals, or marketers since digital content is created by all stakeholders (Lund et al., 2018).

Step 3: image annotation and clustering

To obtain a description of the photographic contents, Google Cloud Vision API was applied to annotate the image labels (i.e., the entities of a picture such as general objects, locations, activities, and animal species). It detected 10 objects with a confidence level between 0 and 1 for each label. Only those labels with a confidence level above 0.5 were returned by Cloud Vision API (Google Cloud, 2020). First, the labels were transformed into vectors based on term frequency-inverse document frequency and calculated by taking the number of times a word appears in a corpus divided by the total number of words in that corpus. Term frequency-inverse document frequency indicates to what extent a label contributes to a picture. A non-negative value tends to appear, but, depending on the frequency of a term, it can also extend beyond 1. Notably, there is no pre-defined number of vectors for term frequency-inverse document frequency. In this study, the number depends on the tally of image labels (with a confidence score above 0.5) for each picture.

Next, to categorize the tourism pictures established by the detected labels, the Louvain algorithm was applied. It is a network-based clustering method that maximizes the intra-cluster similarity and minimizes the inter-cluster similarity (Browet et al., 2011). While the Louvain algorithm is typically used for community detection, researchers have also adopted this technique for image segmentation (Browet et al., 2011; Nguyen et al., 2018). In this case, the Louvain method was specifically used to convert the dataset into several clusters based on highly interconnected nodes (entities in the data). The image labels were considered as the edges (relationships between those entities) that connect different pictures, forming an image-network-graph and leading to a clustering of highly-connected images.

Table 1
Summary of data collection.

Hashtags	Total posts	1st data collection	2nd data collection
#Beach	239,651,135	834	501
#Cityscape	15,268,232	921	531
#Forest	37,509,322	850	552
#Gastronomy	4,044,242	900	501
#Heritage	6,560,126	832	521
#Lake	43,120,069	900	523
#Mountain	35,600,441	850	544
#Museum	18,765,693	900	554
#Temple	11,719,484	900	530
Total		7887	4757

Step 4: calculation of engagement rate

The next step was to calculate the average engagement rate of each identified cluster by taking the total number of likes and comments of a post and dividing it by a given user's follower numbers (Stevanovic, 2020). Engagement rate is used because it is the official measurement across social media platforms (Jaakonmäki et al., 2017; Stevanovic, 2020). Meanwhile, engagement rate is considered as the most common metric for the evaluation of Instagram marketing (Stevanovic, 2020).

Step 5: color conversion

Thereafter, to analyze how color triggers consumer engagement, Google Cloud Vision was applied in order to detect a picture's dominant colors. Cloud Vision returned up to 10 RGB values and their representative scores for each image. The score, ranging from 0 to 1, suggests the color's degree of confidence level. A higher score indicates a higher level of confidence/certainty that the color is prominent in an image. To ensure that the color presented is in line with human visual perception, RGB color codes were converted to HSL color space (i.e., hue, saturation, lightness) using *CodePen*. Hue is measured in 360 degrees with a 30-degree interval according to the color wheel, resulting in 12 major colors: orange, orange-yellow, yellow, yellow-green, green, blue-green, blue, blue-violet, violet, violet-red, red, and red-orange. Finally, to attain the percentage of color across the entire image, an individual color's score was divided by the sum of all the scores returned from Cloud Vision. Lightness and saturation were disregarded due to high correlation with the hues, which, in this study, would cause a loss of focus regarding a color's role.

Step 6: implementation of machine learning methods

The final step is to analyze the relationship between color and the engagement rate of each cluster. For regression analysis, two machine learning methods (support vector machine and random forest) were applied with the *Auto Model Tool* provided by *RapidMiner*. Support vector machine is a distance-based algorithm suitable for nonlinear data and high dimensional space (e.g., image pixels). Random forest is a tree-based method based on several decision trees that were trained on a random sample of observations/attributes.

Concerning random forest, since trees normally maximize the amount of information obtained from a random variable (i.e., *information gain*) (Schmid, 2013), observations with little value are often overlooked. Take the current dataset as an example, the color attributes, such as red and yellow-green, in the training set of pictures featuring seascape may contain a value close to zero because this type of photos is mainly dominated by blue and blue-violet. Thus, findings based on random forest might be biased. This can be supported by existing research, arguing that the accuracy score of the support vector machine is normally higher than that of the random forest's (Ahmad et al., 2018). Nevertheless, to achieve higher reliability, this study still compares the relative performance for both methods.

