

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Journal of Destination Marketing & Management

journal homepage: www.elsevier.com/locate/jdmm

Understanding engagement with Instagram posts about tourism destinations

Sofía Blanco-Moreno^{a,*}, Ana M. González-Fernández^a, Pablo Antonio Muñoz-Gallego^b, Luis V. Casaló^c

^a Universidad de León, Spain

^b Universidad de Salamanca, Spain

^c Universidad de Zaragoza, Spain

ARTICLE INFO

Keywords:

Instagram
Destination image
Artificial intelligence
Machine learning
Deep learning
Social media engagement

ABSTRACT

This study analyses the social media engagement (SME) received by Instagram posts from a tourism destination based on communication and mental imagery theories. This research considers both the type of sender (tourists vs. residents) and the content of the message (pictorial stimuli: places of interest vs. hospitality services; centrality stimuli: people vs. without people). Web scraping technique is used for data collection. Content analysis is then applied on 27,088 Instagram posts using artificial intelligence techniques (machine learning and deep learning); and a univariate generalized linear model is conducted to analyze differences in SME. Results show that pictorial stimulus determines SME, being higher for images focused on places of interest, and photographs with people get higher SME too. The type of sender also influences SME and exerts a moderating role reinforcing the effect of centrality on SME for tourists. These results provide interesting insights for destination marketing managers and Instagram users.

1. Introduction

A positive and strong tourism destination image (TDI) acts as an attraction element for other tourists. Specifically, a strong TDI can be a competitive advantage over other destinations, something more important today than ever, since tourism has been the sector most affected by the COVID-19 pandemic, and TDI can help the recovery of tourism markets (Zuo et al., 2023). A powerful TDI makes a good impression, and a destination only has one opportunity to make a good first impression, something essential to succeed in today's highly competitive tourism market, where photos have acquired a prominent role in achieving it (Picazo & Moreno-Gil, 2019).

For this aim, destination marketing organizations (DMO) use social media to promote their TDI, but it remains a challenge for DMO to understand the type of content that attracts the most attention from users on social media in order to promote visits to the destination (Abbasi, Tsiotsou, Hussain, Rather, & Ting, 2023). In this respect, social media engagement is an important success metric, commonly used to assess marketing results, because it influences the attitude toward tourist

destinations and the perception of hospitality services (Filieri, Yen, & Yu, 2021; Li & Xie, 2020), and it is also tied to the virality of user-generated content. More specifically, with the emergence of social media, research that analyses TDI through user-generated content, and specifically by tourists, has grown and has established itself as a popular and very useful topic for the development of TDI (Arefieva, Egger, & Yu, 2021; Picazo & Moreno-Gil, 2019; Zuo et al., 2023).

As aforementioned, a powerful source of information that can be found in social media is photography. Photos have always been an inseparable part of the tourism experience and are also linked to the TDI displayed on social media, as visual content offers irrefutable proof that something has happened at a certain moment (Tribe & Mkonko, 2017). In addition, in the big data era, photos of destination experiences shared on social media platforms have become the main source of information through which audiences receive the image of the destination (Deng & Liu, 2021). But tourism researchers have persistently used textual data, ignoring image analysis, which today can be performed automatically through artificial intelligence, and that allows the obtaining of different relevant data on tourist behavior (Balomenou & Garrod, 2019). Indeed,

* Corresponding author.

E-mail addresses: sblanm@unileon.es (S. Blanco-Moreno), amgonf@unileon.es (A.M. González-Fernández), pmunoz@usal.es (P.A. Muñoz-Gallego), lcasalo@unizar.es (L.V. Casaló).

<https://doi.org/10.1016/j.jdmm.2024.100948>

Received 2 October 2023; Received in revised form 4 October 2024; Accepted 12 October 2024

Available online 19 November 2024

2212-571X/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

the role that images play in generating engagement remains a largely unexplored question (Li & Xie, 2020).

Photos allow a holistic understanding of experiences and provide tourism researchers with a different type of information that is capable of encompassing those experiences (Bell & Davison, 2013). Tourists use images as a means to build their vacation experience, capture their memories, and share them with their community on platforms such as social media (Lo & McKercher, 2015). It is true that several authors highlight the subjectivity of photos, since the choice of what to photograph is an inherent part of the photographic process, but that choice rests with the photographer, who chooses what to photograph, when, and where, in order to show the most decisive aspects in the configuration of their own tourism experiences (Balomenou & Garrod, 2019). Therefore, photos can convey complex meanings and insights on their own, with the indissoluble link between the tourism experience and photography (Tribe & Mkono, 2017).

The report *The 2023 Experiences Traveler* concludes that Instagram is the most influential platform for those looking to plan activities while traveling, and more and more people are turning to Instagram to explore other users' experiences, get inspired, and see what it is possible to do on their travels, preferring this type of visual option over reading long reviews in other sources such as TripAdvisor (Arival, 2023). This report confirms also that the main social media platform where users share their photo experiences is Instagram, which has 1.3 billion users that generates hundreds of millions of photos and videos daily (DataReportal, 2023). For example, the hashtag #travel has 682 million posts (Instagram, 2023). These hashtags are often used by tourists to select their favorite destinations, decide before the trip where to travel, and take their photos and share them online during the trip, as taking photos has become a popular and indispensable tourism activity (Deng & Liu, 2021). For this reason, Instagram is the extremely lively visual platform that contributes the most to the formation of the TDI (Volo & Irimiás, 2021). Despite its relevance, an in-depth analysis of the visual elements in Instagram images is still lacking in the literature (Hauser, Leopold, Egger, Ganewita, & Herrgessell, 2022). Indeed, image databases were rarely studied as they were considered to lack objective truth, but rigorous investigation of social media images could establish the legitimacy of visual content, because users show their experience like a showcase: the content they want to attract their audience with will reward them with likes and comments (Volo & Irimiás, 2021).

In addition, it is undeniable that the TDI is the direct result of the co-creation of experiences not only by tourists, but also by residents, destination managers, and tourism intermediaries (Yüksel & Yanik, 2014). On the one hand, the DMOs try to control their projected image and direct their communication campaigns on social media, but on the other hand, tourists also participate in this creation of the TDI by sharing their experiences (Paül & Agustí, 2021; Volo & Irimiás, 2021), and there is also no doubt that the residents themselves who live in the destinations also contribute to forming the TDI (Zuo et al., 2023). In this respect, previous literature has examined the overlapping of different tourist images distributed through official tourist brochures, travel guides, and user-generated content on Instagram (Paül & Agustí, 2018; 2021), but to the best of our knowledge, co-creation between residents and tourists has not been examined deeply (Lin, Chen, & Filieri, 2017). Therefore, there is a need to understand how followers in social media engage with the content shared by residents and tourists regarding a destination.

Similarly, tourism implies the use and enjoyment of a set of services, such as tourist attractions and hospitality services (Lugosi & Walls, 2013). Finding references for both in the form of visual content is important for tourists, since in the planning phase, they try to imagine what their overall experience will be like. There is evidence on what type of environmental stimuli related to restaurants, accommodation, or tourist attractions encourages users to post photos on their social media (Li, Zhang, & Hsu, 2023); however, for the moment, it is not known what type of photographic content promotes greater engagement on

Instagram (An, Ma, Du, Xiang, & Fan, 2020; Apaolaza, Paredes, Hartmann, & D'Souza, 2021; Chen, Chan, & Egger, 2023).

Finally, the tourist experience also involves people, and consequently these people show themselves reflected in the photos they share with their community. It is common to find research that classifies the content of the photos into different categories such as food or accommodation, but it is also necessary to analyze the consequences of including people in the photos (Huai, Chen, Liu, Canters, & Van de Voorde, 2022; Li et al., 2023; Wang, Luo, & Huang, 2020), because those people are one of the most important elements in the TDI (Aramendia-Muneta, Olarte-Pascual, & Ollo-López, 2021), and allow the enhancing of engagement in social media (Tamaki, 2021).

Bearing all these in mind, the current research contributes to previous literature, both theoretically and methodologically, in the following ways.

- First, we aim to understand engagement with Instagram publications based on the characteristics of the photographic content. Specifically, we differentiate between places of interest and hospitality services as the focus of the photo, and we compare whether the photo includes persons or not. In addition, we evaluate potential differences in the influence of the photographic content on engagement due to the characteristics of the sender of the photo (i.e., tourists vs. residents).
- Second, this study used photographs as a data source, which helps reduce the gap between theory and practice in terms of the use of visual data in tourism research (Balomenou & Garrod, 2019), and provides a novel method of data collection based on big data techniques (i.e., web scraping).
- Third, to advance tourism research in the big data era (Deng & Liu, 2021; Zhang, Chen, & Lin, 2020), artificial intelligence techniques were applied for the analysis of the downloaded data: machine learning models were applied for the analysis of polarity text, and deep learning models in the field of computer vision were applied for visual content analysis in this study.

To do this, we developed a large data set by downloading 139,273 Instagram posts between 2010 and 2022 with their photos, texts, and metadata. After applying artificial intelligence techniques to identify the research variables, 27,088 posts shared by tourists and residents were finally analyzed. All these posts belong to a cultural and gastronomic destination of the Camino de Santiago, UNESCO World Heritage Site since 1993 (UNESCO, 2023). Lastly, communication theory (Schramm & Roberts, 1954) and mental imagery theory (MacInnis & Price, 1987) provide theoretical support to the proposed relationships.

2. Literature review

2.1. Communication theory

One of the historical and central concerns of marketing research is the development of effective communications that successfully achieve marketing objectives (Baker, 1976). For this, Schramm and Roberts (1954) developed their general Theory of Communication involving three central elements (i.e., source, message, and receiver), that may also apply in the social media environment (Walton & Rice, 2013). Specifically, the classical communication process involves a sender that transmits a message through a channel to a receiving audience (Bao & Chang, 2014), with feedback and interaction between the sender and the receiver being key elements in communication (Schramm & Roberts, 1954). In traditional advertising, a company (sender) creates an advertisement (message) that is disseminated through various media channels such as television, print, or online platforms (channel) to reach consumers (audience). The effectiveness of this communication is often measured by the consumers' responses, such as purchasing the advertised product or engaging with the brand (feedback).

