‘Could we know whether you had good time there?’ Real and artificial tourist pictures underlying (un)happiness through AI and LLMs

'Could we know whether you had good time there?' Real and artificial tourist pictures underlying (un)happiness through AI and LLMs

DOI: https://doi.org/10.63355/MrGf2346

Eleonora Pantano (corresponding)
e.pantano@bristol.ac.uk
AND
Nikolaos Stylos
n.stylos@bristol.ac.uk
University of Bristol Business School, University of Bristol, BS81SD Bristol UK

Abstract:

Purpose. The aim of this paper is to demonstrate the extent to which it is possible to automatically extract photo content data in terms of human-embedded emotions such as un/happiness and if it is possible to analytically detect and recreate tourists› emotions through Artificial Intelligence (AI) and Large Language Models (LLMs).

Methodology. We built and trained a classifier machine to automatically analyse pictures of real tourists in five international destinations. We then compared them with a silicon sample of tourists generated by AI and LLMs.

Findings. This study extends our knowledge and practice of tourists› emotions identification by utilising new methods involving AI. This study demonstrates the advantages of combining facial analysis of individuals› emotional reactions, by offering an alternative to the self-reports. Also, our work provides further evidence of the limited adequateness of LLMs in associating the information in the provided textual data (prompts).

Originality. To the best of our knowledge, this is the first empirical study that attempts to analytically detect and recreate tourists› emotions through Artificial Intelligence (AI) and large language models (LLMs) by utilising synthetic data based on a silicon sample of tourists.

Practical implications. Our work shows how to evaluate consumers› psychological state or emotional reactions towards a specific destination with new tools not completely relying on tourists› self-reports. In our work, instead, we discuss a new possible approach to capture real emotions and how they could be measured, allowing extracting virtual insights into tourists› experiences and preferences towards specific destinations and locations.

1. Introduction:

Researchers have largely exemplified the importance of emotions in explaining tourists' behaviour (Bigne & Andreu, 2004; Nawijn et al., 2013; Zhao et al., 2024; Li et al., 2022). They have been reported as the most significant element affecting the travel industry (Mitas et al., 2012). In particular, emotions, as these are shaped during visitation, have been acknowledged for their role in influencing tourists' level of satisfaction, word-of-mouth recommendations, and revisit intentions (Hosany et al. 2015, 2017; Prayag et al., 2017). Previous studies (e.g., Jordan & Prayag, 2022; del Bosque & San Martin, 2008; Lin et al., 2014; Nørfelt et al., 2023) have used the positive/negative emotions dichotomy as "it exemplifies the positive effects vacationing has on tourists' emotions" (Lin et al., 2014, p.417).

Nevertheless, until now, the vast majority of studies mainly follow a cognitive perspective when theorising and modelling tourists' evaluations of their travel experiences (e.g., Kim & Ritchie, 2014; Ma et al., 2013), although there is consensus on the need for further unravelling the role of tourists' emotions in shaping the overall travel experience (Carlson et al., 2016). Hence, only recently authors have attempted to understand the role of emotions in the context of tourism and hospitality (e.g., Hosany et al., 2021; Hsu et al., 2024; Prayag et al., 2017; Ruiz-Mafé et al., 2016). These studies are drawn upon surveys involving consumers, thus the results are based on the tourists' actual state when replying and need the interaction between researcher and respondent. Still, there is a need for more empirical studies in the field (Isaac & Budryte-Ausiejiene, 2015), as the mechanism of emotions creation and the link with affect are complex and largely undefined (d'Hauteserre, 2015; Li, Scott, & Walters, 2015). In this vein, Stylos (2022) posits that logical and rational processes do not always drive individual decision-making. Instead, emotions may play a key role in shaping decisions, which should be included in relevant consumer behaviour modelling. In this vein, Ameen and colleagues (2024) postulate that advancing our capabilities with better detection of human emotions and interactions via AI tools can be very beneficial so that authentic human emotions can be tracked down.

Interestingly, until now no study has empirically investigated tourists' emotional expressions through facial coding on images and utilising machine learning techniques in the analysis framework, although there are several studies on the importance of photo sentiment on tourist behaviour (Li et al., 2022), or of human facial expressions in other than tourism fields (Cho et al., 2014; Kalsi & Rai, 2017; Zhao et al., 2015). Most of these studies demonstrates the technical aspect of operationalising facial analysis in images and the level of particular software applications' success in capturing individuals' emotional states via (static) images (e.g. Ahn et al.; Verma & Sharma, 2013).

The recent progress in artificial intelligence (AI), with an emphasis on generative AI, made available many tools to automatically generate a large range of content, from adverts to new product designs to recommendations to consumer services. Accordingly, scholars are debating on using them constructively and ethically also in research (Acikgoz et al., 2023; Sarstedt et al., 2024). Other scholars suggested the possible usage of generative AI to create "artificial or silicon samples" of users, namely synthetic data samples in consumer research, for instance to achieve synthetic interview data that could be easily interpreted and analysed (Sarstedt et al., 2024). However, it is not yet clear how generative AI can reflect human behaviours in each dimension, especially in the tourism context (Viglia et al., 2024). Indeed, recent authors are debating how generative AI tools can supplement or fabricate data production (Islam and Greenwood, 2024) or capture the complexity of human emotions (Coppini et al., 2023). For instance, recent studies found that the level of abstraction provided by generative AI tools like ChatGPT provides recommendations that might be largely different from the traditional ones based instead on humans (Kirshner, 2024).

The aim of this paper is to demonstrate the extent to which it is possible to automatically extract photo content data in terms of human-embedded emotions such as un/happiness and if it is possible to analytically detect and recreate tourists' emotions through Artificial Intelligence (AI) and Large Language Models (LLMs). This study contributes to the current body of research on tourists' emotions, information systems research literature on generative AI and silicon sample generation. Specifically, our paper contributes to the literature on tourism (cognitive) behaviour using internet multimodal data, and it posits new challenges that tourism managers may face prompted by new technological advances.

2. Literature Review:

2.1. Emotions in Tourism Research

Emotions have been conceptualised as positive or negative affect (Ahn & Kwon, 2022; Nawijn, 2011) which have a direct effect on a person's thinking and behaviour (Mitas et al., 2012; Magids et al., 2015) and can influence the quality of life (Fredrickson 2000). Bagozzi, Gopinath, and Nyer (1999, p. 184) defined emotion as "a mental state of readiness that arises from cognitive appraisals of events or thoughts; has a phenomenological tone; is accompanied by physiological processes; is often expressed physically (e.g., in gestures, posture, facial features); and may result in specific actions to affirm or cope with the emotion, depending on its nature and meaning for the person having it". Similarly, Isaac and Budryte-Ausiejiene (2015) assert that emotions "are affective states characterised by occurrences or events of intense feelings associated with specific evoked response behaviours". Individuals are usually aware of their emotions, while their moods are more general and subtle, and often work beneath their consciousness (Goossens, 2000). Malone and colleagues (2014) claimed that emotions are very subjective, intense and salient. Emotions are expressed at three different levels: through subjective experience, through expressive behaviour, and physiological changes (Ekman, 1992). Because of these characteristics, researchers (Lin et al., 2014; Mitas et al., 2012) point out that emotions are most helpful in understanding tourists' experiences.

