Predictive Modeling of Instagram User Engagement with tourist photos based on Visual Attributes: The case of Taquile Island – Peru

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Abstract
In the tourism sector, photography has evolved from capturing memories to be-coming a tourism digital marketing strategy. The goal of this study is to identify the most important visual attributes that increase Instagram Engagement of the tourist destination Taquile Island (Peru). A predictive model that relates visual attributes and Engagement was developed using 439 photos of Taquile Island extracted from Instagram. These attributes were quantified using Image Analy-sis tools. Neural networks were used for the predictive model construction. This research shows that the most important visual attributes to increase the en-gagement on Instagram are lifestyle and natural landscape.

Keywords
Predictive model, engagement, neural networks, visual destination image, visual content analysis

1. Introduction

A tourist photo content has multiple visual attributes which are conditioned by the type of places visited. Although visual attributes can be relevant to predict the engagement of an image posted on Instagram, not all the attributes may be considered important (De et al. 2017) [1]. There are many qualitative-exploratory studies that focus on predicting reactions on Instagram; however, the quantitative approach that approximates the prediction of reactions using neural networks with a focus on tourism is scarce. Considering this information gap, the present study develops a predictive model that relates the engagement of tourist photographs and their visual attributes in the social network Instagram for the case of Taquile Island (Peru).

For this purpose, visual attributes of the photographs were quantified using Image Analysis Software APIs for the analysis of images, turning them into numerical data. Since engagement is a quantitative variable, neural networks were used. This study expands the knowledge about destination images regarding the most important visual attributes of user-generator content (UGC) on Instagram based on a rural destination in relation to the use of Instagram as a tourism promotion tool.

2. Literature Review

The perception of a tourist destination is not only related to information, but also transmitted through images; DMOs and DMCs use photos as part of their digital marketing strategy to promote tourist destinations. As a result, tourists build an image of the tourist destination in their brain (Millet, 2011) [2], therefore, image plays an important role in tourism (Diez & Crespo, 2020) [3] given that for tourists who have not visited the destination, it becomes a fundamental reference and a key factor when selecting a tourist destination which reflects what they expect to see at the tourist destination (Fakeye & Crompton, 1991) [4]. In the case of tourism, as there is no physical movement of products and services from where the offer is located to where the demand is found, an effective destination advertising that

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provides a good image and encourages the desire to visit the place is very important. Fatanti and Suyadnya (2015) [5] pointed out that Instagram has developed as a mean of tourist destination promotion that goes from being a tool for organizations to promote and position tourism destination brands around the world to spread user-generated content through tourist photos.

There are several attributes in a photo, not all of them can be described as indicators associated with tourism. Likewise, previous research in tourism has tried to categorize the visual attributes that are present in a photo (Fahmy et al. 2014) [6]. For example, in the Peruvian context, the visual attributes of a photo were studied by Stepchenkova and Zhan (2013) [7] in their work Visual destination images of Peru: Comparative content analysis of DMO and user-generated photography. These researchers identified ten visual attributes in the photos taken by travelers in the Peruvian territory: (1) natural landscape, (2) people, (3) archaeological sites, (4) life style, (5) traditional clothing, (6) architecture, (7) wild life, (8) adventure, (9) art object, (10) tourist facilities.

Predictive modeling is a process that consists in discovering relationships among data to predict some desired outcomes in the future using historical data (Mitchell, 2019) [8]. To do so, a set of predictors or relevant variables are used through the study of both present and historical data (Bhavya & Pillai, 2020). In the field of Data Science, a sector of the academy has embarked on building models that can predict the engagement of publications on social networks using different algorithms such as neural networks (De et al., 2017) [1]

2.1. Study Site

The Southern Route of Peru is one of the most demanded among foreign tourists for including the visit to Machupicchu. Lake Titicaca, the highest navigable lake in the world, is one of the most important attractions in this route (MINCETUR, 2020) [9].

Among the habitable islands in this lake lays Taquile Island, the object of study in this research, that has 3 essential elements: natural; cultural and human element; which allow to identify and quantify the largest number of visual attributes.