Social media is thus the perfect channel to study Schramm and Roberts's model (1954) as social media is oriented toward bidirectionality, where the sender and the receiver interact in a process in which the design of the message is the key to the success of the communication, and in which the sender intentionally seeks the success of their communication (Mikáčová & Gavlaková, 2014).

The communicative act arises from the sender, who wants the communication to take place, and designs a key message for a successful communication of their message, and that communication only occurs if the receiver understands the message (Stidsen, 1975). In a context of social media, this implies that the user (sender) chooses how, when, and where to share their experience (message) on social media (channel), in such a way that the community (receivers) understands that message and interacts with the user (for example, liking or commenting the sender's publication; that is, generating receivers' engagement). This last point is very important because communication theory considers that the reception of a message depends on the responses it generates (Peetz, De Rijke, & Kaptein, 2016).

In the context of tourism and hospitality, communication theory has been applied to understand how DMOs effectively communicate with potential tourists. For instance, DMOs create promotional campaigns (message) that are broadcasted through social media platforms (channel) like Instagram to attract tourists (audience). The engagement metrics such as likes, shares, and comments (engagement) indicate how well the message has been received and can influence the audience's travel decisions (Filiari et al., 2021).

Specifically in the context of experiences, the sender-message-receiver communication model is appropriate as tourists (senders) can share their photos of the destination (messages) on social media (channel) which are interpreted at the receiving end of the communication channel by their community (receivers), influencing their attitudes and behavior toward content and destination; therefore, it is not surprising that communication theory has been applied in social media platforms such as Flickr (Kim & Stepchenkova, 2015) and Twitter (Peetz et al., 2016). However, to the best of our knowledge, the communication theory model has not been extensively applied to the context of Instagram, which is currently the most successful social media platform for sharing photographic content (Arival, 2023).

In addition, previous studies suggest that the effectiveness of the communication process via social media in the tourism and hospitality context may depend on the characteristics of the sender and the message (Akdin, 2021). Therefore, even though no differentiation has been made in previous literature between types of users who build the TDI (e.g., tourists vs. residents), this communication process may also hold for residents who may post their photos of their place of residence. Similarly, message characteristics such as whether the picture is focused on a place of interest or on a hospitality service (pictorial stimulus), the main themes displayed in the social media images relate to the TDI (Lai & To, 2015), and whether the photo includes persons or not (centrality stimulus), are one of the most important elements that affects engagement in social media TDIs (Aramendia-Muneta et al., 2021; Tamaki, 2021) and may affect customer responses. As a result, based on communication theory, this study will differentiate between senders (tourists vs. residents) who share a photo post (message) with different characteristics on Instagram (channel), and how the community (receivers) interacts and engages with that content (feedback).

2.2. Mental imagery theory

As shown, communication has traditionally been understood as the process through which a sender transmits information to a receiver, and it is particularly relevant to distinguish between the different functional roles played by sender and receiver (Ferretti, Adornetti, & Chiera, 2022). The key factor that the sender considers is the effect that their message will have on the receivers. However, from a receiver's point of view, the key factor is the information received, and their behavior will

change if they receive enough information and know how to interpret it (Carazo & Font, 2010).

Images are one of the key elements that make transmitted messages powerful in influencing receivers, since they allow the generation of visual and mental representations of a scene that has properties similar to the representations elicited by external stimuli (Ferretti et al., 2022). To address the need to understand how these images drive consumer behavior, this study turned to mental imagery theory, which places the customer's imagination at the center of their decision-making (Heller, Chylinski, de Ruyter, Mahr, & Keeling, 2019).

Mental imagery is a mental experience generated from different stimuli that arises in the absence of true physical stimuli, triggering a process by which visual information is represented in working memory (MacInnis & Price, 1987; Schifferstein, 2009). For example, when they see an image of a tourist enjoying a tourism experience, customers use mental images to generate a representation in their mind and visualize it in their lives, that is, users have the ability to generate and transform images outside of their sensory experience (Heller et al., 2019; Pearson, Naselaris, Holmes, & Kosslyn, 2015).

The mental activity that leads to imaginary visualization can be provoked with different stimuli: visual, olfactory, gustatory, or haptic (Miller & Stoica, 2004). Specifically, it has been found that mental images induced by visual stimuli, such as photos, are the most relevant to the process of learning and establishing information (Heller et al., 2019; Schifferstein, 2009). In addition, it has been shown that, among the different sensory stimuli that a tourism destination transmits (such as images, sounds, and texts), only images promote the creation of mental images, reinforcing a positive attitude toward the destination (Khalilzadeh, Pizam, Fyall, Tasci, & Hancock, 2023; Lee & Gretzel, 2012).

However, in spite of the relevance of visual stimuli, little attention has been paid to the role of mental imagery in social media, and specifically Instagram (Arival, 2023). Today, users spend more than 2.2 h of their leisure time on social media, which accounts for the largest single share of their connected media time (35% of the total; DataReportal, 2022), and most declare that they are inspired by social media to select their next destination (Arival, 2023). Since the choice of destination is influenced by the mental images that tourists form based on the expected experience in the destination (Lee & Gretzel, 2012; Oh, Fiore, & Jeoung, 2007), it is necessary to delve into this aspect of the research and find the reasons that lead users to interact with the photos of the destination, making them go viral. Thus, this study associates the mental images that allow the cognitive mechanisms of information processing prior to the trip to the destination, with a key variable that defines receivers' satisfaction with the content shared about the experience, that is, engagement.

2.3. Social media engagement

When people use their social media profiles, they enter into a circle of continuous information sending and receiving, in which the main interaction action is social media engagement (SME) (Abbasi et al., 2023). Specifically, SME is defined from a behavioral perspective as the post-interaction in terms of the number of likes and comments (Mele, Filiari, & De Carlo, 2023).

In the tourism and hospitality context, SME is an important success metric for a DMO, because it influences attitude toward tourism destinations (Filiari et al., 2021) and consumers' perception of a hospitality service company (Dijkmans, Kerkhof, & Beukeboom, 2015). In addition, user engagement with social media content reflects its effectiveness, since higher levels of engagement with certain content can translate into actual user behavior, for example word-of-mouth about or visiting the destination (Pino et al., 2019). That is, the benefits of posting tourism images for the DTI will only be realized if the receivers respond to the content, since the response (i.e., likes, comments, and shares) means that others reflected on the post and considered its content as important

(Tamaki, 2021).

As a result, SME metrics are commonly used to measure and evaluate the marketing results obtained by certain content on social media, and several studies have examined the determinants that drive the virality of user-generated content when this content is text (Chintagunta, Gopinath, & Venkataraman, 2010; Tan, Lee, & Pang, 2014). However, the role that images and their content play on generating engagement has remained a largely unexplored question (Li & Xie, 2020). In this respect, there is evidence that SME is affected not only by the content of the message (e.g., pictorial content), but also by who sends the message (Pino et al., 2019). These types of characteristics can predict differences in engagement in social media (de Vries, Peluso, Romani, Leeftang, & Marcati, 2017). Even though the literature on tourism devotes more and more attention to such effects (Pino et al., 2019), we still lack a comprehensive view of the visual content-related features of images that trigger engagement. Based on the aforementioned theories and focused on the Instagram context, this research aims to shed some light on this issue.

3. Formulation of hypotheses

3.1. Hospitality services and points of interest as pictorial stimulus

Tourism implies the use and enjoyment of a set of services, such as transportation, tourist attractions, tourist activities, gastronomy, or accommodation, promoting the tourist experiences of the destinations (Lugosi & Walls, 2013). In the planning phase of visiting destinations, tourists consider several important things. On the one hand, they aim to understand or imagine what places of interest they will visit on a destination and how their experience will be. On the other hand, they also consider hospitality services (e.g., accommodation options) that may affect their experience at the destination (Han, Kim, & Hyun, 2011).

Based on mental imagery theory (Schiffenstein, 2009), social media photos may be fundamental to anticipate the tourist experience nowadays. However, previous research has not analyzed images differentiating between the characteristics of the tourist environment: the places of interest and the hospitality services (Zhang, Zhang, & Yang, 2023; Zuo et al., 2023). In general, places of interest represent the essence of a tourist destination better than hospitality services, and the receiver, in their mental representation of the photo (Aramendia-Muneta et al., 2021; Tamaki, 2021), can better understand the positive emotions of the message transmitted by the sender, resulting in greater interaction with the published content. Therefore, we propose the following hypothesis.

H1. Instagram posts focused on places of interest in a tourist destination will generate greater engagement than those Instagram posts focused on hospitality services.

3.2. Centricity as centrality stimulus

When analyzing the visual content shared by tourists, it is important to consider the differentiation between photos with and without people at the destination. Although some studies have classified the types of images that are photographed at the destination, reaching the conclusion that the vast majority are related to food, accommodation, or points of interest (Huai et al., 2022; Li et al., 2023; Wang, Luo, Huang, & Sam, 2020), it is necessary to make a subclassification to consider whether or not people appear in the depicted scene, since the person is a central element in the engagement that receives a photo (Aramendia-Muneta et al., 2021; Tamaki, 2021; Zhang et al., 2023). The concept of centricity, as used in this study, refers to whether photographs include people or not. This is supported by prior research indicating that photos featuring people tend to attract more engagement in terms of likes and comments, specifically photos with faces are significantly more likely to receive likes and comments compared to those without faces (Bakhshi, Shamma, & Gilbert, 2014). The fact that people appear in the

photographs, and the context, are one of the most important variables in the study of TDI (Aramendia-Muneta et al., 2021). The content that tourists show in the images can be classified into different categories, such as “self-centric,” photos that show users experiencing the destination, and “site-centric,” photos focused on the attributes of the destination, without focus on people (Tussyadiah & Fesenmaier, 2009), among other types.

In this respect, some authors argue that the way in which a place is represented reflects the way in which the self is represented through photography, being able to choose whether the tourist becomes the site or not (Dinhopl & Gretzel, 2016; Lo & McKercher, 2015). Some studies suggest that posts that express the presence of the person encourage likes (Tamaki, 2021), probably because it is easier for the receiver to imagine the positive experience that the sender is living. Furthermore, a recent study also concludes that the presence of a person in photographs allows users to imagine their future travel experiences in the depicted travel scenes, contributing to the perceived attractiveness of the destination (Li & Wan, 2025).