In the tourism context, prior studies examined the relationship between emotions and satisfaction (e.g., Bagheri et al., 2024; del Bosque & San Martin, 2008; Hosany & Prayag 2013; Prayag et al., 2017), intention to return (e.g. Han & Back, 2007; Peng et al., 2023); customer loyalty (e.g., Qi et al., 2023; Stylos & Bellou. 2019), behavioural intentions (e.g. Bigné, Andreu, & Gnoth, 2005; Jang & Namkung, 2009; Soltani et al., 2021), willingness to recommend (e.g. Hosany & Prayag 2013; Jang & Namkung, 2009; Wang et al., 2023); word of mouth (Ladhari, 2007; Stylos et al., 2024), perceived overall image (e.g. Li et al., 2023; Prayag et al., 2017); personality (Lin et al., 2014); place attachment (e.g. Io, 2018; Zheng et al., 2023), emotions as a segmentation basis for leisure and tourism services (e.g. Bigné & Andreu, 2004; Millán et al., 2016) and as an influencer on decisions to purchase tourism and leisure services (e.g. Kwortnik & Ross, 2007; Pop et al., 2022).

Prayag et al. (2017) and Hosany and colleagues (2021) conclude that (1) types (positive or negative) and intensity of emotions vary across products and stages of the travel; (2) positive emotions are more extensive in tourists' recalled experiences; and (3) emotions are significant antecedents to satisfactory tourist experiences and/or behavioural intentions. However, emotions from tourism pictures have been analysed only in terms

of colours/brightness, considering the dichotomy of positive/negative sentiment when associated with text reviews (Li et al., 2022).

From a methodological point of view, several different methods and approaches have been employed to explore emotions and their effects in the tourism field, such as semi-structured in-depth interviews, surveys, text-mining/content analysis and sentiment analysis of online reviews (e.g., Godnov & Redek, 2016; Magnini et al., 2011; van Es & Reijnders, 2016). However, it has been suggested that reporting emotions via interviews, surveys, blogs and reviews, provided sometime after coming back from the trip, may not be the best way to capture tourists' emotions, considered as conscious (or self-reported) techniques for evaluating emotional responses in market research that might interfere with the accuracy of the research, since the report is made after the experience and much of the emotion processing happens below the level of conscious awareness (Marci & Murray, 2017). Indeed, a reason for this is that tourists start shaping memories outside of their lived experiences at the destination, thus altering the emotions felt during visitation (Hosany et al., 2017; Kahneman et al., 1999). In this vein, researchers started using biometrics, such as facial recognition and other tools to measure an individual's emotional response (Lu & Zhang, 2017). Nevertheless, Mauss and Robinson (2009, p.228) argue that "there is no 'gold standard' measure of emotional responses".

2.2. Facial Expressions

Since ancient times, in every culture, there was the belief that the face is a window to a person's true nature, and there is a direct connection between facial appearance and personality (Todorov et al., 2015). The study of the facial expression of emotion originated in 1872, with Charles Darwin's The Expression of Emotions in Man and Animals being a seminal work. He indicated that facial expressions transmit information concerning a human or animal's basic behavioural intentions and emotional tendencies to others (Ekman, 2003; Fagerstrøm et al., 2017).

Drawing from experimental psychology, a clear link between emotions and human facial and body reactions has been made by Ekman and Friesen (1978), who observed that emotions pop out, resulting in facial expressions. Several distinct emotions have been extensively studied, and a systematisation that relates them to facial expressions has been released and tested in various settings over the last forty years (Ekman & Rosenberg, 1997; Kohler et al., 2004). Researchers generally agree that the human face is one of the most important non-verbal means of communication since it can divulge information about a person's emotions (Popa et al., 2017). Furthermore, there is strong evidence that facial expressions can play a critical role in predicting individuals' preferences (Choi et al., 2016; Ekman & Oster, 1979; Somerville et al., 2011) and thus benefit both the signalers and the receivers of those 'messages' (Fagerstrøm et al., 2017; Fridlund, 1997; Söderlund & Sagfossen, 2017).

The human face is considered the fundamental nonverbal source of communication of felt emotions (Small & Verrochi, 2009) and is easily accessible for others to spot (Carroll & Russell, 1996). From the expressions of others, we can extract information about their underlying emotions resulting from social intentions and motivations with other humans (Harker & Keltner, 2001; Reeve, 2024; Schmidt & Cohn, 2001; Söderlund & Sagfossen, 2017; Somerville et al. 2011) or with artificial agents (e.g., Borghi & Mariani, 2022; Flavian et al., 2024). People can make up to 10,000 combinations of facial movements (Ekman & Rosenberg, 1997); thus, facial expressions are critical stimuli in social interaction (Schmidt & Cohn, 2001). Zhi and colleagues (2017) pointed out that analysing facial expressions is one of the most essential methods for revealing consumers' emotions and associated attitudes.

People are particularly well-equipped to assess the level of happiness in a face, so this expression is recognised very rapidly (Batty & Taylor, 2003). Previous studies (e.g., Hack, 2014; Magnini et al., 2013) indicate that people with happy facial expressions (i.e., a smile) are considered to own more positive characteristics (e.g., being friendly and sociable) than people with non-happy facial expressions. Ert and Fleischer (2016) also found that Airbnb hosts' photos influence guests' decisions and that a more trustworthy photo leads to higher prices and increased intention to book. Similarly, attractive profile photos on Facebook initiate friendships (Wang et al., 2010). However, visual analytics in the tourism and hospitality sector is still lower investigated (Xu et al., 2024; Giglio et al., 2020).

3. Methodology:

The research is based on a three-step approach that involves (1) developing a machine learning algorithm for effective automatic appraisal of real tourists' emotions (Study 1); (2) using GAI to generate images of tourists showing two fundamental emotions (happiness and sadness) (Study 2); and (3) comparing the results of the emotional analytics of the real VS silicon sample.