3 Materials and Methods

3.1. Population Sample

The population of this study consists of the total set of photos of Taquile Island on Instagram which exceeds 100,000 units. The type of sampling used was non-probabilistic for convenience. Inclusion criteria consisted of: (1) photos obtained using the geotag “Taquile Island-Puno” on Instagram; (2) clear and non-fragmented photos; (3) photos of public profiles due to Instagram’s privacy policy; (4) photos posted from May 2015 to September 2019; (5) photos of unique posts (with a single photograph). The sample size included 439 photos, being the most representative sample as compared to similar previous scientific research.

3.2 Construction of the Model

For the construction of the predictive model, 17 study variables from different research articles were defined, and different tools were used to measure such variables. These variables and their corresponding descriptions are shown in Table 1. Regarding the variable “likes”, Almgren, Lee, and Kim (2016) [10] found that likes can predict the future popularity of images on social networks. Also, the variable “awesome” was used by Deng and Li (2018) [11] to create a machine learning-based model to help DMOs at the moment of selecting photos. The importance of aesthetic characteristics of a destination is determinant in tourism literature as natural beauty plays a critical role in the destination choice process (Kirillova, Fu, Lehto, & Cai, 2014) [12]

Table 1.
Study variables

Variable	Type	Description	Reference
Engagement	Dependent	Likes+comments. (Engagement)	Zohourian et al. (2018) [13].
Followers	Independent	# of account followers	Chatzopoulou, Sheng, and Faloutsos, (2010) [14].
Hashtag	Independent	# of hashtags in the publication	
Number_days	Independent	# of days since publication on Instagram (collection data minus data of publication of the photo)	Data collection process
User_ type	Independent and dichotomous	Shared by organizations (1) or by a person (0)	
Text_presence	Independent and dichotomous	Presence of text (1) or not (0)	Zhang, Chen, and Li (2009) [15].
Beauty	Independent	Beauty level (0 - 100%)	Scott, Le, Becken, and Connolly (2019) [16].; Kirillova, Fu, Lehto, and Cai (2014) [12].; Todd (2009) [17].
Awesome	Independent	Independent rating level as awesome (0 - 100%)	Deng and Li (2018) [11].
Natural_landscape	Independent	Presence of natural landscape. Values from 0	Stepchenkova and Zhan (2013) [7].
Traditional_clothing	Independent	Presence of traditional clothing. Values from 0	
Architecture	Independent	Presence of architecture. Values from 0	
Archaeological _sites	Independent	Presence of architecture. Values from 0	
Art_object	Independent	Presence of art object. Values from 0	
Life_style	Independent	Presence of scenarios associated with lifestyle. Values from 0	
Wild_life	Independent	Presence of wildlife. Values from 0	
People	Independent	Presence of people. Values from 0	
Adventure	Independent	Presence of adventure activities. Values from 0	
Tourist_facilities	Independent	Presence of tourist facilities. Values from 0	

- The following tools were used:
- Downloader for Instagram: Used to download Instagram photos in ".jpeg" format
- applying the inclusion criteria detailed in the point 3.1.

- Google Vision AI: Used to measure the 10 independent variables, proposed by Stepchenkova and Zhan (2013) [7]. Immediate results were obtained; JSON file was needed to visualize them completely.
- EyeEm Vision: Used to measure the variable “beauty”.
- Everypixel: Used to determine the level in which a photo can be qualified as “awesome”.
- SPSS Statistics: The steps followed for the modeling process of the white canvas were:(1)assigning a type (i.e., dependent or independent variable) in the data of
- origin (i.e., dataset) (2) dividing the data from the model of neural networks into training and testing data.