Based on the above, this study suggests that Instagram post including photos with people will generate more engagement and proposes the following hypothesis.

H2. Instagram posts with photos including people will generate greater engagement than those without people.

3.3. Tourists and residents as content generators

The sender of the message in a tourism context related to social media is extremely important, since it is the person who decides what experience to show to their community, when to do it, and through what stimuli (Kim & Stephenkova, 2015). In this respect, two types of senders may emit a message about a destination: tourists and residents (Lin et al., 2017). Both tourists and residents are key stakeholders of cities (Molinillo, Anaya-Sánchez, Morrison, & Coca-Stefaniak, 2019) as well as content generators that co-create the image of the destination, which can shape the city image, and that interact with each other through the content generated on social media (Priporas, Stylos, & Kamenidou, 2020). However, previous studies mostly focus on tourists (e.g., An et al., 2020; Bufquin, Park, Back, Nutta, & Zhang, 2020; Tamaki, 2021).

There is evidence showing that these groups behave differently. For example, tourists are more likely to take pictures related to place identity, sculptures, and buildings (Huai et al., 2022), whereas residents prefer to frequent places of entertainment, shopping, and hospitality services such as restaurants (Khan, Wan, & Yu, 2020), and pay more attention to the natural environment and culture (Zhang et al., 2020). In any case, when traveling, tourists show different images from usual, while residents show common places and elements (Gunter & Önder, 2021), so that tourists' followers may be more impressed due to the novelty and react with more likes and comments to the tourists' posts. In addition, based on mental imagery theory (Schiffenstein, 2009), followers will more easily identify with the positive tourist experience when the focus of the picture is a place of interest and when people are included in the photo. On the one hand, places of interest are more representative of the identity of the destination (e.g., Belanche, Casaló, & Flavián, 2017), so that followers may more easily imagine how positive and special the experience is. On the other hand, a picture is worth a thousand words, so it is easier to imagine the positive touristic experience when people are included in the picture. In turn, residents' followers may be more familiar with the posts as they include content that is more related to the daily life of the resident. As a result, this study proposes the following hypotheses.

H3. Tourists' Instagram posts will generate greater engagement than residents' Instagram posts.

H4. The type of sender (tourist vs. resident) will moderate the effect

proposed in H1, so that this effect will be reinforced when the sender is a tourist.

H5. The type of sender (tourist vs. resident) will moderate the effect proposed in H2, so that this effect will be reinforced when the sender is a tourist.

In summary, this study develops a theoretical model on how the characteristics of the message and the sender affect the receiver and their behavior with that content. In addition, this research considers the number of hashtags and mentions as control variables, knowing that the reason for users deploying them is to become popular and get more likes (Chatzopoulou, Filieri, & Dogruyol, 2020). Likewise, another variable that allows us to control this study is the influence rate, measured through the followers and followee count. These measures have already been previously tested for their effect on engagement on Instagram (Tafesse & Wood, 2021). The research framework can be seen in Fig. 1.

4. Methodology

To test the proposed model, this research implemented different techniques for downloading data (first phase), structuring and cleaning the database (second phase), analysis of textual data (third phase) and photographic data (fourth phase), manipulation of variables (fifth phase), and the final statistical analysis (sixth analysis). The research procedure is presented in Fig. 2 and the classification of the variables employed in this research in Fig. 3.

The first phase consisted of downloading images, texts, and metadata of the destination’s points of interest. Specifically, 139,273 posts shared by Instagram users at the selected destination were downloaded using the web scraping technique. The chosen destination belongs to one of the Camino de Santiago’s routes, a cultural UNESCO World Heritage destination (UNESCO, 2023) with specific and homogenous characteristics that allow analysis without bias related to the behavior of tourists, as can exist in other type of destinations, such as sun and beach.

Web scraping is a technique that has grown rapidly in the disciplines of marketing and the tourism context, and consists of extracting data from web pages in an organized and automated way (Yu & Egger, 2021). The web scraping technique reflects three main advantages. The first one is that it allows the automated, structured, and fast download of data on the network (Arefeva & Egger, 2022). Another advantage is that it allows the obtaining of any type of data shared on Instagram, such as photos in.jpg or.png format, UTF-8 texts and emojis, and metadata of the users who share the content, such as their username and location, the likes and comments of the post, or the followers and the followings of the user. The third advantage is that this data is anonymized at the time of construction of the download database, prior to downloading, allowing

us to comply with the European Data Protection Law (Yu & Egger, 2021).

The web scraping technique is crucial to improve the analysis of social media engagement and the understanding of travelers’ behavior as engagement has been shown to determine travel intentions (Tran & Rudolf, 2022).

The second phase consisted of differentiating between tourists and residents within the database, given the importance of knowing the profile of the sender. In this case, the photos analyzed were shared between 2010 and 2022. Each photo is accompanied by metadata that allows the user to be identified through an anonymized ID. This code allows us to know how many photos each user has uploaded in that time period; therefore, by grouping all the information for each anonymized code of each user, we can know if that person is a tourist or a resident. In order to distinguish between tourists and residents in this database, two methods were applied.

The first was to label the database into two types: users who had published photos in that destination for 30 consecutive days or less, in this case they were considered visitors, and users who had published photos for more than 30 days, in this case they were considered residents (Gunter & Önder, 2021). The second method consisted of labeling and dividing the database among users who had published 30 photos or less in the destination, in which case they were considered tourists (Gomez, Gomez, Gibert, & Karatzas, 2019). In addition, to reduce the risk of miss election, posts containing business data such as email accounts and phone numbers, and posts containing a high rate of hashtags were discarded (Gomez et al., 2019). The high rate of hashtags in a post was achieved through machine learning techniques explained below.

The third phase consisted of analysis of the sentiment of the texts accompanying the photos using machine learning techniques, once the database was labeled with tourists and residents. Advanced methodologies such as machine learning have been employed to enhance the measurement and analysis of destination brand experiences before (Calderón-Fajardo, Anaya-Sánchez, & Molinillo, 2024). In this research, the machine learning model NLTK (NLTK, 2023) was implemented for the sentiment analysis is based on Python code and belongs to open-source software. This tool with a machine learning approach allows sentiment analysis to be carried out through text content analysis using a pre-trained model, and returns a rating between -1 (the most negative text possible) and 1 (the most positive possible). Since the goal of this study is to understand how Instagram posts may help develop a positive and strong TDI (Holbrook & Hirschman, 1982), sentiment analysis allowed us to detect positive transmitted experiences, avoiding neutral or negative experiences, which are not the subject of this study. Finally, 27,088 positive sentiment posts were obtained (with a polarity between 0.5 and 1, as can be seen in Table 1, which reflects a positive or extremely positive publication). These posts were analyzed using deep learning techniques, explained below. The machine learning technique also made it possible to find out the number of hashtags and the number of mentions to other Instagram users in each post, two of the control variables in this study.

The fourth phase consisted of extracting information from the photos. For this, deep learning methods were applied through the convolutional neural network framework for Python with different classifications. It is important to note that although machine learning and deep learning are both artificial intelligence techniques, they have important differences. While machine learning techniques work with regression algorithms and/or decision trees, deep learning techniques use neural networks that try to imitate the functioning of biological neural networks (T.K. et al., 2021).

The most useful artificial intelligence method for image classification is neural networks, since they allow, among others, the classification of images based on the different objects found within the image (such as people, monuments, targets, etc.) These networks are trained from millions of images. This database is divided into training and testing tests, and this allows the neural networks to learn from the pixels and the

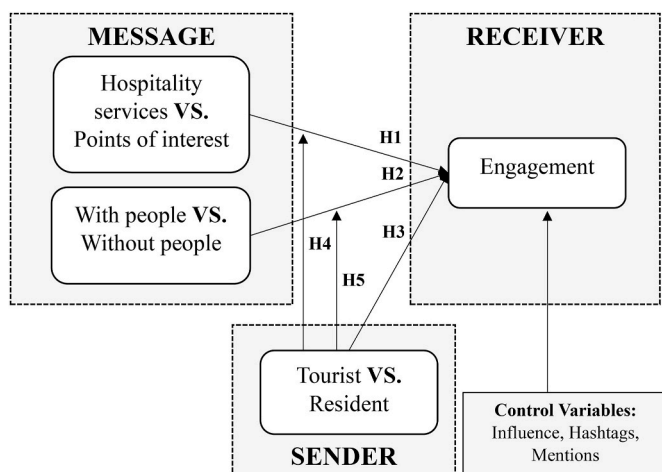


Fig. 1. Research framework.