Specific to the procedure of machine learning, the engagement rate was first selected as the target variable, and the color attributes were treated as input variables for prediction. Subsequently, feature selection of the color attributes for each cluster was implemented based on four criteria: (1) the number of missing values; (2) the extent of correlation to the target variable; (3) the fraction of constant non-missing values; and (4) the fraction of unique values. *Auto Model* indicates the quality of color attributes with a color-coded status bubble (red/yellow/green). Red indicates an attribute of poor quality (i.e., with more than 90% of all values being the same), whereas yellow indicates having either a very low (below 0.01%) or a very high (above 40%) correlation with the target variable. For this study, only the attributes with a green-colored status were selected since they would contribute most to the quality of the resulting model. The reasoning thereof will be explained in the Results section.

Next, the support vector machine and random forest were implemented based on the automatic optimization feature, optimizing the number of trees for the random forest and the *gamma* and *C* hyperparameter for the support vector machine. The models' performance was evaluated by finding (1) the mean squared error, a simple metric that squares the individual prediction, and (2) the root mean squared error, a calculation that computes the average model prediction error and is particularly suitable for data with large errors (Willmott, 1982). Although there is no definite value for model performance, a higher value typically suggests a poor prediction.

Essentially, *Auto Model* automatically generates optimized cross-validated models and highlights the model's most influential variables based on weight vectors (RapidMiner, 2020). The contribution of the model's selected color was ranked based on weight vectors. Weights are always model-specific and are calculated based on a local interpretable model explanations method (Ribeiro et al., 2016). Technically, this method first generates random samples around neighboring inputs and finds correlation weights for each input in the dataset. By summing up the weights of the color attributes based on their extent of contribution to engagement rate, a final output is then given.

Results

From the nine categories/hashtags, a total of 4757 posts on Instagram were identified as the data sources. Pictorial content of these posts was extracted, and by using the Louvain algorithm, 24 image clusters were generated. First, Table 2 provides an overview of the identified image clusters with their corresponding engagement rate. The label with the highest term frequency-inverse document frequency was included as a keyword to facilitate the naming process of each cluster. To ensure the compatibility of the algorithms' results with human interpretation, intercoder reliability was performed in which ten pictures per cluster were randomly selected for coding. Two external coders, with a background in tourism, used Cohen's kappa to validate how well a picture matches a specific cluster (Zwick, 1988). Cohen's kappa value reached 0.79, suggesting substantial agreement among the raters (Landis & Koch, 1977).

Overall, the clusters "mountains and water", "water and natural impressions", "atmospheric moods", "urban views", and "plants and flowers" have the highest engagement rate. Notwithstanding other potential factors that can trigger users' intention to engage with a post (e.g., personal interests, visual appeals), this study focuses on the effects of color.

This study used support vector machine and random forest to examine the role of color in influencing engagement rates. Note that clusters 21, 22, 23, and 24 were removed from the analysis due to small sample sizes (below 100) and unattainable model training. Cluster 18 ("monochrome shots") was also excluded because of its black and white feature. Table 3 presents the algorithms' performance through mean squared error and root mean squared error values, ranging from 0 to ∞. Essentially, the higher the value, the weaker the learning performance is. Consistent with previous literature (Ahmad et al., 2018), the accuracy score of the support vector machine was better than the random forest's in most of the cases. Therefore, to compare the different clusters, the results from the support vector machine were preferred.

Table 4 presents the selected input variables and their corresponding local weights, ranging from 0 to 1. Notably, since the support vector machine maximizes the margin between two classes (Ahmad et al., 2018), 0 weight does not necessarily imply that a specific color is useless; rather, the local interpretable model explanations method returns local weights and only focuses on the most relevant ones.

Violet specifically has the highest weight within several clusters including "random travel photography", "art", "urban views", "vehicles", "interior design", and "beach impressions", while violet-red conquers in "seascape" and blue-violet in "water and natural impressions" as well as "high-end cuisine". Moreover, blue contributes the most to "mountains and water" and "places of worship". Complementary to blue color schemes, red appears to be the most important when it comes to "local delicacies". Furthermore, orange-yellow has the highest weight in "posters and ad materials", and yellow-green contributes greatly to "outdoors and nature", "real estate", "fashion accessories", and "selfies". Lastly, yellow reaches the highest weight in "atmospheric moods", while green overpowers in "forest and wildlife". To provide an overview, Table 5 visualizes the optimal color combinations that can be used to maximize engagement rate on Instagram. Take "art" for example; to achieve the highest engagement rate possible within this cluster, a picture should be composed more of violet, green and yellow shades while slightly minimizing blue-green touches.