3.3 Data Collection and Analysis

Data collection involved a series of stages. Initially, photographs were obtained by applying the inclusion criteria explained in “Population and Sample”, using the geotag “Taquile Island-Puno” on Instagram. Then, data taken by direct observation was registered (e.g., date of publication, date of collection, followers, likes, comments, user type, presence of text, hashtags). Photos were downloaded using the Instagram Downloader application, and then they were stored for further analysis with the instruments of Image Analysis (i.e., Google Vision AI, EyeEm Vision and EveryPixel). This action was carried out in parallel with data recording. Next, data derived from direct observation and the results of the analysis with Image Analysis instruments explained in previous steps were consolidated into an SPSS spreadsheet. Finally, the SPSS Statistics software for automatic analysis of data was used, the consolidated dataset was imported, and the construction of the prediction model using Neural Networks was performed, and its accuracy was measured (SPSS output).

4 Results

The interrelationships between input nodes (predictor variables), hidden variables (10 of them in two hidden layers), and the output node (Engagement) are illustrated in Figure 1. The independent variables (i.e., visual attributes) were combined using two functions: hyperbolic tangent in the two hidden layers and identity in the output layer.

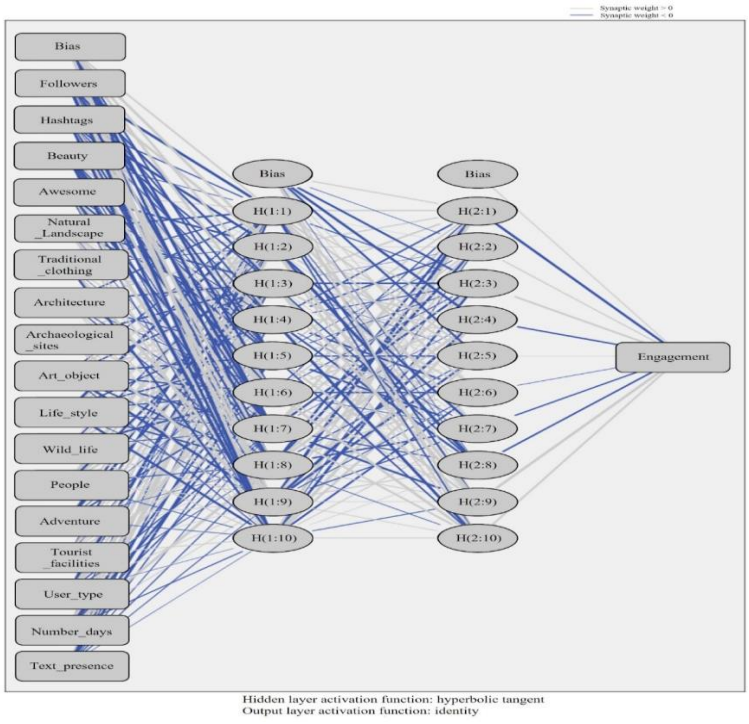

Fig. 1. Artificial neural network output diagram with insets for each layer. Output figure generated by IBM SPSS Statistics for Windows, Version 22.0. (Armonk, NY, USA)

The parameters of the neural network are also shown (Table 3). Regarding the general results of the neural networks model, it was observed that the model reached an accuracy of 70.20%. (Table 4)

Table 3.
Model Parameters

Predictor		Predicted							
		Hidden layer1							Output layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	Engagement
Imput layer	(Bias)	-.435	.471	-.110	-.366	-.516	-.244	.113	
	Followers	-.156	-.301	-.613	.470	-.235	.767	-.292	
	Hashtags	.203	-.349	-.539	.055	.002	.091	.109	
	User_type	.401	.211	-.271	-.249	-.193	-.226	-.137	
	Text_presence	.219	.012	-.289	.201	.269	-.046	-.040	
	Number_days	-.180	.229	-.055	-.265	.393	.233	-.236	
	Beauty	.331	.248	-.225	-.307	-.438	.389	.079	
	Awesome	.113	.402	.095	-.436	.131	.137	-.275	
	natural_landscape	-.413	.316	-.567	.438	-.304	.085	.265	
	traditional_clothing	.421	.195	-.255	.297	.257	.033	.343	
	Architecture	.093	.627	.150	.173	-.274	.332	.353	
	archeological_sites	-.269	.588	-.215	.380	-.188	.030	.440	
	art_object	.345	.324	-.201	-.110	-.477	-.047	.119	
	life_style	.182	-.054	-.293	-.143	.576	.605	-.107	
	wild_life	.340	.012	.184	-.314	.043	.017	.181	
	People	.278	-.180	-.177	.202	.307	-.097	-.018	
	Adventure	-.247	.340	.153	-.327	-.444	.174	-.147	
	tourist_facilities	.430	.188	-.244	-.430	-.130	-.039	-.429	
Hidden layer 1	(Bias)								.177
	H(1:1)								.014