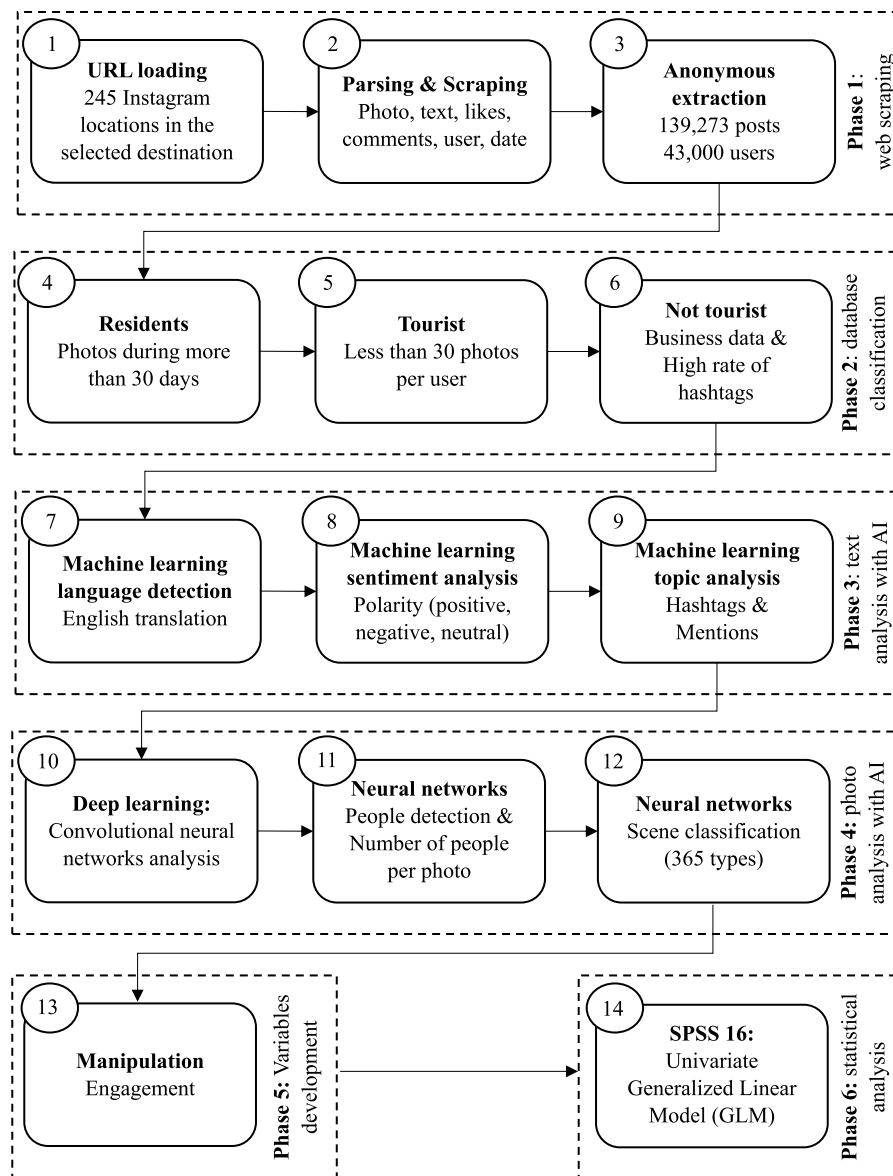


Fig. 2. Research procedure.

labels of the images. The networks create different layers and convolutions and become models that users can adapt in the last layers to implement in their databases (Fig. 4). For this reason, this research applied different open-source neural networks that are already pre-trained.

The first implemented neural network is DeepFace (Serengil, 2023), an open-source model that allows easy recognition and analysis of facial attributes using Python. This neural network was developed using state-of-the-art models such as VGG-Face, Google FaceNet, OpenFace, Facebook DeepFace, DeepID, ArcFace, Dlib, and SFace. Its accuracy is higher than that of the human brain, located at 97.53%. This first neural network made it possible to know if people appear in the photos or not. In addition, it was possible to know the total number of people in each photo. This allowed us to obtain the centrality variable of this study, in which zero people means “without people,” and one or more people means “with people.”

The second neural network, called places365 (Kalliatakis, 2020), allowed the knowledge of the type of scene transmitted in each photo. This neural network was trained with 1.8 million images from 365 scene categories and implemented the Keras models of the pre-trained VGG16

CNNs on Places365-Standard (Zhou, Lapedriza, Khosla, Oliva, & Torralba, 2018). This variable, together with the location of each photo obtained from the metadata of the web scraping download, allowed us to distinguish between scenes at the destination (photos with monuments, museums, general destination characteristics, etc.), or scenes related to hospitality services (photos in bars, pubs, restaurants, etc.).

The fifth phase consisted in the creation and manipulation of the variables once the database was obtained. First of all, following the most widespread metric in academia, the SME rate refers to the average number of interactions, in the case of Instagram comments and likes (as sharing is not readily available on Instagram (Li & Xie, 2020), and on the number of followers during the selected period time, expressed as a percentage (Yost, Zhang, & Qi, 2021). Therefore, we measure engagement with each publication as the total number of likes and comments in relation to the number of followers of the user who published the Instagram post (Hauser et al., 2022).

Regarding control variables, we identified the number of hashtags and mentions of the publication, and differentiated between those with and without hashtags and mentions. Likewise, an influence rate is calculated by comparing the number of followers and followees of the

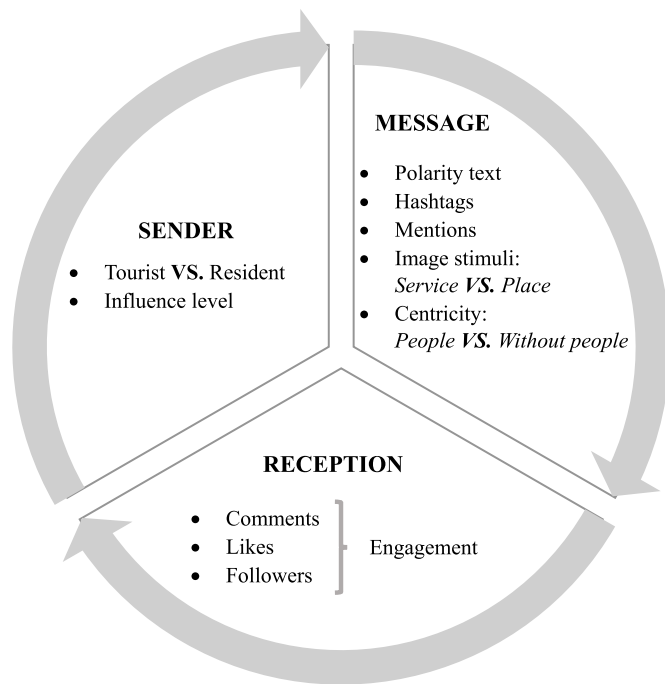


Fig. 3. Classification of variables under the research framework.

sender. In this respect, a greater influence is associated to the sender when they have a greater number of followers than of followees (Tafesse & Wood, 2021). The structure and classification of the whole database obtained after these five stages can be seen in Table 1.

As a result of this process, our final data set to be analyzed consisted of 27,088 posts. It is important to note that all groups considered in this research (according to different sender types, and different stimulus on the message) were highly represented (Table 2).

The sixth phase consisted of a statistical analysis to analyze the effect of the different independent variables on engagement. An IBM SPSS statistics v.26 univariate generalized linear model (UGLM) analysis was carried out. This type of method provides a regression analysis and an analysis of variance for a dependent variable using several factors or variables. In addition, this methodology allows introducing the effects of covariates or control variables (IBM, 2022), which allowed the measuring of the effect of hashtags, mentions, and the influence of the sender in the model. In addition, this type of analysis made it possible to study both the direct effects between variables and the moderating effect of the sender variable in the relationship between the type of content and engagement.

Table 1
Classification of variables.

Variable	Measure	Type	Technique	Author
Engagement	Likes + Comments Followers	Continuous	Web scraping	Yost et al. (2021)
Pictorial stimulus	1 = Places of interest 0 = Hospitality services	Dichotomous	Web scraping & Deep learning	Zhang et al. (2020)
Centricity	1 = With people 0 = Without people	Dichotomous	Web scraping & Deep learning	Adapted from Aramendia-Muneta et al. (2021)
Sender	1 = Tourist 0 = Resident	Dichotomous	Web scraping	Kim and Stephenkova (2015); Peetz et al. (2016)
Influence	Followers >1 = Influencer Following = <1 = Non-influencer	Dichotomous	Web scraping	Tafesse and Wood (2021)
Hashtags	1 = Hashtags included 0 = Hashtags not included	Dichotomous	Web scraping & Machine learning	Chatzopoulou et al. (2020)
Mentions	1 = Mentions included 0 = Mentions not included	Dichotomous	Web scraping & Machine learning	Chatzopoulou et al. (2020)
Polarity	Between -1 and 1	Continuous	Web scraping & Machine learning	Bhatt and Pickering (2023)

5. Results

Results from the UGLM analysis show that there are significant differences in engagement (Table 3 shows descriptive results for engagement according to the different subgroups formed by the independent variables). First, focusing on direct effects, we find support for H1 as the pictorial stimuli influences engagement ($F_{1, 27,086} = 16.443, p < 0.01$). Specifically, greater engagement emerges when posts are about places of interest ($M = 8.999$) rather than hospitality services ($M = 4.335$). These results are in line with previous reviews of the literature that found that photos related to restaurants or hotels received fewer comments and likes (Aramendia-Muneta et al., 2021). Similarly, UGLM analysis reveals significant differences in the engagement obtained when the centricity type changes, thus, H2 is also supported ($F_{1, 27,086} = 3.858, p < 0.01$). In this case, greater engagement is found for photos with people ($M = 9.410$) than without people ($M = 6.311$). This result also allows us to ratify previous results in the literature on the human being as a central element of photography to achieve greater engagement (Aramendia-Muneta et al., 2021; Zhang et al., 2020), so that photos must include people that show they are having fun and being entertained during their experience to obtain a higher engagement (Hou & Pan, 2023). In addition, in support of H3 ($F_{1, 27,086} = 5.375, p < 0.01$), we also find significant differences in the engagement obtained when the sender type changes. Higher engagement is observed when the sender is a tourist ($M = 8.662$) than when they are residents ($M = 5.741$). Therefore, our results are consistent with previous literature indicating that tourists receive more comments and likes than destination residents (Gunter & Önder, 2021). Indeed, when tourists travel, they are showing a facet of their daily life that is different from the usual, while residents show common places and elements with their community, which are not as impressive as the content shown by a tourist, and therefore receive a lower engagement rate (Gunter & Önder, 2021).

Turning to the moderating effects proposed in the research model, we find a significant moderating effect of sender profile on the influence of centricity on engagement, which supports H5 ($F_{1, 27,086} = 7.036, p < 0.01$). In particular, the effect proposed in H2 is strengthened when the sender is a tourist. Specifically, if a tourist shares content, greater differences in engagement appear when the photo includes people ($M = 11.581$) than when nobody is included ($M = 6.772$). In turn, almost no difference in engagement arises when the sender is a resident ($M_{with\ people} = 5.0952, M_{without\ people} = 5.611$) (see Fig. 5). Therefore, when tourists share their experience on Instagram, their community expect that their experience be represented by the person in that destination, something inherent to the mental imagery theory. In other words, it is extremely important to see the person enjoying the tourist experience, and for this reason the images of the tourists receive a higher rate of engagement; however, for the viewers of residents' content, the people are not so important, but the context it is important (Zhang et al., 2023).