Discussion

Twenty-four categories were identified through image annotation. Consistent with previous literature, some of the most common features include natural impressions (e.g., mountains, water, outdoors, and wildlife) (Kuhzady & Ghasemi, 2019), heritage (e.g., places of worship, sculptures, and gastronomy) and architecture (Kim & Stepchenkova, 2015), transportation and city views (e.g., vehicles, urban views, and buildings) (Yu et al., 2020). Moreover, this study reports clusters that have rarely been mentioned in the previous tourism literature (Picazo & Moreno-Gil, 2019), such as "fashion accessories", "selfies", "posters and ad materials", and "beverages and drinks". Regarding the engagement rate, it appears that Instagram users are more likely to engage with content featuring nature and the outdoors (Kuhzady & Ghasemi, 2019); for instance, pictures classified as "mountains and water", "water and natural impressions", "atmospheric moods", "urban views", and "plants and flowers". Supported by Pastorella et al. (2017)'s study, water and mountain activities appear to be more popular among Instagram users potentially because of the openness of space in a natural environment. Since humans' perceptions regarding natural environments are generally similar, photographs of mountains and water may have a greater impact on aesthetic consensus (Wang et al., 2016). However, an inconsistent result depicted in previous literature involves pictures related to urban life. Although some tourists prefer pictures featuring urban architecture (Zhang et al., 2019), Schirpke et al. (2019) argued that photographs containing cityscape or road infrastructures are less favorable.

Table 2
Summary of Louvain cluster results.

Cluster	Name	Keywords	No.	EN
1	Mountains and water	mountain; hill; lake; hike; fjord; nature; geology; tarn; crater; escarp	356	0.62 (2.76)
				
2	Random travel photography	people; bird; social; game; photography; caption; collection; flag; circle; selfie	316	0.16 (0.45)
				
3	Outdoors and nature	nature; plant; spring; grass; sunlight; palm; shrubland; bamboo; twig; lawn	305	0.25 (0.88)
				
4	Art	art; paint; draw; exhibit; portrait; tapestry; artist; design; paper; pattern	299	0.19 (0.49)
				
5	Places of worship	temple; site; architecture; church; pagoda; monastery; basilica; shrine; steeple; ancient	287	0.22 (0.37)
				
6	Real estate	door; estate; almshouse; cobblestone; resident; brickwork; cottage; gate; daylight; apartment	265	0.16 (0.42)
				
7	Seascape	ocean; wave; sand; beach; shore; bight; turquois; bay; water; azure	258	0.22 (0.62)
				
8	Urban views	area; downtown; pedestrian; alley; light; town; neighborhood; plaza; transport; commercial	243	0.33 (2.57)
				
9	Atmospheric moods	atmosphere; afterglow; sunrise; nature; calm; dusk; mist; rainbow; sunlight; ecoregion	209	0.39 (0.75)
				
10	Vehicles	car; bicycle; vehicle; transport; wheel; motorcycle; ship; bike; boat; automote	205	0.18 (0.49)
				
11	Local delicacies	cake; food; noodle; dessert; snack; salad; cream chocolate; bread; cook	164	0.11 (0.15)
				
12	Interior design	floor; table; room; design; restaurant; museum; lobby; property; chair; bed	161	0.12 (0.19)
				

Note: EN = average and (standard deviation) of the engagement rate.

Table 2 (*continued*)

13	Posters and ad materials	graphic; logo; brand; advertise; flyer; text; paper; calligraphy; sign; poster	161	0.10 (0.17)
				
14	Water and natural impressions	water; nature; bank; pond; lake; river; reservoir; waterfall; stream; autumn	156	0.39 (1.18)
				
15	Fashion accessories	jewelry; watch; accessory; silver; fashion; coat; blazer; ornament; costume; dress	151	0.13 (0.36)
				
16	Beach impressions	shoe; swimsuit; sunglass; friendship; barechest; bikini; beach; tan; sand; leg	143	0.18 (0.40)
				
17	High-end cuisine	food; chicken; dishware; shrimp; platter; steak; appetizer; superfood supper; breakfast	141	0.10 (0.17)
				