3.1. Study 1: Evaluating emotions from real tourists

Machine learning techniques are specific algorithms able to make predictions based on available data. For this study, we (i) built the classifier machine (i.e. a machine labelling the set of data), (ii) tested/validated it, (iii) developed a system to acquire and input data from Flickr, and (iv) used the emerging machine to evaluate tourists' emotions in five different tourism destinations. In other words, the system receives many image cases of happy/unhappy faces (labelled data) in a set of tourism destinations as input. In this study, following the positive/negative emotions dichotomy used in past studies (e.g., Jordan & Prayag, 2022; del Bosque & San Martin, 2008; Lin et al., 2014; Nørfelt et al., 2023; Li et al., 2022) we limited the data detection to only un/happy, exemplifying the positive effects of the tourism destination has on tourists' emotions (Lin et al., 2014). By generating clustering algorithms that separate the emerging clusters, it "learns" how to distinguish one type of data from another based on available datasets concerning five selected destinations.

3.1.1. Classifier machine setting

A classifier machine m considers as an input a set of elements belonging to a set I, and classifies them while assigning them a unique label (continuous or discrete):

$$\textbf{(1)}\ m\textbf{:}I\rightarrow S$$

In other words

$$\textbf{(2)}\ i\epsilon I\rightarrow \mathrm{m}(i)\epsilon S$$

If $S\subseteq\mathbb{R}$, where $\mathbb{R}$ includes a real number, thus m is a classifier with real values, while if $S\subseteq Z$, where Z includes relative numbers, m is a classifier machine with discrete values. In this study we limit our analysis to the discrete values.

If consider $Si\subset I$ the set of elements of I to guarantee $(x)=si$, $\nabla x\epsilon Si$, thus the elements of Si will be part of I, in other words:

(3)

$$I=Sa\cup Sb\cup\cdots\cup Sn$$

Where $S=\{a,b\cdots n\}$

$$Si\cap Sj=\emptyset,\ \nabla\ i,\ j\epsilon S$$

The formula (3) states that the classifier machine assigns a unique label to each element of I.

We also consider classifier machines with output, in other words with S={0,1}. Since our machine will consider the faces of consumers, and we evaluate only two main emotions (happy/unhappy), thus we assign the value 1 to "happy" and 0 to "unhappy".

Usually, elements of I are

vectors vi: - i with dimension 0, $vi=(ai,bi\cdots c)i$ traditional vectors with n

$(ars)i$ matrix with dimension n*m

$(arst)i$ tensors with 3 indexes with dimension n*m*h.

Accordingly, elements of I will belong to a hyperspace $\mathbb{R}$, $\mathbb{R}n$, $\mathbb{R}n^*m$, $\mathbb{R}n^*m^*h$, etc. The objective is to build a binary classifier machine able to identify the hyperplane in two regions, to ensure that each element of the hyperspace belonging to that set will get the unique label (will be assigned to a certain region of the hyperspace).

In our case we will use only images with the dimension of 80x80 pixels. Thus, the matrix will have 80x80 elements (this means that the images will be reduced/enlarged accordingly):

(4)

$$A=(a_{ij}),i=1,2\cdots 80,\ j=1,2\cdots 80$$

Where aij represents a particular color in RGB format. Cosequently, the elements we want to classify are $A\epsilon$. Using proper metrics, we can find a hyperplane or a hypersurface able to divide $I\subset$ into two subsets to minimise the distances among the elements of the same family, using proper metrics. In trained machines, such as the one we adopt in this research, we can use the set I, whose elements already have a label to train the classifier machine to assign to each element of a label (1 or 0).

3.1.2. Data settings

As anticipated, after identifying the set , we need to build the set I to train the machine. The images included in I will be in RGB format with 80x80 pixels. To each of those, we will assign a label (happy or unhappy) corresponding to the binary value 1 or 0. To distinguish happy and unhappy emotion, we will use Eckmann and Friesen's (1975) research, which describes happy and unhappy emotion through particular patterns of the faces.

Before starting the label assignment, it is necessary to have a massive number of images with different colours (e.g., black and white or greyscale, etc.), brightness and lights with one or more persons or even no persons. To this end, we selected 400 images available on Flicker with at least one person from the available pictures of the different locations. The following step consists of extracting faces from the images. To achieve this task, we used the function "FindFaces" available on the software Wolfram Mathematica. The software allows the use of images as input and extracts all the faces of people through a set of boxes, while the output of FindFaces is used as the input of the function "ImageTrim" and provides an image with the faces included in the box.

The obtained images have different sizes; thus, we need to manipulate them to have a homogenous data set (in this case, the format is 80x80 pixels). We selected 200 images from the internet with happy faces, while the system extracted 467 faces. From this, we identified 150 images (not all the extracted ones were "correct") and manipulated them to be in the proper format (80x80 pixels). We applied the same procedure to 200 images with unhappy people; from this, we obtained 163 images and selected 150 to be manipulated for the format of 80x80 pixels.

3.1.3. Classifier machine buildin

To build the classifier machine, we again used Mathematica software. We defined a table of rules called "hu" (happy/unhappy), whose elements are the final pictures. Wolfram Mathematica considers the table of rules "hu" as the input and provides the classifier machine as the output. Choosing the function "Classify", Mathematica build the classifier machine ("mhu"). In particular, the system provides the following classifier function:

(5)

In this case, the software selected the method "NearestNeighbors" (k-nearest neighbours algorithm) amongst the possible ones as the most convenient one, which is the main one used in pattern recognition (Beliakov & Li, 2012; Datta et al., 2016; Xu et al., 2013). To test the machine's correct functioning, we created two sets of images with faces, U and H. We collected these images using the same procedure we used for machine building. We manually assigned a label to the faces and compared the results with the machine-generated one. Since the machine learning is supervised (in other words, the machine learns to classify the elements training), we manually verified that in the case of U, the results meet those expected for 43 images out of 50 (86%), while 41 out of 50 (82%) for H.

3.1.4. Findings

To this end, we included the specific location of 5 tourism destinations and asked the system to limit the data collection to the pictures available on Flickr referring to that specific location. In particular, we selected Cancun (Mexico), Copacabana Beach (Brazil), Waikiki (Hawaii, US), Sharm el Sheik (Egypt), and Rome (Italy). To achieve this task, we wrote a web app in PHP and Javascript format. To increase the speed of implementation of the web app through the usage of API, we used a wrapper (written in PHP: phpFlickr (available at https://github.com/dan-coulter/phpflickr), which allows the use of all the methods available through Flickr API (including visualisation, uploading, downloading, etc.). We chose Flickr since the photos uploaded on the platform can be used by others, as claimed in the agreement forms signed by registered uploaders. Moreover, this platform has been largely used in tourism research, and considered a reliable source of tourists pictures for related insights (Mor et al., 2023; Giglio et al., 2019).

The emerging code is the following, where "$radius" represents the maximum distance from the exact location (in this case, 1km). We collected 123 pictures for Cancun, 340 for Copacabana Beach, 529 for Waikiki, 69 for Sharm el Sheik and 2220 for Rome. The system extracted 43 faces from the pictures of Cancun, 88 from Copacabana Beach, 111 from Waikiki, 22 from Sharm el Sheik, and 163 from Rome.