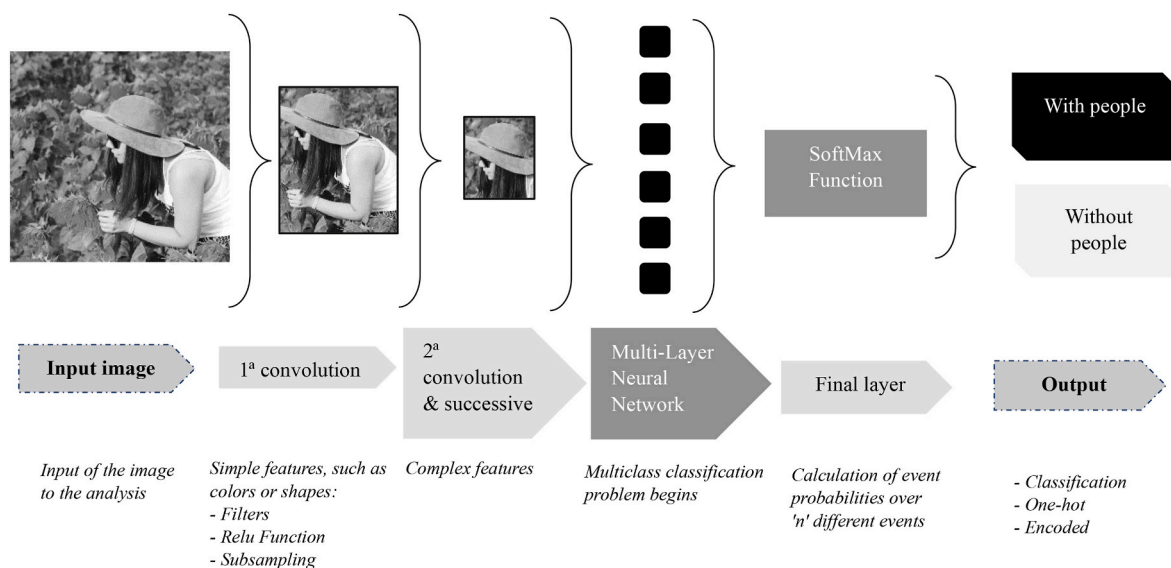


Fig. 4. Classification procedure of a neural network. Source: Adapted from Blanco-Moreno, González-Fernández, Muñoz-Gallego, and Egger (2024).

Table 2 Sample classification.

Construct	Variables	n
Pictorial stimulus	Places of interest	18,459
	Hospitality services	8629
Centricity	With people	10,538
	Without people	16,550
Sender	Tourist	16,437
	Resident	10,651

However, H4 is not supported as the sender profile does not moderate the influence of pictorial stimuli on engagement ($F_{1, 27,086} = 0.002$; $p > 0.1$). The results show that, compared to a service context, photos in places of interest increases engagement in a similar way for both types of senders (see Fig. 6). In any case, regardless of whether the photo is taken in a place of interest or hospitality service context, the users who obtain the most engagement are tourists, probably because, as aforementioned, they are in a different context from their routine. In turn, residents show photos in a context that most of their community is familiar with.

Regarding the control variables, both the influence level of the user that posts the image ($F_{1, 27,086} = 12.844$, $p < 0.01$) and the number of hashtags ($F_{1, 27,086} = 15.068$, $p < 0.01$) are significant, but the number of mentions to other Instagram users is not ($F_{1, 27,086} = 0.074$). Although users make use of hashtags and mentions to other users to get more engagement and be more popular, it can be seen that the use of more mentions is not significant (Chatzopoulou et al., 2020). The results are consistent when we consider likes or comments separately. Although the antecedents influencing engagement are similar, it is important to note that most of the engagement is made up of likes. This observation aligns with existing literature, which suggests that likes are more prevalent due to the ease and minimal effort required compared to comments (Tamaki, 2021). For instance, posts that feature the presence of a person tend to encourage more likes, as they facilitate the receiver’s ability to imagine the sender’s positive experience, thereby fostering a quick and effortless form of engagement (Roma & Aloini, 2019; Smith, Fischer, & Yongjian, 2012). This highlights a significant distinction in how likes and comments contribute to overall engagement, with likes being the dominant form due to their simplicity.

6. Discussion

This research analyzes the engagement received by 27,088 Instagram posts from different types of users (tourists and residents) depending on their content (hospitality services and places of interest), and its centricity (with people or without people), drawing on the theories of communication and mental imagery to understand the responses of users to the TDI in social media publications. In addition, the moderating effect of the type of sender is analyzed and their influence is controlled through the number of hashtags, mentions, and the influence itself. Prior to the statistical analysis, a filtering of the database and a content analysis using artificial intelligence of texts, images, and metadata was carried out. The results provide DMO and social media users with insights into their Instagram strategies.

6.1. Theoretical implications

This study contributes to a better understanding of the mechanisms that explain the creation of a link with the destination caused by the display of visual content generated by both tourists and residents about the tourist destination in social media. Specifically, the results allow us to confirm both communication theory and mental imagery theory as explanatory theories of behavior in social media in tourist contexts. On the one hand, communication theory helps to explain the communication process that exists in social media when residents or tourists (sender) post a picture about a destination (message) on Instagram (channel) that can be seen by other users of the application (receivers), who can interact with the publication (feedback).

On the other hand, mental imagery theory serves to understand why both pictorial stimuli (hospitality services vs. points of interest) and centrality stimuli (with vs. without people) of the message affect the receivers’ response. In this respect, mental imagery theory supports the idea that receivers identify more easily with the positive tourist experience when people are included in the photo (so it is easier to see what they are feeling) and when the focus of the picture is a place of interest, which better represents the essence of a tourist destination. In addition, due to the novelty of visiting a touristic destination, the effect of centrality stimuli is reinforced when the sender is a tourist, as it is easier for the receiver to understand how the sender is enjoying the situation when they appear in the publication. As a result, this study expands the literature on tourism and destination management by focusing on visual content and empirically testing the effect of the aforementioned stimuli

Table 3
Descriptive statistics (dependent variable: engagement).

Centricity	Sender	Pictorial stimulus	Mean	Standard deviation	n	
Without people	Resident	Hospitality service	2.692	3.616	3440	
		Place of interest	8.814	66.303	3134	
		Total	5.611	45.952	6574	
	Tourist	Hospitality service	4.413	7.296	2399	
		Place of interest	7.519	25.435	7577	
		Total	6.772	22.492	9976	
	Total	Hospitality service	3.399	5.503	5839	
		Place of interest	7.898	41.761	10,711	
		Total	6.311	33.822	16,550	
	With people	Resident	Hospitality service	4.819	5.241	1635
			Place of interest	6.711	7.161	2442
			Total	5.952	6.525	4077
Tourist		Hospitality service	8.381	21.920	1155	
		Place of interest	12.277	119.697	5306	
		Total	11.581	108.875	6461	
Total		Hospitality service	6.294	14.765	2790	
		Place of interest	10.523	99.166	7748	
		Total	9.410	85.389	10,538	
Total		Resident	Hospitality service	3.377	4.324	5075
			Place of interest	7.893	49.940	5576
			Total	5.741	36.325	10,651
	Tourist	Hospitality service	5.703	13.980	3554	
		Place of interest	9.479	79.285	12,883	
		Total	8.662	70.509	16,437	
	Total	Hospitality service	4.335	9.633	8629	
		Place of interest	8.999	71.701	18,459	
		Total	7.512	59.477	27,088	

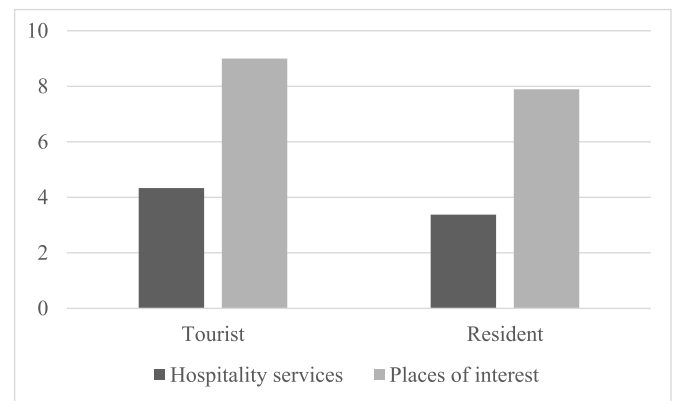


Fig. 6. Engagement means according to the type of sender and the type of pictorial stimulus.

visual elements such as photos of places of interest and hospitality services. The response (R) is the engagement measured through likes, comments, and shares. The missing component, the organism (O), involves the cognitive and emotional processing by the audience, which can be explained through mental imagery theory. Mental imagery theory posits that visual stimuli, such as photos, trigger mental images in the audience’s minds, making it easier for them to imagine experiencing the depicted scenes themselves. This ease of imagining would act as the organism (O) in the S-O-R model, mediating the relationship between the stimulus and the response. Further research should confirm this proposal in an experimental design.

In addition, this study contributes to previous research that analyzed the relation between scenes and engagement rate (Aramendia-Muneta et al., 2021), by differentiating between points of interest and hospitality services in the destination, revealing that engagement rate is higher in the former, as explained above. Finally, the study provides important implications for the TDI literature, as it serves to understand under which stimuli (included in the photo posted on Instagram) greater engagement with the content is generated and, consequently, a more positive TDI may be formed.

6.2. Managerial implications

The findings of this study provide evidence to understand what type of content is best to use in visual marketing promotions on social media. This research makes it possible to propose strategic lines of action for DMOs. Firstly, it is surprising to learn that both destination-focused photos and hospitality-focused photos gain more engagement when people are in the photos. Thus, since content marketing on social media is growing more and more, DMOs must encourage tourists and tourism managers to share photos with a human element. In addition, results suggest that a greater influence level of the user that posts the image may serve to increase engagement. To take advantage of this result, a good strategy could be, within a process of collaboration and co-creation of TDI, to cooperate with influencers from social media platforms, urging them to share experiences with human elements (Femenia-Serra, Gretzel, & Alzua-Sorzabal, 2022; Zhang et al., 2023).

Besides, since point of interest and hospitality service photos gain more engagement when the sender is a tourist, this study recommends encouraging the posting of photos during the tourism experience (Araujo-Batlle, Garay-Tamajón, & Morales-Pérez, 2023). More specifically, since destination photos double the engagement rate of hospitality services, DMOs should promote taking photos on “instagrammable places,” for example, creating selfie points. In any case, our results suggest that managers of hospitality services in the destination should include customers in their photos to obtain a higher engagement rate on the posts related to the hospitality service.