18	Monochrome shots	monochrome; white; photograph; style; art; arch; dome; black; architecture; carve	135	0.20 (0.53)
				
19	Selfies	hair; cheek; eyebrow; sunglass; moustache; blond; beard; denim; eye; cap	100	0.26 (0.48)
				
20	Forest and wildlife	forest; nature; lodgepole; redwood; rainforest; birch; jungle; grove; meadow; valdivian	143	0.24 (0.63)
				
21	Sculptures	carve; sculpture; monument; artifact; memory; museum; figurine; dinosaur; finial; cage	73	0.11 (0.15)
				
22	Plants and flowers	plant; flower; rose; amaryllis; lotus; bud; fern; barberry; burdock; dandelion	68	0.28 (0.87)
				
23	Animals	dog; cat; retrieve; fox; wolfdog; snout; deer; leopard; macaque; bank	45	0.24 (0.30)
				
24	Beverages and drinks	bottle; party; wine; alcohol; drink; coffee; juice; stemware; champagne; glass	44	0.06 (0.11)
				

Table 3
Performance of support vector machine and random forest.

Cluster	Mean squared error		Root mean squared error	
	Support vector machine	Random forest	Support vector machine	Random forest
1: Mountains and water	0.236	0.417	0.424	0.605
2: Random travel photography	0.016	0.067	0.125	0.236
3: Outdoors and nature	0.028	0.224	0.147	0.428
4: Art	0.948	0.449	0.908	0.519
5: Places of worship	0.101	0.208	0.297	0.402
6: Real estate	0.038	0.038	0.183	0.185
7: Seascape	0.039	0.045	0.181	0.208
8: Urban views	0.125	0.058	0.315	0.224
9: Atmospheric moods	0.081	0.397	0.262	0.627
10: Vehicles	0.123	0.084	0.307	0.247
11: Local delicacies	0.036	0.047	0.186	0.210
12: Interior design	0.031	0.027	0.161	0.153
13: Posters and ad materials	0.037	0.054	0.163	0.193
14: Water and natural impressions	0.267	0.064	0.379	0.231
15: Fashion accessories	0.007	0.023	0.068	0.148
16: Beach impressions	0.026	0.046	0.152	0.206
17: High-end cuisine	0.054	0.050	0.202	0.196
19: Selfies	0.133	0.154	0.257	0.335
20: Forest and wildlife	0.467	0.318	0.485	0.377

Note: number in bold indicates better performance

Nevertheless, Instagram users engaged less with images categorized as "beverages and drinks", "posters and ad materials", "high-end cuisine", and "local delicacies". Regarding the poster materials, although user-generated content is generally published by first-person unbiased accounts (Lund et al., 2018), this research argues that the selective attention of consumers filters out pictures that appear too commercial. Since the engagement rate of a post depends on its visual elements (Lin et al., 2017), another justification would be the simplicity of a poster's graphic design in comparison to a natural photo (Yu & Ko, 2017). Surprisingly, this study revealed that gastronomy images (i.e., "local delicacies" and "high-end cuisine") were amidst the categories with the lowest engagement rates. In stark contrast to earlier research, food has always been one of the main factors attracting tourists to visit a specific destination (Yu & Sun, 2019). Thus, the tough competition within gastronomy tourism leads to an interesting question on how to boost the popularity of food photography on social media. In today's digital environment, it is even more necessary to investigate the influence of subliminal factors (e.g., color) on consumer engagement (Yu et al., 2020). Nonetheless, while this study focuses particularly on the effects of color, one needs to note that there are many other reasons for consumers to engage with a post (e.g., aesthetics) (Schirpke et al., 2019).

Table 4
Local weights of the color compositions.