When the classifier evaluates a face, it assigns to each one a certain probability p of happy/unhappy. If $p>0.5$, the face is evaluated as happy; otherwise, it is evaluated as unhappy. The results shows that the majority of the faces demonstrates happy expressions (as expected since people tend to share pictures when happy) (Table 1). Figure 1 summarizes

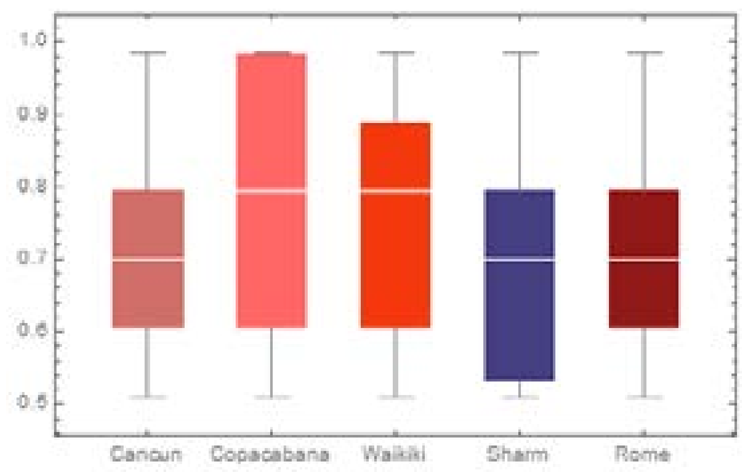
the probability distribution for each tourism destination, as emerging from the classifier.

Table 1: Number, mean, median and standard deviation of happy faces for each place (Source Authors).

	Cancun	Copacabana	Waikiki	Sharm	Rome
Happy expression	41	85	102	19	135
Mean	0.71728	0.774888	0.767791	0.703710	0.724799
Median	0.62781	0.655090	0.568117	0.587242	0.684731
Standard Deviation	0.138373	0.178658	0.149931	0.14711	0.155855

Figure 1 summarizes the probability distribution of happy faces in quartiles (where the white line represents the median) for each place.

Figure 1: Probability distribution in quartiles (Source: Authors).



3.2. Study 2: GAI generation of consumers' images:

Despite the numerous GenAI tools to create appealing, vivid, and memorable images from texts (prompts) aligning with the users' imaginary increasingly relevant for the tourism industry (Miao & Yang, 2023), we used Midjourney due to its availability and ease of usage. The prompt consists of the command "/image" and the following request to generate images of a tourist displaying a particular emotion in the specific place. Consistent with Study 1, the same number of faces have been considered. Accordingly, 43 faces from the pictures of Cancun, 88 from Copacabana Beach, 111 from Waikiki, 22 from Sharm el Sheik, and 163 from Rome have been extracted from the system-generated images. Figure 2 shows an example of the final images and the related prompt, which did not include any specific reference to the demographics of the tourists.

Figure 2: exemplar of images generated by AI for Cancun, Copacabana Beach, Waikiki, Sharm el Sheik, and Rome.

رجب 1446هـ - ديسمبر 2024م
العـــدد (170)

The same classifier machine used in Study 1 was applied here, assigning to each expression the probability p of being happy or unhappy. Contrary to Study 1, Study 2 results show that there are very few happy faces in the AI-generated images of tourists (Table 2). Contrary to Study 1, Study 2 results show that there very few happy faces in the AI-generated images of tourists (Table2).

Table 2: Number, mean, median and standard deviation of happy faces for each place.

	Cancun	Copacabana	Waikiki	Sharm	Rome
Happy expression	5	7	15	1	5
Mean	0.116279	0.079545	0.135135	0.045454	0.030864
Median	0.00	0.00	0.00	0.00	0.00
Standard Deviation	0.324353	0.272139	0.343418	0.2132	0.172967

Consistent with Study 1, Study 2 results show how it is possible to extract tourists' emotions from static pictures of tourists. Moreover, when comparing the pictures of real tourists and the synthetic pictures generated by AI, we noticed that the synthetic pictures show a minimal percentage of pictures (less than 5%) of happy tourists. Also, if considering other analyses related to demographics, tourists are most aged between 2035-, and close to 90% have a white background, while gender is equally distributed in male/female. The results change if we impose the condition of generating images of happy tourists, black tourists or other minorities, or a specific age range. Thus, the automatic generation of images does not entirely reflect a random sample of real tourists.

4. Discussion and Conclusion:

Our study contributes to the existing body of research relating to how tourists' pictures represent a way to express their feelings towards a particular tourism destination, taking into consideration that posting a picture might be much easier than writing a review describing the experience (Xu et al., 2024; Li et al., 2022), with emotions showed in tourists pictures almost overlooked. Specifically, our study extends our knowledge and practice of tourists' emotion detection and contributes to the ongoing research on their classification (Mauss & Robinson, 2009; Coppini et al., 2023) by further utilising new methods involving AI. In doing so, we provide additional results based on the facial expressions of tourists, as portrayed on social media posted photos during and after vacations. Thus, while past studies primarily analysed tourists' pictures in terms of metadata (e.g., geographical position, date and time, etc.) or contents (Giglio et al., 2019, 2020; Li et al., 2022; Xu et al., 2024), we considered photo content data in terms of human embedded emotion, which is new in tourism literature. In doing so, our paper shows that (i) tourists' emotions can be automatically detected from static pictures (via the automatic extraction of faces); (ii) it is possible to understand the sentiment embedded in the pictures from tourists' faces, and this understanding provides new insights of tourists' emotional state when in the destination; and (iii) even if only positive, they provide insights of tourists state in a particular place within the tourism destination, which can replace or be associated with traditional self-reports tools. Thus, our paper contributes to the literature on tourism (cognitive) behaviour using internet multimodal data.

In particular, our paper develops a model that automatically recognises tourists' emotions through pictures based on two fundamental expressions: happiness and unhappiness (see Eckmann & Friesen, 1975, 1978). By developing the model to automatically examine user-generated photos in social media, we achieved highly accurate matching between depicted facial expressions and the corresponding machine's capability to recognise the underlying emotions. Our findings shed light on the information contained within destination pictures in terms of tourists' emotions, showing how this approach led to a deeper understanding of photo sentiment features, illuminating tourists' emotions.