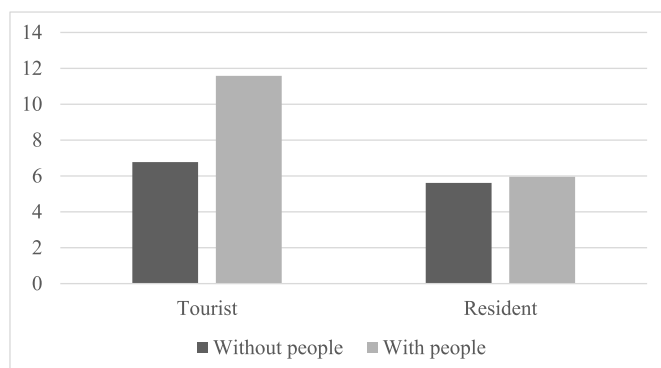


Fig. 5. Engagement means according to the type of sender and centricity.

included on pictures posted on Instagram (centricity and pictorial) on the engagement that the content generates.

In addition, mental imagery could be integrated into the Stimulus-Organism-Response (S-O-R) model (Mehrabian & Russell, 1974) to understand why the audience interacts with the content. According to the S-O-R model, the stimulus (S) is the Instagram post, which includes

Finally, this study advocates artificial intelligence technology and automatic analysis of content shared on social networks through big data and machine learning and deep learning techniques. Numerous open-source models are already available to help DMOs efficiently and accurately detect the visual properties of tourist-generated photos (Zhang et al., 2023).

6.3. Limitations and future research

This study has limitations that could be addressed in future research mainly due to the specific context of analysis. First of all, the study was carried out under a single destination approach with its own peculiarities. Future research should validate these findings in other destinations with different characteristics (e.g., sun and beach destinations, nature destinations, or urban destinations). Second, this research was carried out with a sample of 139,273 Instagram posts in a context of positive tourism experience, which could limit the generalizability of the findings. It would be interesting to replicate these findings with different experiences, particularly with negative experiences (Kim, Guo, & Wang, 2022), but it would be interesting to analyze negative comments to predict and avoid TDI crises. Third, the characteristics of the receiver are omitted in this investigation. However, differences at the viewers' individual level (e.g., personality) could moderate the behavior of users in the interaction with the content. Future research should focus on understanding the role of these receivers' characteristics. Fourth, focusing on the sender, only content from users has been analyzed, that is, tourists and residents, but not from organizations or companies that also contribute to the image of the destination. Fifth, even though we focused on text-based variables (e.g., hashtags, mentions, or polarity), it would also be important to carry out a more in-depth analysis of the text, in which variables such as irony, the subjectivity of the message, and even photo-text congruence are taken into account. Similarly, a limitation of the neural network is that it identifies just the main scene of the photo, but it may be a combination (e.g. a restaurant in front of the Eiffel Tower). Even though most of the photos just show one scene, future improvements of neural networks may overcome this issue.

In addition, only Instagram image posts were analyzed, while this social media platform is in continuous evolution and has recently incorporated other types of content such as stories or reels through which tourists also show their tourist experience. As other visual sensory modalities represented on Instagram, such as videos with sound, can induce mental imagery, it is recommended to analyze these new types of content, even new social platforms such as TikTok (Barta, Belanche, Fernández, & Flavián, 2023).

Besides, as aforementioned, future research could deepen on integrating our research model into the S-O-R and employ experimental designs to confirm that mental imagery processing acts as the organism; that is, the underlying mechanism that explains the influence of the post (the stimulus) on engagement (the response). Since communication theory considers that the reception of a message depends on two aspects: the responses it generates, and particularly the sentiment (Peetz et al., 2016), it is also important to understand what sentiment the posts generate. Therefore, different scenarios could be developed to show various types of Instagram posts and, after being randomly exposed to one of them, participants would be asked to rate the ease with which they can imagine themselves in the depicted scenes, followed by measuring their engagement behaviors. This would help confirm that mental imagery serves as the mechanism through which visual stimuli generate engagement responses.

Another recommendation for future research is to investigate the impact of vibrant and visually appealing content on social media engagement. While the current study focuses on the content type and centrality of Instagram posts, it does not include a variable for the visual attractiveness or the use of filters that enhance the vibrancy of images. Previous research has shown that visual appeal significantly affects user engagement and attitudes towards destinations (Filiari et al., 2021; Kim

& Stepchenkova, 2015). Future studies could explore how the use of vibrant colors, high-quality visuals, and popular filters affect user engagement. This could involve an experimental design where different versions of the same image, with varying degrees of visual appeal, are tested to measure their impact on engagement metrics. Understanding these aspects could provide a more comprehensive view of how online visual elements influence the audience's interaction with tourism-related content (Molinillo et al., 2019).

CRedit authorship contribution statement

Sofia Blanco-Moreno: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Ana M. González-Fernández:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization. **Pablo Antonio Muñoz-Gallego:** Writing – review & editing, Validation, Supervision, Conceptualization. **Luis V. Casaló:** Writing – review & editing, Supervision, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

none.

References

- Abbasi, A. Z., Tsiotsou, R. H., Hussain, K., Rather, R. A., & Ting, D. H. (2023). Investigating the impact of social media images' value, consumer engagement, and involvement on eWOM of a tourism destination: A transmittal mediation approach. *Journal of Retailing and Consumer Services*, 71, Article 103231. <https://doi.org/10.1016/j.jretconser.2022.103231>
- Akdim, K. (2021). The influence of eWOM. Analyzing its characteristics and consequences, and future research lines. *Spanish Journal of Marketing - ESIC*, 25(2), 239–259. <https://doi.org/10.1108/SJME-10-2020-0186>
- An, Q., Ma, Y., Du, Q., Xiang, Z., & Fan, W. (2020). Role of user-generated photos in online hotel reviews: An analytical approach. *Journal of Hospitality and Tourism Management*, 45, 633–640. <https://doi.org/10.1016/j.jhtm.2020.11.002>
- Apaolaza, V., Paredes, M. R., Hartmann, P., & D'Souza, C. (2021). How does restaurant's symbolic design affect photo-posting on Instagram? The moderating role of community commitment and coolness. *Journal of Hospitality Marketing & Management*, 30(1), 21–37. <https://doi.org/10.1080/19368623.2020.1809594>
- Aramendia-Muneta, M. E., Olarte-Pascual, C., & Ollo-López, A. (2021). Key image attributes to elicit likes and comments on Instagram. *Journal of Promotion Management*, 27(1), 50–76. <https://doi.org/10.1080/10496491.2020.1809594>
- Araujo-Battle, A., Garay-Tamajón, L. A., & Morales-Pérez, S. (2023). Recreation and tourism selfies versus conservation: The influence of user-generated content in the image of protected natural spaces. *Journal of Outdoor Recreation and Tourism*, Article 100644. <https://doi.org/10.1016/j.jort.2023.100644>
- Arefeva, V., & Egger, R. (2022). When BERT started traveling: TourBERT—a natural language processing model for the travel industry. *Digital*, 2(4), 546–559. <https://doi.org/10.3390/digital2040030>
- Arefeva, V., Egger, R., & Yu, J. (2021). A machine learning approach to cluster destination image on Instagram. *Tourism Management*, 85, Article 104318. <https://doi.org/10.1016/j.tourman.2021.104318>
- Arival. (2023). The 2023 experiences traveler. <https://arival.travel/research/the-2023-experiences-traveler/>.
- Baker, M. J. (1976). Communication theory and marketing. In M. J. Baker (Ed.), *Macmillan studies in marketing management*. London: Palgrave. https://doi.org/10.1007/978-1-349-15703-7_5.
- Bakhshi, S., Shamma, D. A., & Gilbert, E. (2014). Faces engage us: Photos with faces attract more likes and comments on Instagram. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 965–974). <https://doi.org/10.1145/2556288.2557403>
- Balomenou, N., & Garrod, B. (2019). Photographs in tourism research: Prejudice, power, performance and participant-generated images. *Tourism Management*, 70, 201–217. <https://doi.org/10.1016/j.tourman.2018.08.014>
- Bao, T., & Chang, T. S. (2014). Why Amazon uses both the New York Times Best Seller List and customer reviews: An empirical study of multiplier effects on product sales from multiple earned media. *Decision Support Systems*, 67, 1–8. <https://doi.org/10.1016/j.dss.2014.07.004>
- Barta, S., Belanche, D., Fernández, A., & Flavián, M. (2023). Influencer marketing on TikTok: The effectiveness of humor and followers' hedonic experience. *Journal of Retailing and Consumer Services*, 70, Article 103149. <https://doi.org/10.1016/j.jretconser.2022.103149>
- Belanche, D., Casaló, L. V., & Flavián, C. (2017). Understanding the cognitive, affective and evaluative components of social urban identity: Determinants, measurement, and practical consequences. *Journal of Environmental Psychology*, 50, 138–153.