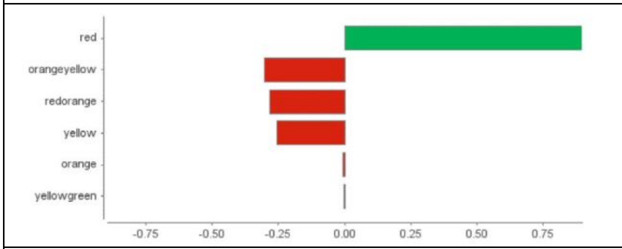
Cluster	Orange	Orange-yellow	Yellow	Yellow-green	Green	Blue-green	Blue	Blue-violet	Violet	Violet-red	Red	Red-orange
1: Mountains and water	0	0	0.263	–	–	0	0.727	0	–	–	–	0.064
2: Random travel photography	0	0.054	–	0.206	–	0	0.100	–	0.909	0	0	0.135
3: Outdoors and nature	0.021	0	–	0.716	0	0	0	0.142	–	–	–	0
4: Art	0.083	0.121	0.441	0.039	0.577	0.008	0.070	0.002	0.713	–	–	0.122
5: Places of worship	0.125	0.095	0.130	0	–	0	0.716	0.071	–	–	–	–
6: Real estate	0.188	0.154	0	0.734	–	0	0.059	0.344	0.038	0	–	0.170
7: Seascape	0.331	0.102	0.230	0	–	0.441	–	0.092	0.304	0.695	–	0
8: Urban views	–	0.094	0.089	0.264	–	0.155	0.022	0.061	0.401	0.031	–	0.219
9: Atmospheric moods	0.124	0.264	0.631	–	–	0	0	0	0.089	0	0	0
10: Vehicles	0	0	0.336	0	0	0	–	0	0.435	–	–	0.017
11: Local delicacies	0.059	0	0	0	–	–	–	–	–	–	0.891	0
12: Interior design	0	–	–	–	–	–	0	0.050	0.956	–	0	0.293
13: Posters and ad materials	0.055	0.312	0.049	0.195	–	0.001	0.068	0.193	0.122	0.107	0.055	0.002
14: Water and natural impressions	0	0.071	0	0.262	0	0.240	0.056	0.579	–	–	–	–
15: Fashion accessories	–	0.145	0.069	0.499	–	–	–	0	–	0	0	0.302
16: Beach impressions	0.108	0.011	0.047	–	–	0.016	0.001	0.012	0.455	–	–	0.006
17: High-end cuisine	0.108	0.176	0.110	0	–	–	0	0.949	–	–	–	0.132
19: Selfies	–	0.038	0	0.633	–	0	0.080	0	0	0	0	0
20: Forest and wildlife	0	0.039	0	0.436	0.838	–	0.076	0.192	–	–	–	–

Table 5
Visualization of the optimal color combinations per cluster.

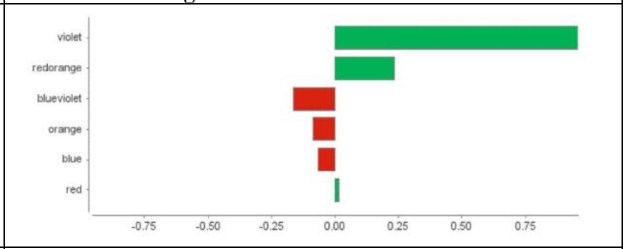
Note: green bar = positive influence on engagement rate; red bar = negative influence on engagement rate.

Table 5 (*continued*)