Table 4.
Summary of the Model based on a Neural Network

Partition	**1_Training**	**2_Testing**
Minimum error	-1.038	-0.73
Maximum error	1.358	1.323
Mean error	0.001	0.012
Mean absolute error	0.274	0.277
Standard deviation	0.356	0.343
Linear correlation	0.711	0.704
Occurrence	299.0	141.0
Accuracy	70.20%	

Figure 2 shows the importance of the predictor variable using Neural Network, the most important visual attributes to increase the engagement on Instagram are lifestyle and natural landscape.

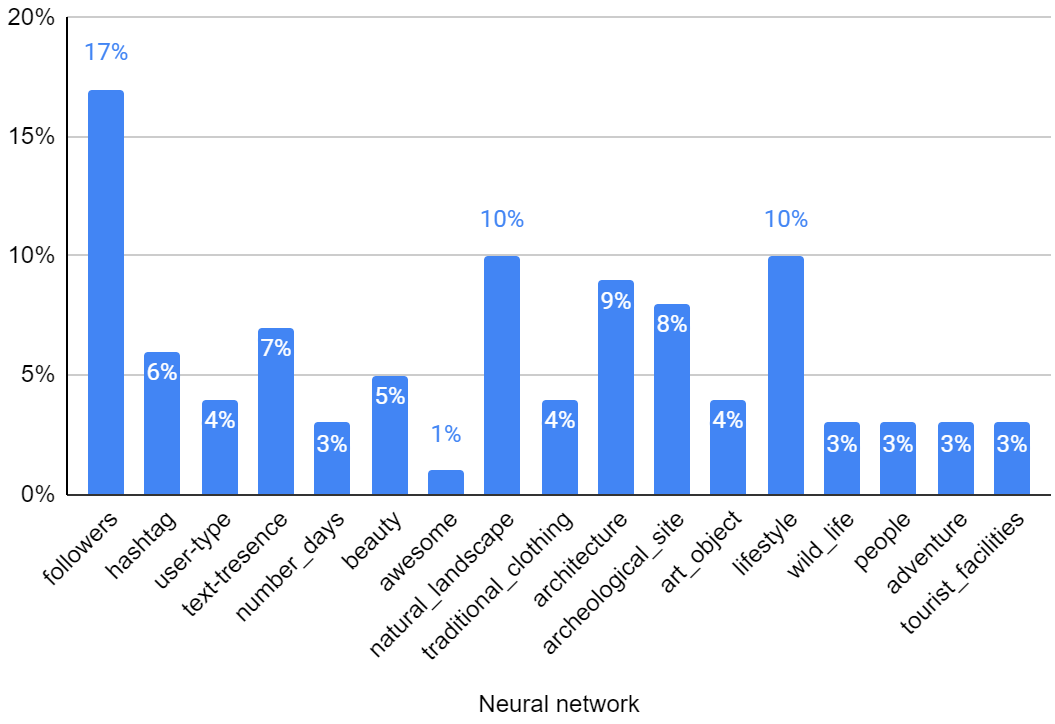

Fig. 2. Importance of the predictor variables using Neural Network. Source: Own elaboration with data from IBM SPSS Statistics for Windows, Version 22.0. (Armonk, NY, USA)

5 Discussion

This study offers several insights into the role of visual attributes present in a photo that enable predicting the Engagement on Instagram. Now we can find an enormous quantity of visual attributes present on a photo such as the presence of animals, persons, natural landscape and even the symmetry, balance, contrasts, colours and golden ratios of the photo are taken into consideration as visual attributes (Thömmes & Hübner, 2018) [18]. Nevertheless, not all of them are relevant to predict the engagement on Instagram (De, Maity, Goel, Shitole, & Bhattacharya, 2017) [1]. This study fills this gap in tourism literature, by building a ranking of the most important visual attributes present in a photo of a given tourist destination using neural network which allow DMCs, DMOs and tourism professionals to elaborate accurate online marketing strategies for tourism destinations on Instagram.