To the best of our knowledge, this study makes one of the earliest attempts to utilise the photo content data in terms of sentiments, and it demonstrates its exploratory power in understanding tourists' emotional state in a specific destination through Artificial Intelligence (AI) and Large Language Models (LLMs). To this end, our study further compares and contrasts real and synthetic data based on a silicon sample of tourists. Accordingly, our work provides further evidence on the limited adequateness of LLMs in associating the information in the provided textual data (prompts), with identifiers like facial expressions underlying emotions that do not fully mimic tourism responses. In this way, we add further evidence on AI's (in)ability to produce synthetic data in the tourism context (Sarstedt et al., 2024; Viglia et al., 2024). Thus, our study opens new directions for tourism marketing research by proposing the increase of classifier machine usage and other computational tools that may lead to the reduction of data collection via queries to tourists.

From a practical point of view, this study also shows the extent to which the new advances in computing capabilities offer new and more effective tools that tourism managers should be able to handle in order to build a competitive advantage for their

organisations. Indeed, the ability to manage large volumes of data and achieve insights from their analysis may create a competitive advantage, as anticipated by Bradlow and colleagues in the retail context (2017). Accordingly, the ability to access cost-effective tools such as the one we proposed to systematically detect possible tourists' underlying emotions–able to identify attitudes and potentially predict tourists' behaviour in particular contexts would be very beneficial for tourism managers in the long run. Indeed, evaluating consumers' psychological state or emotional reactions when in a particular destination is mainly based on self-reported questionnaires, interviews, or post-experience reviews, etc. Instead, in our work, we discuss a new possible approach to capture real emotions and how they could be measured while pointing out the limit of generative AI in reflecting human (tourist) multifaced behaviours. Therefore, tourism managers can benefit significantly from understanding tourists' psychological states when in the destination with new tools, not completely relying on tourists' self-reports, and deepen their understanding of tourists' opinions. Emotions represent a powerful way to understand tourists' preferences, attitudes, and opinions, which could be automatically exploited through our approach. Finally, our results provide a new approach to sentiment analysis of tourists that can be of great use to tourism destination managers and tourism boards to enrich their understanding of overall satisfaction levels within the destination. For instance, if the majority of happy faces emerge in a specific place, then positive sentiment would emerge. Conversely, more negative sentiments would emerge if a particular place is characterised by over-tourism, crowdedness, degradation, etc. Thus, our approach to image analytics allows extracting virtual insights into tourists' experiences and preferences regarding specific destinations and locations.

Table 3: Research Outputs and Managerial Implications sum-up (Source: Authors)

Research outputs	Practical implications
Understanding the sentiment embedded in the pictures from tourists' faces can provide new insights into tourists' emotional state when at the destination.	Managers can understand what works well in terms of the services provided at a tourism destination and the relevant promotional and communication activities.
Pictures provide insights of tourists' state in a certain place within the tourism destination, which can replace or be associated with traditional self-reports tools.	Managers now have a powerful way to gain insights and communicate simply and accurately the outputs of tourists' sentiments at the different stages of the tourist experience.
Highly accurate matching between depicted facial expressions and the corresponding machine's capability to recognise the underlying emotions, via automatically analysing user-generated photos, allows managers to achieve an accurate account of preferences, attitudes, and opinions while minimising field research and method biases.	Managers can achieve an accurate account of preferences, attitudes, and opinions while at the same minimising field research and method biases.
Managing a large volume of data and achieving insights from the analysis of visual data may create competitive advantages for tourism organisations.	Tourism managers and their respective tourism organisations can greatly benefit from advanced computing abilities, thus increasing the effectiveness of their decision-making processes.

رجـب 1446هـ - ديسمبر 2024م
العـــدد (170)

4.1. Limitation and future works

Although static and posed pictures do not fully identify with the nonconscious emotional response, this paper indicates the potential of detecting emotions through photographs and machine learning techniques (Large Language Models (LLMs). Another limitation is that this study only focused on two extreme emotions via happy and unhappy facial expressions. The algorithm developed and applied in this context can be easily used in different ones. Indeed, our work does not provide an evaluation of the specific tourism destinations based on facial recognition. Thus, we used a small sample to exemplify what could be done. Accordingly, future studies might include much larger samples, and extract further information about tourists' evaluation of destinations, and collect images from other social media, and/or from available CCTV cameras. Using real-time data from CCTV would especially overcome the limitation of having only happy faces as a consequence of posting only specific pictures.

Future research could also examine various facial expressions pertaining to a number of different emotions, thus testing the broader applicability of the proposed classifier machine, and evaluate whether similar results would be rendered. Likewise, new studies might aim to understand tourism managers' preparedness to gather and analyse data on consumers and tourists adopting machine learning techniques (as we did in this research).

A further limitation relates to the use of static images for facial recognition. Thus, an extension of the proposed methodology by using as the input set of data videos or not posed pictures taken in different occasions, activities, and visitation contexts may allow the development of more sophisticated systems able to recognise facial micro-expressions and more nonconscious emotional responses to the tourism stimuli, contributing to the relevant growing body of literature. Emerging results would be further beneficial for routine automatic evaluation of tourists' emotions, resulting in delineating tourists' behaviour and supporting the tourism management research and practice at large.

References:

1. Acikgoz, F., Perez-Vega, R., Okumus, F., & Stylos, N. (2023). Consumer engagement with AI-powered voice assistants: A behavioral reasoning perspective. Psychology & Marketing, 40(11), 22262243-, DOI: https://doi.org/10.1002/mar.21873.
2. Ahn, H., Kim, S., & Kim, J. K. (2014). GA-optimized support vector regression for an improved emotional state estimation model. KSII Transactions on Internet & Information Systems, 8(6), 20562069-, DOI: https://doi.org/10.3837/tiis.2014.06.014.
3. Ameen, N., Pagani, M., Pantano, E., Cheah, J. H., Tarba, S., & Xia, S. (2024). The Rise of Human–Machine Collaboration: Managers' Perceptions of Leveraging Artificial Intelligence for Enhanced B2B Service Recovery. British Journal of Management, ahead of print, DOI: https://doi.org/10.11118551.12829-1467/.
4. Bagheri, F., Guerreiro, M., Pinto, P., & Ghaderi, Z. (2024). From tourist experience to satisfaction and loyalty: Exploring the role of a sense of well-being. Journal of Travel Research, 63(8), 19892004-, DOI: https://doi.org/10.117700472875231201509/.
5. Bagozzi, R. P., Gopinath, M., & Nyer, P. U. (1999). The role of emotions in marketing. Journal of the Academy of Marketing Science, 27(2), 184206-, DOI: https://doi.org/10.1177009207039927200/.
6. Barsky, J., & Nash, L. (2002). Evoking emotion: affective keys to hotel loyalty. The Cornell Hotel and Restaurant Administration Quarterly, 43(1), 3946-, DOI: https://doi.org/10.117700108804024310 04/.
7. Batty, M., & Taylor, M. J. (2003). Early processing of the six basic facial emotional expressions. Cognitive Brain Research, 17(3), 613620-, DOI: https://doi.org/10.1016/S09265-00174(03)6410-.
8. Beliakov, G., & Li, G. (2012). Improving the speed and stability of the k-nearest neighbors method. Pattern Recognition Letters, 33(10), 12961301-, DOI: https://doi.org/10.1016/j.patrec.2012.02.016.
9. Bigne, J. E., & Andreu, L. (2004). Emotions in segmentation: An empirical study. Annals of Tourism Research, 31(3), 682696-, https://doi.org/10.1016/j.annals.2003.12.018.
10. Borghi, M., & Mariani, M. M. (2022). The role of emotions in the consumer meaning-making of interactions with social robots. Technological Forecasting and Social Change, 182, art. 121844, DOI: https://doi.org/10.1016/j.techfore.2022.121844.
11. Bradlow, E.T., Gangwar, M., Kopalle, P., & Voleti, S. (2017). The role of big data and predictive analytics in retailing. Journal of Retailing, 93(1), 7995-, DOI: https://doi.org/10.1016/j.jretai.2016.12.004.
12. Carlson, J., Rahman, M. M., Rosenberger III, P. J., & Holzmüller, H. H. (2016). Understanding communal and individual customer experiences in group-oriented event tourism: an activity theory perspective. Journal of Marketing Management, 32(9925-900 ,(10-, DOI: https://doi.org/10.10800267257/X.2016.1181099.
13. Carroll, J. M., & Russell, J. A. (1996). Do facial expressions signal specific emotions? Judging emotion from the face in context. Journal of Personality and Social Psychology, 70(2), 205–218, DOI: https://doi.org/10.10373514.70.2.205-0022/.
14. Caruana, R., & Niculescu-Mizil. A. (2006). An empirical comparison of supervised learning algorithms. In Proceedings of the 23rd International Conference on Machine Learning (pp. 161168-). ACM, DOI: https://doi.org/10.11451143844.114386/.
15. Cho, T., Choi, J. H., Kim, H. J., & Choi, S. M. (2014). Vision-based animation of 3D facial avatars. In Big Data and Smart Computing (BIGCOMP) (pp. 128132-). IEEE, DOI: 10.1109/BIGCOMP.2014.6741422.
16. Choi, I. Y., Oh, M. G., Kim, J. K., & Ryu, Y. U. (2016). Collaborative filtering with facial expressions for online video recommendation. International Journal of Information Management, 36(3), 397402-, DOI: https://doi.org/10.1016/j.ijinfomgt.2016.01.005.
17. Coppini, S., Lucifora, C., Vicario, C.M., & Gangemi, A. (2023). Experiments on real-life emotions challenge Ekman's model. Scientific Reports, 13, art. 9511, DOI: https://doi.org/10.1038/s415985-36201-023-.
18. Darwin, C. (1872). The Expression of the Emotions in Man and Animals. John Murray Publisher.
19. Datta, S., Misra, D., & Das, S. (2016). A feature weighted penalty based dissimilarity measure for k-nearest neighbor classification with missing features. Pattern Recognition Letters, 80, 231237-, DOI: https://doi.org/10.1016/j.patrec.2016.06.023.
20. d'Hauteserre, A.M. (2015). Affect theory and the attractivity of destinations. Annals of Tourism Research, 55, 7789-, DOI: https://doi.org/10.1016/j.annals.2015.09.001.
21. del Bosque, I. R., & San Martin, H. (2008). Tourist satisfaction: A cognitive-affective model. Annals of Tourism Research, 35(2), 551–573, DOI: https://doi.org/10.1016/j.annals.2008.02.006.

22. Ekman, P. (2003). Darwin, deception, and facial expression. Annals of the New York Academy of Sciences, 1000, 205221-, DOI: https://doi.org/10.1196/annals.1280.010.
23. Ekman, P. (1992). An argument for basic emotions. Cognition & Emotion, 6(3–4), 169–200, DOI: https://doi.org/10.108002699939208411068/.
24. Ekman, P., & Rosenberg, E. L (Eds.). (1997). What the Face reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS). Oxford University Press.
25. Ekman, P., & Friesen, W. (1975). Unmasking the Face: A Guide to Recognizing Emotions from Facial Clues. Prentice Hall.
26. Ekman, P., & Friesen, W. V. (1978). Facial Action Coding System (FACS): A Technique for The Measurement of Facial Action. Consulting Psychologists Press.
27. Ekman, P., & Oster, H. (1979). Facial expressions of emotion. Annual Review of Psychology,30(1),527–554,DOI:https://doi.org/10.1146/annurev.ps.30.020179.002523.
28. Ert, E., Fleischer, A., & Magen, N. (2017). Trust and reputation in the sharing economy: the role of personal photos in Airbnb. Tourism Management, 55, 6273-, DOI: https://doi.org/10.1016/j.tourman.2016.01.013.
29. Fagerstrøm, A., Pawar, S., Sigurdsson, V., Foxall, G. R., & Yani-de-Soriano, M. (2017). That personal profile image might jeopardize your rental opportunity! On the relative impact of the seller's facial expressions upon buying behavior on Airbnb™. Computers in Human Behavior, 72, 123131-, DOI: https://doi.org/10.1016/j.chb.2017.02.029.
30. Fredrickson, B. L. (2000). Extracting meaning from past affective experiences: the importance of peaks, ends, and specific emotions. Cognition and Emotion, 14(4), 577606-, DOI: https://doi.org/10.108026999300402808/.
31. Fridlund, A. J. (1997). The new ethology of human facial expressions. Psychology of Facial Expression, 112, 103129-, DOI: https://doi.org/10.10077_6-16999-319-3-978/.
32. Giglio, S., Pantano, E., Bilotta, E., & Melewar, T.C. (2020). Branding luxury hotels: evidence from the analysis of consumers' "big" visual data on TripAdvisor. Journal of Business Research, 119, 495501-, DOI: https://doi.org/10.1016/j.jbusres.2019.10.053.
33. Giglio, S., Bertacchini, F., Bilotta, E., & Pantano, P. (2019). Using social media to identify tourism attractiveness in six Italian cities. Tourism Management, 72, 306-312, DOI: https://doi.org/10.1016/j.tourman.2018.12.007.