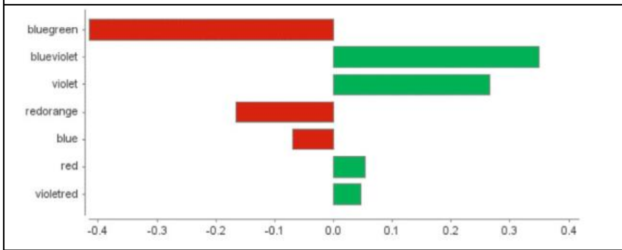
11:Local delicacies



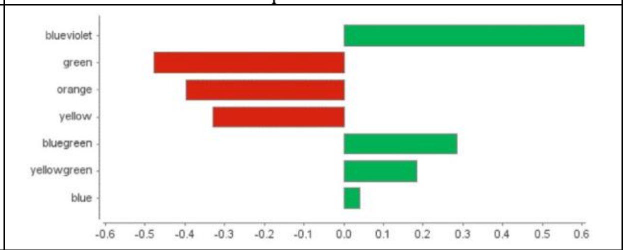
12:Interior design



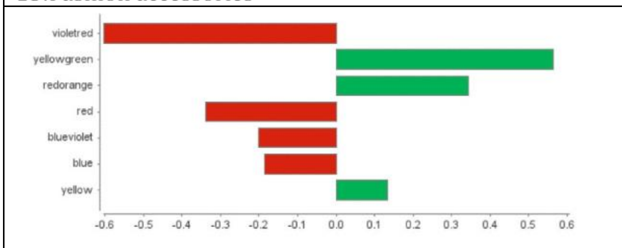
13:Posters and ad materials



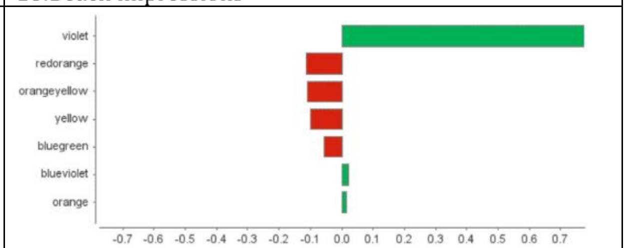
14:Water and natural impressions



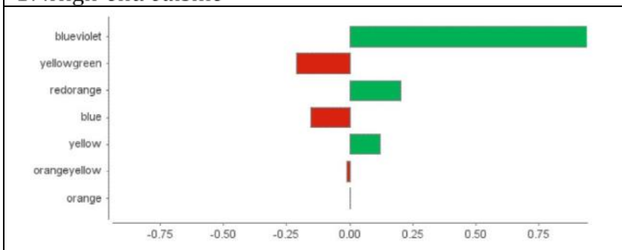
15:Fashion accessories



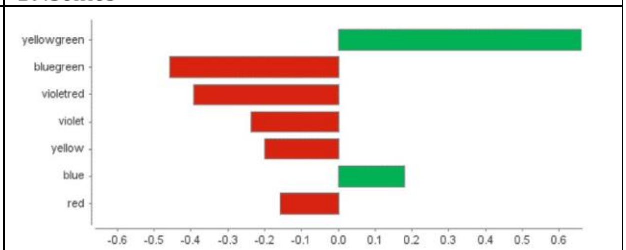
16:Beach impressions



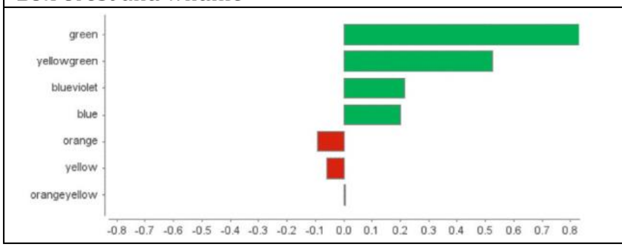
17:High-end cuisine



19:Selfies



20:Forest and wildlife



Turning to the color results, the blue color scheme (e.g., blue, violet, blue-green, blue-violet) appeared to influence user engagement regarding nature pictures in a positive way (e.g., "beach impressions", "seascape", "water and natural impressions", and "mountains and water"). Besides the congruency between color and its natural appearance, nature-based tourism is associated with a sense of uncrowdedness, appreciation, and preservation (Zeppel, 2008). Therefore, since tourists' desires involve seeking pleasant and relaxing feelings (Gao & Kerstetter, 2018), it is important to deliver what they are looking for through visual materials. The results suggested that there appears to be a relationship between the level of engagement and the blue color scheme, presumably due to the characteristics of peacefulness (Hsieh et al., 2018), competence (Labrecque & Milne, 2012), and relaxation

(Bakhshi & Gilbert, 2015). Further evidence is represented by a negative relationship between engagement rate and the red/orange color scheme in "outdoors and nature", "seascape", "beach impressions", and "forest and wildlife". As opposed to the blue color composition, red denotes anger and excitement in digital environments (Labrecque & Milne, 2012). Additionally, socialization is embedded in the color orange, while yellow conveys extraversion (Labrecque & Milne, 2012). Although marketers might want to adjust colors to attract consumers' attention and be different from their competitors (Singh, 2006), this study affirms the ineffectiveness of this practice when advertising nature-based activities. Nonetheless, the blue color scheme was highlighted in this study because the proportion of water/sky scenery appears to be greater than that of mountain scenery. Yet, in the case of "forest and wildlife", the results clearly demonstrated that the green color scheme positively influences engagement rates. Green, as the analogous color of blue, conveys similar meanings to that of nature-based tourism, such as calmness (Labrecque et al., 2013) and security (Labrecque & Milne, 2012).