- Bell, E., & Davison, J. (2013). Visual management studies: Empirical and theoretical approaches. *International Journal of Management Reviews*, 15(2), 167–184. <https://doi.org/10.1111/j.1468-2370.2012.00342.x>
- Bhatt, P., & Pickering, C. M. (2023). Analysing spatial and temporal patterns of tourism and tourists' satisfaction in Nepal using social media. *Journal of Outdoor Recreation and Tourism*, Article 100647. <https://doi.org/10.1016/j.jort.2023.100647>
- Blanco-Moreno, S., González-Fernández, A. M., Muñoz-Gallego, P. A., & Egger, R. (2024). What do you do or with whom? Understanding happiness with the tourism experience: An AI approach applied to Instagram. *Humanities & Social Sciences Communications*, 11(1). <https://doi.org/10.1057/s41599-024-02859-z>
- Bufquin, D., Park, J. Y., Back, R. M., Nutta, M. W. W., & Zhang, T. (2020). Effects of hotel website photographs and length of textual descriptions on viewers' emotions and behavioral intentions. *International Journal of Hospitality Management*, 87, Article 102378. <https://doi.org/10.1016/j.ijhm.2019.102378>
- Calderón-Fajardo, V., Anaya-Sánchez, R., & Molinillo, S. (2024). Understanding destination brand experience through data mining and machine learning. *Journal of Destination Marketing & Management*, 31, Article 100862. <https://doi.org/10.1016/j.jdmm.2024.100862>
- Carazo, P., & Font, E. (2010). Putting information back into biological communication. *Journal of Evolutionary Biology*, 23(4), 661–669. <https://doi.org/10.1111/j.1420-9101.2010.01944.x>
- Chatzopoulou, E., Filieri, R., & Dogruyol, S. A. (2020). Instagram and body image: Motivation to conform to the “Instabod” and consequences on young male wellbeing. *Journal of Consumer Affairs*, 54(4), 1270–1297. <https://doi.org/10.1111/joca.12329>
- Chen, Z., Chan, I. C. C., & Egger, R. (2023). Gastronomic image in the foodstagrammer's eyes – a machine learning approach. *Tourism Management*, 99, Article 104784. <https://doi.org/10.1016/j.tourman.2023.104784>
- Chintagunta, P. K., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science*, 29(5), 944–957. <https://doi.org/10.1287/mksc.1100.0572>
- DataReportal. (2022). Digital 2022: Global overview report. Retrieved 24.06.2023 from <https://datareportal.com/reports/digital-2022-global-overview-report>
- DataReportal. (2023). Instagram statistics and trends. Retrieved 24.06.2023 from <https://datareportal.com/essential-instagram-stats>
- de Vries, L., Peluso, A. M., Romani, S., Leeflang, P. S. H., & Marcati, A. (2017). Explaining consumer brand-related activities on social media: An investigation of the different roles of self-expression and socializing motivations. *Computers in Human Behavior*, 75, 272–282. <https://doi.org/10.1016/j.chb.2017.05.016>
- Deng, N., & Liu, J. (2021). Where did you take those photos? Tourists' preference clustering based on facial and background recognition. *Journal of Destination Marketing & Management*, 21, Article 100632. <https://doi.org/10.1016/j.jdmm.2021.100632>
- Dijkman, C., Kerkhof, P., & Beukeboom, C. J. (2015). A stage to engage: Social media use and corporate reputation. *Tourism Management*, 47, 58–67. <https://doi.org/10.1016/j.tourman.2014.09.005>
- Dinhopl, A., & Gretzel, U. (2016). Selfie-taking as touristic looking. *Annals of Tourism Research*, 57, 126–139. <https://doi.org/10.1016/j.annals.2015.12.015>
- Femenia-Serra, F., Gretzel, U., & Alzua-Sorzabal, A. (2022). Instagram travel influencers in #quarantine: Communicative practices and roles during COVID-19. *Tourism Management*, 89, Article 104454. <https://doi.org/10.1016/j.tourman.2021.104454>
- Ferretti, F., Adornetti, L., & Chiera, A. (2022). Narrative pantomime: A protolanguage for persuasive communication. *Lingua*, 271, Article 103247. <https://doi.org/10.1016/j.lingua.2022.103247>
- Filieri, R., Yen, D. A., & Yu, Q. (2021). #ILoveLondon: An exploration of the declaration of love towards a destination on Instagram. *Tourism Management*, 85, Article 104291. <https://doi.org/10.1016/j.tourman.2021.104291>
- Gomez, R., Gomez, L., Gibert, J., & Karatzas, D. (2019). Learning from #barcelona instagram data what locals and tourists post about its neighbourhoods. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 11134 LNCS, 530–544. https://doi.org/10.1007/978-3-030-11024-6_41
- Gunter, U., & Önder, I. (2021). An exploratory analysis of geotagged photos from Instagram for residents of and visitors to Vienna. *Journal of Hospitality & Tourism Research*, 45(2), 373–398. <https://doi.org/10.1177/1096348020963689>
- Han, H., Kim, W., & Hyun, S. S. (2011). Switching intention model development: Role of service performances, customer satisfaction, and switching barriers in the hotel industry. *International Journal of Hospitality Management*, 30(3), 619–629. <https://doi.org/10.1016/j.ijhm.2010.11.006>
- Hauser, D., Leopold, A., Egger, R., Ganewita, H., & Herrgessell, L. (2022). Aesthetic perception analysis of destination pictures using #beautifuldestinations on Instagram. *Journal of Destination Marketing & Management*, 24, Article 100702. <https://doi.org/10.1016/j.jdmm.2022.100702>
- Heller, J., Chylinski, M., de Ruyter, K., Mahr, D., & Keeling, D. I. (2019). Let me imagine that for you: Transforming the retail frontline through augmenting customer mental imagery ability. *Journal of Retailing*, 95(2), 94–114. <https://doi.org/10.1016/j.jretai.2019.03.005>
- Holbrook, M. B., & Hirschman, E. C. (1982). The experiential aspects of consumption: Consumer fantasies, feelings, and fun. *Journal of Consumer Research*, 9(2), 132–140. <https://doi.org/10.1086/208906>
- Hou, L., & Pan, X. (2023). Aesthetics of hotel photos and its impact on consumer engagement: A computer vision approach. *Tourism Management*, 94, Article 104653. <https://doi.org/10.1016/j.tourman.2022.104653>
- Huai, S., Chen, F., Liu, S., Canters, F., & Van de Voorde, T. (2022). Using social media photos and computer vision to assess cultural ecosystem services and landscape features in urban parks. *Ecosystem Services*, 57, Article 101475. <https://doi.org/10.1016/j.ecoser.2022.101475>
- IBM. (2022). GLM univariate analysis. Retrieved 24.06.2023 from <https://www.ibm.com/docs/en/spss-statistics/saas?topic=features-glm-univariate-analysis>
- Instagram. (2023). #travel. Retrieved 24.06.2023 from <https://www.instagram.com/explore/tags/travel/>
- Kalliatakis, G. (2020). Keras | VGG16 Places365 - VGG16 CNN models pre-trained on Places365-Standard for scene classification. Retrieved 24.06.2023 from <https://github.com/GKalliatakis/Keras-VGG16-places365>
- Khalilzadeh, J., Pizam, A., Fyall, A., Tasci, A. D. A., & Hancock, P. A. (2023). Destination imagination: Development of the ootomodal mental imagery (OMI) scale. *Tourism Management Perspectives*, 45. <https://doi.org/10.1016/j.tmp.2022.101051>
- Khan, N. U., Wan, W., & Yu, S. (2020). Spatiotemporal analysis of tourists and residents in shanghai based on location-based social network's data from Weibo. *ISPRS International Journal of Geo-Information*, 9(2), 70. <https://doi.org/10.3390/ijgi9020070>
- Kim, J. H., Guo, J., & Wang, Y. (2022). Tourists' negative emotions: Antecedents and consequences. *Current Issues in Tourism*, 25(12), 1987–2005. <https://doi.org/10.1080/13683500.2021.1935793>
- Kim, H., & Stepchenkova, S. (2015). Effect of tourist photographs on attitudes towards destination: Manifest and latent content. *Tourism Management*, 49, 29–41. <https://doi.org/10.1016/j.tourman.2015.02.004>
- Lai, L. S. L., & To, W. M. (2015). Content analysis of social media: A grounded theory approach. *Journal of Electronic Commerce Research*, 16(2), 138–152.
- Lee, W., & Gretzel, U. (2012). Designing persuasive destination websites: A mental imagery processing perspective. *Tourism Management*, 33(5), 1270–1280. <https://doi.org/10.1016/j.tourman.2011.10.012>
- Li, Y., & Wan, L. C. (2024). Inspiring tourists' imagination: How and when human presence in photographs enhances travel mental simulation and destination attractiveness. *Tourism Management*, 106, Article 104969. <https://doi.org/10.1016/j.tourman.2024.104969>
- Li, Y., & Xie, Y. (2020). Is a picture worth a thousand words? An empirical study of image content and social media engagement. *Journal of Marketing Research*, 57(1), 1–19. <https://doi.org/10.1177/0022243719881113>
- Li, H., Zhang, L., & Hsu, C. H. C. (2023). Research on user-generated photos in tourism and hospitality: A systematic review and way forward. *Tourism Management*, 96, Article 104714. <https://doi.org/10.1016/j.tourman.2022.104714>
- Lin, Z., Chen, Y., & Filieri, R. (2017). Resident-tourist value co-creation: The role of residents' perceived tourism impacts and life satisfaction. *Tourism Management*, 61, 436–442. <https://doi.org/10.1016/j.tourman.2017.02.013>
- Lo, I. S., & McKercher, B. (2015). Ideal image in process: Online tourist photography and impression management. *Annals of Tourism Research*, 52, 104–116. <https://doi.org/10.1016/j.annals.2015.02.019>
- Lugosi, P., & Walls, A. R. (2013). Researching destination experiences: Themes, perspectives and challenges. *Journal of Destination Marketing & Management*, 2(2), 51–58. <https://doi.org/10.1016/j.jdmm.2013.07.001>
- MacInnis, D. J., & Price, L. L. (1987). The role of imagery in information processing: Review and extensions. *Journal of Consumer Research*, 13(4), 473–491. <https://doi.org/10.1086/209082>
- Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. The MIT Press.
- Mele, E., Filieri, R., & De Carlo, M. (2023). Pictures of a crisis. Destination marketing organizations' Instagram communication before and during a global health crisis. *Journal of Business Research*, 163, Article 113931. <https://doi.org/10.1016/j.jbusres.2023.113931>
- Mikáčová, L., & Gavilaková, P. (2014). The role of public relations in branding. *Procedia - Social and Behavioral Sciences*, 110, 832–840. <https://doi.org/10.1016/j.sbspro.2013.12.928>
- Miller, D. W., & Stoica, M. (2004). Comparing the effects of a photograph versus artistic renditions of a beach scene in a direct-response print ad for a caribbean resort island: A mental imagery perspective. *Journal of Vacation Marketing*, 10(1), 11–21. <https://doi.org/10.1177/135676670301000102>
- Molinillo, S., Anaya-Sánchez, R., Morrison, A. M., & Coca-Stefaniak, J. A. (2019). Smart city communication via social media: Analysing residents' and visitors' engagement. *Cities*, 94, 247–255. <https://doi.org/10.1016/j.cities.2019.06.003>
- NLTK. (2023). SentimentAnalyzer. Retrieved 24.06.2023 from https://www.nltk.org/api/nltk.sentiment.sentiment_analyzer.html
- Oh, H., Fiore, A. M., & Jeoung, M. (2007). Measuring experience economy concepts: Tourism applications. *Journal of Travel Research*, 46(2), 119–132. <https://doi.org/10.1177/0047287507304039>
- Paül i Agustí, D. (2018). Characterizing the location of tourist images in cities. Differences in user-generated images (Instagram), official tourist brochures and travel guides. *Annals of Tourism Research*, 73, 103–115. <https://doi.org/10.1016/j.annals.2018.09.001>
- Paül i Agustí, D. (2021). The clustering of city images on Instagram: A comparison between projected and perceived images. *Journal of Destination Marketing & Management*, 20. <https://doi.org/10.1016/j.jdmm.2021.100608>, 100608.
- Pearson, J., Naselaris, T., Holmes, E. A., & Kosslyn, S. M. (2015). Mental imagery: Functional mechanisms and clinical applications. *Trends in Cognitive Sciences*, 19(10), 590–602. <https://doi.org/10.1016/j.tics.2015.08.003>
- Peez, M. H., De Rijke, M., & Kaptein, R. (2016). Estimating reputation polarity on microblog posts. *Information Processing & Management*, 52(2), 193–216. <https://doi.org/10.1016/j.ipm.2015.07.003>
- Picazo, P., & Moreno-Gil, S. (2019). Analysis of the projected image of tourism destinations on photographs: A literature review to prepare for the future. *Journal of Vacation Marketing*, 25(1), 3–24. <https://doi.org/10.1177/1356766717736350>