Visual destination images have been studied in different researches. However, Stepchenkova and Zhan's (2013) [7] were the only ones that compared the content-analysis of DMO and user-generated photographs taken in Peru. They considered that a photo can be fragmented in different visual attributes denominated as categories. In their study they identified ten main categories associated with photographs taken in Peru. These categories were identified as a point of reference for the methodology of this study, they were measured using different image analysis tools. Moreover, a ranking for the most and least important visual image attributes according to different mathematics techniques was elaborated.

When a photo is perceived as beautiful, it increases the number of likes and comments on Instagram posts (Colliander & Marder, 2018) [19]. In this study, we found out that the variable "beauty" has a direct relationship with the Engagement on Instagram Moreover, Scott et al. (2017) [16] found in their research the importance of using beautiful photos in tourism marketing to capture tourist attention, using an eye-tracking software and the Likert-type scale surveys. For this study, the variable "beauty" was also measured using a specialized software but for image analysis, which means that traditional tools such Likert-type scale surveys - like the one used by Thömmes and Hübner (2018) [18] to measure the "beauty" of architectural photos - can be replaced with artificial software for image analyses which contributes to bias reduction or can be used as a complement tool.

Whereas, Deng and Lin (2018) [11] used the attribute "awesome" as a part of a machine learning model which enabled DMO to find the right photo for their marketing campaigns. They extracted emotional keywords

comments from UGC, 20,000 photos on Flickr to create this machine learning model. In contrast, in this study the attribute "awesome" was measured with the tool EveryPixel using instead of words, image analysis.

Moreover, Belk and Hsiu-yen Yeh (2011) [20] indicated that the level of human activity has a direct bearing on the fact that a photograph is captured. However, taking a photograph does not necessarily mean it will be shared on social media networks. This study suggests that in traditional and rural destinations like Taquile Island, when a photo shows human activity performed by the local population as a way to show their "lifestyle", it generates better reactions (likes and comments) in social media networks.

Some attributes have a greater impact to predict the Engagement on Instagram than others. Ferwerda, Schedl, and Tkalcic (2015) [21], Bakhshi, Shamma, and Gilbert (2014) [22] and Araujo, Damilton Correa, Couto Da Silva, Prates, and Meira (2014) [23], all of them pointed out that the presence of people in a photo generates likes. On the other hand, the findings of this study revealed that the variable "people" is one of the least important to predict the Engagement on Instagram.

Finally, Hausmann et al. (2017) [24] collected geotagged photos from tourists on Instagram to find out what tourists would particularly like to see or experience when visiting a National Park. They agreed that tourists are interested in big animals and to experience nature through biodiversity-related activities. However, in this study it was found out that the variable "wildlife" is not meaningful to predict engagement on Instagram. This can be explained by the fact that travelers perceived Taquile Island as a rural tourism destination, whereas Kruger National Park stands out due to its large fauna

5.1 Conclusions

This research developed a predictive model which allows us to quantify the visual attributes of tourist destination photos, as well as to measure the level of Engagement on Instagram combining different visual attributes. Additionally, in the present research, the most important variables were "number of followers", followed by "lifestyle" and "natural landscape", which are the two most important visual image attributes to increase the engagement on Instagram. The variable that contributes least is "awesome".

Finally, although the neural network model is more complex than other prediction models it did not present bias, and it registered a high accuracy (70.20%), which means that through the neural network model it is feasible to approach the prediction of engagement on Instagram from visual attributes.