Regarding the gastronomy images, the clustering results disclosed two distinct experiences; namely, fine dining ("high-end cuisine") and casual dining ("local delicacies"). Common features of a casual dining restaurant include convenience, efficiency, and reasonable prices, whereas a fine dining restaurant characterizes high quality, luxurious atmospheres, and premium prices (Jeong & Jang, 2018). To arouse sensuality and, in turn, receive positive reactions, subliminal factors, such as food presentation and color, are vital (Aslam, 2006). This study confirms that the engagement rate of "high-end cuisine" was positively influenced by the blue color scheme (i.e., blue-violet), associating it with high quality (Hsieh et al., 2018), luxury (Labrecque & Milne, 2012), and cleanliness (Amsteus et al., 2015). Additionally, blue is often linked to common dishes, such as healthy foods and desserts, in fine dining restaurants (Aslam, 2006). Concerning "local delicacies", red in particular positively influenced the engagement rate. In gastronomic experiences, red usually stimulates appetite and is considered a popular color when designing casual dining environments (Singh, 2006). Red is also related to street food, for instance pizza (Aslam, 2006). However, since gastronomy pictures received a relatively low engagement rate, this study looked at the color compositions of these clusters in more detail. Surprisingly, "high-end cuisine" was mainly composed of warm colors (e.g., orange-yellow (44%) and orange (40%)), whereas the blue color scheme (e.g., blue-violet (2%) and blue (1%)) had the lowest composition. Similarly, "local delicacies" contained mostly orange (45%) and orange-yellow (29%) with red averaging at only 2%. This likely explains the reasons behind the inadequacy of consumers engaging with gastronomic pictures.

Moving on to art-related pictures, aesthetic experiences tend to support social understanding (Brinck, 2018) and reduce stress (Binnie, 2010). From a color perspective, this is imaginably due to the fact that green and violet can decrease anxiety levels (AL-Ayash et al., 2016). Meanwhile, warm colors (e.g., yellow, red, and orange) are arousing and cheerful (Labrecque et al., 2013). Notably, only blue-green slightly affected photographs related to art in a negative way. Hence, to encourage consumer engagement, art-related images should incorporate a multicolor design. Regarding "atmospheric moods", the results showed that yellow significantly influenced the engagement rate, and cool colors (e.g., blue-green and blue-violet) had negative effects. One possible reason for this might be that the majority of the pictures contained yellow-ish aspects (e.g., a sunrise, the sunlight, and rainbows), which symbolize relaxation and harmony (Cyr et al., 2010).

As for the photos featuring urban environments, this study showed interesting insights to which violet-red appeared to be highly divergent from the engagement rate. In fact, this particular color combination has rarely been tested in any marketing context. The color composition presented in this research implied the nature of cityscape that is visual, vivid, and recognizable (Zhang, 2016). To influence consumers' reactions, a combination of colors is critical in "urban views". Agreeing with Yu et al.'s (2020) study, the coexistence of violet and warm colors plays a significant role in urban tourism photos. In a slightly different context, consumers prefer the combination of complementary colors (violet and yellow) rather than the analogous one (violet-red) when it comes to displayed retail products (Phillips et al., 2007). Similarly, this notion also reflects the effects of color on "interior design", although the engagement rate was mainly influenced by violet and red-orange. Since pictures from the cluster "interior design" were more related to the interior of service properties/buildings (e.g., hotel lobbies, hotel rooms, and restaurants), this potentially explains the importance of violet, which might denote high quality and luxury (Labrecque & Milne, 2012).

With respect to religious tourism pictures, "places of worship" mainly contained images of architecture (e.g., churches, basilicas, and pagodas). Prior to this discussion, it is important to note that, because the exterior color generally follows religious norms, the results cannot necessarily be generalized (e.g., Chinese temples use warm colors). In "places of worship", blue positively affected the engagement rate, but yellow-green presented an adverse impact. This is potentially due to blue depicting spirituality and serenity in cultural contexts, while yellow-green symbolizes power (He et al., 2015). In the same vein of having a sense of power, yellow-green contributed to the engagement rate of "fashion accessories" (e.g., jewelry and silver accessories) as well. This can be corroborated even further through the negative influence of violet-red: as it denotes error (Hsieh et al., 2018), violet-red contradicts the actual nature of fashion accessories.

Finally, it is worth mentioning that the aim of this study is not to argue a causal relationship between user engagement and the act of booking of a trip. Engagement and color might not directly impact travel intentions, per se, but effective visual materials on Instagram do play a critical role in decision-making and may have the capability to influence consumers' subsequent actions.