34. Ghesh, N., Alexander, M., & Davis, A. (2024). The artificial intelligence-enabled customer experience in tourism: a systematic literature review. Tourism Review, 79(5), 10171037-, DOI: https://doi.org/10.1108/TR-040255-2023-.
35. Godnov, U., & Redek, T. (2016). Application of text mining in tourism: Case of Croatia. Annals of Tourism Research, 58, 162166-, DOI: 10.1016/j.annals.2016.02.005.
36. Goossens, C. (2000). Tourism information and pleasure motivation. Annuals of Tourism Research, 27(2), 301321-, DOI: https://doi.org/10.1016/S01605-00067(99)7383-.
37. Hack, T. (2014). Forming impressions: effects of facial expression and gender stereotypes. Psychological Reports, 114(2), 557571-, DOI: https://doi.org/10.246607.17/.PR0.114k17w6.
38. Han, H., & Back. K-J. (2007). Investigating the effects of consumption emotions on customer satisfaction and repeat visit intentions in the lodging industry. Journal of Hospitality & Leisure Marketing, 15(3), 5–30, DOI: https://doi.org/10.1300/J150v15n03_02.
39. Hosany, S., Martin, D., & Woodside, A. G. (2021). Emotions in tourism: Theoretical designs, measurements, analytics, and interpretations. Journal of Travel Research, 60(7), 13911407-, https://doi.org/10.11770047287520937079/.
40. Hosany, S., & Prayag, G. (2013). Patterns of tourists' emotional responses, satisfaction, and intention to recommend. Journal of Business Research, 66(6), 730–737, DOI: https://doi.org/10.1016/j.jbusres.2011.09.011.
41. Hosany, S., Prayag, G., Deesilatham, S., Caušević, S., & Odeh, K. (2015). Measuring tourists' emotional experiences: Further validation of the destination emotion scale. Journal of Travel Research, 54(4), 482495-, DOI: https://doi.org/10.11770047287514522878/.
42. Hosany, S., Prayag, G., Van Der Veen, R., Huang, S., & Deesilatham, S. (2017). Mediating effects of place attachment and satisfaction on the relationship between tourists' emotions and intention to recommend. Journal of Travel Research, 56(8), 1079–1093, DOI: https://doi.org/10.11770047287516678088/.
43. Hsu, C. H., Chen, N., & Zhang, S. (2024). Emotion regulation research in hospitality and tourism. International Journal of Contemporary Hospitality Management, 36(6), 20692085-, DOI: https://doi.org/10.1108/IJCHM-010049-2023-.

44. Isaac, R. K., & Budryte-Ausiejiene, L. (2015). Interpreting the emotions of visitors: a study of visitor comment books at the Grūtas park museum, Lithuania. Scandinavian Journal of Hospitality and Tourism, 15(4), 400424-, DOI: https://doi.org/10.1080150/22250.2015.1024818.

45. Islam, G., Greenwood, M. (2024). Generative artificial intelligence as hypercommons: ethics of authorship and ownership. Journal of Business Ethics, 192, 659663-, DOI: https://doi.org/10.1007/s105519-05741-024-.

46. Jordan, E. J., & Prayag, G. (2022). Residents' cognitive appraisals, emotions, and coping strategies at local dark tourism sites. Journal of Travel Research, 61(4), 887-902, DOI: https://doi.org/10.117700472875211004761/.

47. Kahneman, D., Diener, E., & Schwarz, N. (Eds.). (1999). Well-Being: Foundations of Hedonic Psychology. Russell Sage Foundation.

48. Kalsi, K. S., & Rai, P. (2017). A classification of emotion and gender using approximation image Gabor local binary pattern. In Cloud Computing, Data Science & Engineering-Confluence, 2017 7th International Conference on (pp. 623628-). IEEE, DOI: 10.1109/CONFLUENCE.2017.7943227.

49. Knani, M., Echchakoui, S., & Ladhari, R. (2022). Artificial intelligence in tourism and hospitality: Bibliometric analysis and research agenda. International Journal of Hospitality Management, 107, art. 103317, DOI: https://doi.org/10.1016/j.ijhm.2022.103317.

50. Kim, J. H., & Ritchie. J. B. (2014). Cross-cultural validation of a memorable tourism experience scale (MTES). Journal of Travel Research, 53(3), 323335-, DOI: https://doi.org/10.117700472875134 96468/.

51. Kohler, C. G., Turner, T., Stolar, N. M., Bilker, W. B., Brensinger, C. M., Gur, R. E., & Gur, R.C. (2004). Differences in facial expressions of four universal emotions. Psychiatry Research, 128(3), 235244-, DOI: https://doi.org/10.1016/j.psychres.2004.07.003.

52. Kotsiantis, S. B. (2007). Supervised machine learning: a review of classification techniques. In I. Maglogiannis, K. Karpouzis, M. Wallace, & J. Soldatos (Eds.). Emerging Artificial Intelligence Applications in Computer Engineering (pp. 324-). IOS Press.

53. Kirshner, S. N. (2024). GPT and CLT: The impact of ChatGPT's level of abstraction on consumer recommendations. Journal of Retailing and Consumer Services, 76, art. 103580, DOI: https://doi.org/10.1016/j.jretconser.2023.103580.

54. Kwortnik, R. J., & Ross, W. T. (2007). The role of positive emotions in experiential decisions. International Journal of Research in Marketing, 24(4), 324335-, DOI: https://doi.org/10.1016/j.ijresmar.2007.09.002.

55. Ladhari, R. (2007). The effect of consumption emotions on satisfaction and word-of-mouth communications. Psychology & Marketing, 24(12), 10851108-, DOI: https://doi.org/10.1002/mar.20195.

56. Li, H., Ji, H., Liu, H., Cai, D., and Gao, H. (2022). Is a picture worth of thousand words? Understanding the role of review photo sentiment and text-photo sentiment disparity using deep learning algorithms. Tourism Management, 92, art. 104559, DOI: https://doi.org/10.1016/j.tourman.2022.104559.

57. Li, H., Zhang, L., & Hsu, C. H. (2023). Research on user-generated photos in tourism and hospitality: A systematic review and way forward. Tourism Management, 96, art. 104714, https://doi.org/10.1016/j.tourman.2022.104714.

58. Lin, Y., Kerstetter, D., Nawijn, J., & Mitas, O. (2014). Changes in emotions and their interactions with personality in a vacation context. Tourism Management, 40, 416-424, DOI: https://doi.org/10.1016/j.tourman.2013.07.013.

59. Lu, Z., & Zhang, L. (2016), Face recognition algorithm based on discriminative dictionary learning and sparse representation. Neurocomputing, 174B(22), 749755-, DOI: https://doi.org/10.1016/j.neucom.2015.09.091.

60. Ma, J., Gao, J., Scott, N., & Ding, P. (2013). Customer delight from theme park experiences: The antecedents of delight based on cognitive appraisal theory. Annals of Tourism Research, 42, 359381-, DOI: https://doi.org/10.1016/j.annals.2013.02.018.

61. Magids, S., Zorfas, A., & Leemon, D. (2015). The new science of customer emotions. Harvard Business Review, 76, 6674-.