5.2 Theoretical and Practical Implications

The present research makes a meaningful contribution to the tourism industry literature in relation to Instagram. First, this study expands the knowledge about destination images regarding the most important visual attributes of user-generator content (UGC) on Instagram based on a rural destination in relation to the use of Instagram as a tourism promotion tool. Moreover, this study can be considered as a point of reference for DMOs, DMCs, tourism marketing professionals or those who want to analyze photo records in tourism related research, taking advantage that UGC provides credible and easy-to-obtain data for tourism image research (Xiao, Fang, & Lin, 2020) [25] in a context where travelers themselves freely share photos of their trips on social media. Furthermore, it is useful for them in order to achieve cost-effective tourism promotions campaigns on Instagram and effective digital marketing KPIs. It provides insights for DMOs, DMCs and tourism marketing professionals to reduce resources, increase efficiency at the moment of choosing the right photo according to their needs, select the appropriate destination marketing strategies and increase the level of engagement on this social network. The competitiveness of the tourism destination increases with a right tourism image, which improves the satisfaction and loyalty of tourists (Kim & Stepchenkova, 2015) [26]. In fact, the methodology from this study can be replicated and/or adapted to other tourism destinations to determine which are the most important attributes based on the destination characteristics. Also, this methodology can be replicated in studies of exotic or urban destinations, in order to obtain other types of visual attributes different from those found on Taquile Island, as a rural destination. Additionally, although there are many studies based on visual content analysis in the field of tourism, this study is one of the first ones that measures the visual attributes of a photographics and its influence on Instagram Engagement. This study allows creating a new approach to tourism promotion using specialized software in a way that allows it to be a reference for future research and provide valuable insights for tourism professionals.

5.3 Limitations and Recommendations for future research

This study makes a significant contribution to tourism literature to understand the Engagement on Instagram, but it has some limitations. First, in the methodology of this study, a convenience sampling was used. This does not mean that the results lack validity, but it is necessary to clarify that the model is significant for the sample analyzed; and it is probably that they should have similarities with a population-based study.

Second, the instruments used (e.g., EyeEm Vision, Everypixel) were provided by third parties and are constantly being updated using algorithms based on the perceptions of professional photographers so what is considered beautiful or amazing may vary over time. Further, there are people who consider that computers' perception of meaning is far from the perception of the human brain. In photographs, not all the content is literal and an example of this are the "memes", which are representations with other meanings that differ from the literal one. In tourism, unstructured data such as the photos shared by tourists in their social media networks can be quantitatively studied with specialized software.

This study did not analyze posts in the "carousel" format, it was considered unique posts (a single photograph), due to the appreciation of users regarding the set of photos it is subjective. In that sense, metrics such as likes and comments are not precise. For instance, if a user gives a "like" this would not imply that they like all the photos in a carousel post. Also, it affects the SOR framework proposed by Mehrabian and Russell (1974) [27] by not being able to break down the photographs individually, and could not be able to identify and quantify their respective attributes that generated greater engagement (likes and comments). It should be noted that according to Duangkae (2018) [28] influencers prefer to publish single posts rather than carousel posts, because single posts obtain a higher average engagement rate. Moreover, Stine (2020) [29] and Duangkae (2018) [28] pointed out that the engagement generated by carousel posts goes against nature on Instagram. The reason is that carousel posts consist of many cards, whereby a user has to swipe right to left to see the other photos. However, Instagram users are accustomed to swipe up to view the next piece of content.

Finally, this study intends to explore the visual attributes of a photograph using instruments that can obtain image patterns, which can hopefully lead to expand this topic in future research, since there are few similar academic studies related to the tourism sector. Thus, it is recommended to continue using these tools as well as to replicate the model in other destinations comparable to Taquile Island in order to identify differences and similarities in the modeling. It is also suggested to keep a record of the observed and predicted values and to adjust the indicators of the model in order to update its parameters, since preferences may vary over time. The photographic content is the greatest determinant of engagement; however, in case that two photos have a similar content, the publication of the one that has more aesthetics or has the capacity to cause amazement is recommended. This can be controlled with elements such as effects and color balance, among others. Moreover, this research can be complemented with qualitative studies with the aim of comparing similarities and differences. Also, for future research, there is the possibility of building models in which travelers are segmented according to personal characteristics (e.g., gender, national or foreign origin, etc.).

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