- Pino, G., Peluso, A. M., Del Vecchio, P., Ndou, V., Passiante, G., & Guido, G. (2019). A methodological framework to assess social media strategies of event and destination management organizations. *Journal of Hospitality Marketing & Management*, 28(2), 189–216. <https://doi.org/10.1080/19368623.2018.1516590>
- Priporas, C. V., Stylos, N., & Kamenidou, I. (2020). City image, city brand personality and generation Z residents' life satisfaction under economic crisis: Predictors of city-related social media engagement. *Journal of Business Research*, 119(Eirini), 453–463. <https://doi.org/10.1016/j.jbusres.2019.05.019>
- Roma, P., & Aloini, D. (2019). How does brand-related user-generated content differ across social media? Evidence reloaded. *Journal of Business Research*, 96, 322–339. <https://doi.org/10.1016/j.jbusres.2018.11.055>
- Schiffstein, H. N. J. (2009). Comparing mental imagery across the sensory modalities. *Imagination, Cognition and Personality*, 28(4), 371–388. <https://doi.org/10.2190/ic.28.4.g>
- Schramm, W., & Roberts, D. F. (1954). How communication works. In *The process and effects of mass*. University of Illinois Press.
- Serengil, S. I. (2023). DeepFace. Retrieved 24.06.2023 from <https://github.com/serengil/deepface>.
- Smith, A. N., Fischer, E., & Yongjian, C. (2012). How does brand-related user-generated content differ across YouTube, Facebook, and Twitter? *Journal of Interactive Marketing*, 26(2), 102–113. <https://doi.org/10.1016/j.intmar.2012.01.002>
- Stidsen, B. (1975). Market segmentation, advertising and the concept of communication systems. *Journal of the Academy of Marketing Science*, 3(1), 69–84. <https://doi.org/10.1007/BF02729959>
- B, T. K., Annavarapu, C. S. R., & Bablani, A. (2021). Machine learning algorithms for social media analysis: A survey. *Computer Science Review*, 40, Article 100395. <https://doi.org/10.1016/j.cosrev.2021.100395>
- Tafesse, W., & Wood, B. P. (2021). Followers' engagement with instagram influencers: The role of influencers' content and engagement strategy. *Journal of Retailing and Consumer Services*, 58, Article 102303. <https://doi.org/10.1016/j.jretconser.2020.102303>
- Tamaki, S. (2021). Likes on image posts in social networking services: Impact of travel episode. *Journal of Destination Marketing & Management*, 20, Article 100615. <https://doi.org/10.1016/j.jdmm.2021.100615>
- Tan, C., Lee, L., & Pang, B. (2014). The effect of wording on message propagation: Topic and author-controlled natural experiments on Twitter. In *52nd annual meeting of the association for computational linguistics, ACL 2014 - proceedings of the conference* (Vol. 1, pp. 175–185). <https://doi.org/10.3115/v1/p14-1017>
- Tran, N. L., & Rudolf, W. (2022). Social media and destination branding in tourism: A systematic review of the literature. *Sustainability*, 14(20), Article 13528. <https://doi.org/10.3390/su142013528>
- Trobe, J., & Mkono, M. (2017). Not such smart tourism? The concept of e-lienation. *Annals of Tourism Research*, 66, 105–115. <https://doi.org/10.1016/j.annals.2017.07.001>
- Tussyadiah, I. P., & Fesenmaier, D. R. (2009). Mediating tourist experiences. Access to places via shared videos. *Annals of Tourism Research*, 36(1), 24–40. <https://doi.org/10.1016/j.annals.2008.10.001>
- UNESCO. (2023). Routes of Santiago de Compostela: Camino Francés and Routes of Northern Spain. Retrieved 24.06.2023 from <https://whc.unesco.org/en/list/669/lot/her-es>.
- Volo, S., & Irimiás, A. (2021). Instagram: Visual methods in tourism research. *Annals of Tourism Research*, 91. <https://doi.org/10.1016/j.annals.2020.103098>
- Walton, S. C., & Rice, R. E. (2013). Mediated disclosure on Twitter: The roles of gender and identity in boundary impermeability, valence, disclosure, and stage. *Computers in Human Behavior*, 29(4), 1465–1474. <https://doi.org/10.1016/j.chb.2013.01.033>
- Wang, R., Luo, J., Huang, S., & Sam. (2020). Developing an artificial intelligence framework for online destination image photos identification. *Journal of Destination Marketing & Management*, 18, Article 100512. <https://doi.org/10.1016/j.jdmm.2020.100512>
- Yüksel, A., & Yanik, A. (2014). Co-creation of value and social media: How? In N. K. Prebensen, J. S. Chen, & M. Uysal (Eds.), *Creating experience value in tourism* (pp. 182–206). CABI.
- Yost, E., Zhang, T., & Qi, R. (2021). The power of engagement: Understanding active social media engagement and the impact on sales in the hospitality industry. *Journal of Hospitality and Tourism Management*, 46, 83–95. <https://doi.org/10.1016/j.jhtm.2020.10.008>
- Yu, J., & Egger, R. (2021). Color and engagement in touristic instagram pictures: A machine learning approach. *Annals of Tourism Research*, 89, Article 103204. <https://doi.org/10.1016/j.annals.2021.103204>
- Zhang, K., Chen, Y., & Lin, Z. (2020). Mapping destination images and behavioral patterns from user-generated photos: A computer vision approach. *Asia Pacific Journal of Tourism Research*, 25(11), 1199–1214. <https://doi.org/10.1080/10941665.2020.1838586>
- Zhang, K., Zhang, J., & Yang, J. (2023). The influence of human elements in photographs on tourists' destination perceptions and intentions. *Tourism Management*, 95, Article 104684. <https://doi.org/10.1016/j.tourman.2022.104684>
- Zhou, B., Lapedriza, A., Khosla, A., Oliva, A., & Torralba, A. (2018). Places: A 10 million image database for scene recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(6), 1452–1464. <https://doi.org/10.1109/TPAMI.2017.2723009>
- Zuo, B., Tsai, C. H., Ken, Su, C. H., Joan, Jantes, N., et al. (2023). Formation of a tourist destination image: Co-Occurrence analysis of destination promotion videos. *Journal of Destination Marketing & Management*, 27, Article 100763. <https://doi.org/10.1016/j.jdmm.2023.100763>

Sofia Blanco-Moreno: Sofia Blanco-Moreno is a Marketing and Tourism expert with specialization in Digital Marketing and technologies such as Web Scraping and Artificial Intelligence (Machine Learning and Deep Learning) applied in Tourism and Hospitality. She is also a PhD student and an assistant professor at the University of León (Spain), and she has worked as a Digital Marketing expert on international companies such as Meliá Hotels. She has received several research awards, such as the best communication at the AIRSI and AIM 2023 conferences, IUAM-ASSECO Business Case Award 2022 and "Proof of concept" within the University-Business Knowledge Transfer Plan for the platform *Photo Data Tour Analytics*.

Ana M. González-Fernández: Dr. Ana M. González-Fernández is a Senior Lecturer in Marketing at the University of León, Spain. She holds a Ph.D. in Management. She is Director of the Department of Business Management and Economics at the University of León. Her research interests mainly deal with marketing and consumer behaviour applied to travel and tourism. She mainly applies her research in the tourism field. She has published quite a number of articles in SSCI-Ranked journals as well as books in relevant Publishing houses. She has actively participated in more than fifteen competitive research projects and ten company projects.

Pablo A. Muñoz-Gallego: Dr. Pablo Antonio Muñoz Gallego. Doctor in Economics and Business by the University of Oviedo. University Professor in the area of Marketing and Market Research at the University of Salamanca. He has been Dean of the Faculty of Economics and Business at the University of Salamanca, department director and director of the Doctoral Program and the Master's Degree in Research in Business Economics. He held the position of President of the Economic and Social Council of Castilla y León. He has published research in *Tourism Management*, *Journal of Travel Research*, *International Journal of Hospitality Management* and *Journal of Retailing*, among others.

Luis V. Casalo: Luis V. Casalo (PhD) is a full professor of Marketing at the University of Zaragoza (Spain). His research interest focuses on the application of new technologies (e. g., artificial intelligence, service robots ...) to the service context (e.g., tourism) and its influence on consumer behavior. He has published papers in top tourism, hospitality and service journals such as *Tourism Management*, *Journal of Service Research*, *Journal of Service Management*, *International Journal of Hospitality Management* or *International Journal of Contemporary Hospitality Management*. He is listed on the Stanford University's Top 2% Most Cited Scholars in the world.