Conclusion

Theoretical contribution

By bridging color psychology, as a novel field in aesthetic philosophy, into data science and marketing, this study is interdisciplinary and exhibits several theoretical contributions. Overall, this study adds knowledge to the user-generated content literature in Instagram marketing through the means of machine learning approaches (Bharadwaj et al., 2020; Arefieva et al., 2021). The findings have gone beyond the volume and valance of big data (Wedel & Kannan, 2016) by uncovering pictorial contents through image annotation and Louvain clustering. Different from other consumer products, this study highlights the uniqueness of tourism aesthetics, which taps into one's emotions and feelings (Gao & Kerstetter, 2018; Lee, 2020) based on the messages embedded in Instagram pictures. Additionally, as tourism aesthetics is often investigated in physical contexts (Kirillova et al., 2014; Tang et al., 2020), this research transcends the status quo by bringing the notion of aesthetics into digital tourism spaces. By having a particular focus on color, as a proxy of tourist experiences underpinned in landscape research (Lee, 2020), this study extends our knowledge by empirically testing the relationship between tourism photographs and consumer engagement on Instagram (Valentini et al., 2018; Yu et al., 2020; Zailskaitė-Jakštė et al., 2017). Meanwhile, this study expands on the current understanding of a color composition's role in Instagram users' behaviors. It also underlines certain areas (e.g., the effects of violet-red) that warrant further investigation. Moreover, applying supervised machine learning to Instagram data offers a new form of analysis for tourism and digital marketing in general. This study provides a hands-on guide for marketers to bring images presented on Instagram to light in order to optimize their marketing contents based on consumers' preferences and interests. Finally, this research provides some indications as to where and how future studies could collect data in a more structured fashion; namely, by including geocoding techniques or differentiating between the type and demography of users.

Managerial implications

By analyzing the relationship between color and engagement rates, this study offers insights into how to effectively manipulate the dominant color in a photo when advertising a certain activity (e.g., mountaineering tourism, food experience, water sports, and art and cultural events), especially on Instagram. The results indicated that pictures featuring local cuisine should contain red elements, although this practice would be ineffective when targeting high-end gastronomy. The inclusion of a blue color scheme can be used to improve engagement rates with nature. For instance, despite the outdoors being predominantly green, marketers can opt to present more blue by ensuring the visibility of the sky and lakes, or by minimizing forest greenery.Artwork-related photographs, on the other hand, should comprise of a variety of color. Violet, together with some warm colors, can positively influence consumer behavior and optimize advertising outcomes. Thus, marketers are encouraged to use filters and color tuning to adjust the digital lighting of tourism photographs. Furthermore, marketers should be aware of the style of advertising materials. Even though destination management organizations might already have several Instagram followers, conventional practices (e.g., poster designs) would not be suitable for picture-based social media platforms.

Limitations and recommendations

This study is not without its limitations. Firstly, the causality remains unknown, making interpretations more difficult. While this study explained the results based on earlier literature, experimental research is recommended. Researchers could conduct experiments by simulating biological measurements with in-depth interviews to gain a better understanding of one's behavior. Secondly, although the research design was theory-driven based on a comprehensive review of destination attributes (Picazo & Moreno-Gil, 2019), only one hashtag was used in the data extraction phase. Future researchers could consider scrapping data based on co-hashtags (e.g., #mountain + #tourism) (Rama & Han, 2018) to tackle tourism activities more precisely. Furthermore, various types of user-accounts could be taken into consideration (i.e., locals, tourists, and marketers) for a more effective comparison of implementing color usage. This could be achieved by looking at the Instagram users' bio data. For example, by tagging a location outside of what he/she indicates in the bio, a user can be noted as a tourist or a local. Likewise, the extracted samples are based on a global scale. Yet, since color psychology is highly relevant to socio-cultural differences, specific users may have geographically-clustered followers. As this study did not categorize pictures based on locations, it is also critical to note that a destination might be dominated by certain colors (e.g., countries in north Africa might be more brown due to the Sahara Desert). Future studies could incorporate the use of Instagram geotags to analyze the effects of color in different locations. Meanwhile, although engagement rate is used as a proxy for liking, comments on Instagram may be either positive or negative. For recommendations, researchers can first conduct sentiment analysis based on the comments, and exclude those with negative expressions if needed. Finally, as color is not the only factor that influences engagement, other variables (e.g., textures and shapes) should also be examined through Google Cloud Vision API.

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Declaration of competing interest

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

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