62. Magnini, V. P., Baker, M., & Karande, K. (2013). The frontline provider's appearance: A driver of guest perceptions. Cornell Hospitality Quarterly, 54(4), 396405-, DOI: https://doi.org/10.1177193896551349 0822/.

63. Magnini, V. P., Crotts, J. C., & Zehrer, A. (2011). Understanding customer delight: An application of travel blog analysis. Journal of Travel Research, 50(5), 535545-, DOI: https://doi.org/10.117700472875103 79162/.

64. Malone, S., McCabe, S., & Smith, A. P. (2014). The role of hedonism in ethical tourism. Annals of Tourism Research, 44, 241254-, DOI: https://doi.org/10.1016/j.annals.2013.10.005.

65. Marci, C., & Murray, B. (2017). Emotions. In Consumer Neuroscience, Cerf M. & Garcia-Garcia M. (Eds.), (pp151176-). The MIT Press.
66. Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: a review. Cognition and Emotion, 23(2), 209237-, DOI: https://doi.org/10.1080026999308022046 77/.
67. Millán, A., Fanjul, M. L., & Moital, M. (2016). Segmenting the business traveler based on emotions, satisfaction, and behavioral intention. Psychology & Marketing, 33(2), 8293-, DOI: https://doi.org/10.1002/mar.20856.
68. Mitas, O., Yarnal, C., Adams, R., & Ram, N. (2012). Taking a "peak" at leisure travelers' positive emotions. Leisure Sciences, 34(2), 115135-, DOI: https://doi.org/10.1080014/90400.2012.652503.
69. Mor, M., Dalyot, S., & Ram, Y. (2023). Who is a tourist? Classifying international urban tourists using machine learning. Tourism Management, 95, art. 104689, DOI: https://doi.org/10.1016/j.tourman.2022.104689.
70. Nawijn, J., Mitas, O., Lin, Y., & Kerstetter, D. (2013). How do we feel on vacation? a closer look at how emotions change over the course of a trip. Journal of Travel Research, 52(2), 265–74, DOI: https://doi.org/10.11770047287512465961/.
71. Nawijn, J. (2011). Determinants of Daily Happiness on Vacation. Journal of Travel Research, 50(5), 559–66, DOI: https://doi.org/10.11770047287510379164/.
72. Nawijn, J. (2010). The holiday happiness curve: a preliminary investigation into mood during a holiday abroad. International Journal of Tourism Research, 12(3), 281-290, DOI: https://doi.org/10.1002/jtr.756.
73. Nørfelt, A., Kock, F., Karpen, I. O., & Josiassen, A. (2023). Pleasure through pain: an empirical examination of benign masochism in tourism. Journal of Travel Research, 62(2), 448468-, DOI: https://doi.org/10.11770047287521106755 0/.
74. Peng, J., Yang, X., Fu, S., & Huan, T. C. T. (2023). Exploring the influence of tourists' happiness on revisit intention in the context of Traditional Chinese Medicine cultural tourism. Tourism Management, 94, art. 104647, DOI: https://doi.org/10.1016/j.tourman.2022.104647.
75. Pop, R. A., Săplăcan, Z., Dabija, D. C., & Alt, M. A. (2022). The impact of social media influencers on travel decisions: The role of trust in consumer decision journey. Current Issues in Tourism, 25(5), 823843-, DOI: https://doi.org/10.1080136/83500.2021.1895729.

76. Popa, M. C., Rothkrantzy, L. J. M., Wiggers, P., & Shan, C. (2017). Assessment of facial expressions in product appreciation. Neural Network World, 27(2), 197213-, DOI: 10.14311/NNW.2017.27.009.
77. Prayag, G., Hosany, S., Muskat, B., & Del Chiappa, G. (2017). Understanding the relationships between tourists' emotional experiences, perceived overall image, satisfaction, and intention to recommend. Journal of Travel Research, 56(1), 4154-, DOI: https://doi.org/10.11770047287515620567/.
78. Prayag, G., Hosany, S., & Odeh, K. (2013). The role of tourists' emotional experiences and satisfaction in understanding behavioral intentions. Journal of Destination Marketing & Management, 2(2), 118127-, DOI: https://doi.org/10.1016/j.jdmm.2013.05.001.
79. Qi, X., Shi, D., Huang, Z., & Chang, W. (2023). Fostering customer loyalty across countries in hospitality and tourism: a meta-analysis of cultural values as moderators. International Journal of Contemporary Hospitality Management, 35(5), 16021619-, DOI: https://doi.org/10.1108/IJCHM-040496-2022-.
80. Reeve, J. (2024). Understanding motivation and emotion. John Wiley & Sons.
81. Richins, M. L. (1997). Measuring emotions in the consumption experience. Journal of Consumer Research, 24(2), 127146-, DOI: https://doi.org/10.1086209499/.
82. Sarstedt, M., Adler, S.J., Rau, L., Schmitt, B. (2024). Using large language models to generate silicon samples in consumer and marketing research: challenges, opportunities, and guidelines. Psychology and Marketing, 41(6), 12541270-, https://doi.org/10.1002/mar.21982.
83. Schmidt, K. L., & Cohn. J. F. (2001). Human facial expressions as adaptations: evolutionary questions in facial expression research. American Journal of Physical Anthropology, 116(33), 3–24, DOI: https://doi.org/10.1002/ajpa.20001.
84. Small, D. A., & Verrochi. N. M. (2009). The face of need: facial emotion expression on charity advertisements. Journal of Marketing Research, 46(6), 777787-, DOI: https://doi.org/10.1509/jmkr.46.6.777_JMR6F.
85. Söderlund, M., & Sagfossen, S. (2017). The depicted service employee in marketing communications: An empirical assessment of the impact of facial happiness. Journal of Retailing and Consumer Services, 38, 186193-, DOI: https://doi.org/10.1016/j.jretconser.2017.06.006.
86. Soltani, M., Soltani Nejad, N., Taheri Azad, F., Taheri, B., & Gannon, M. J. (2021). Food consumption experiences: a framework for understanding food tourists' behavioral

intentions. International Journal of Contemporary Hospitality Management, 33(1), 75100-, DOI: https://doi.org/10.1108/IJCHM-030206-2020-.

87. Somerville, L.H., Fani, N., & McClure-Tone, E.B. (2011). Behavioral and neural representation of emotional facial expressions across the lifespan. Developmental Neuropsychology, 36(4), 408428-, DOI: https://doi.org/10.108087565641.2010.5498/65.

88. Stewart, D. W., Hecker, S., & Graham, J. L. (1987). It's more than what you say: Assessing the influence of nonverbal communication in marketing. Psychology & Marketing, 4(4), 303322-.

89. Stylos, N. (2022). An integrated duality theory framework (IDTF): marking pathways for consumer decision-making researchers in the hospitality and tourism industry. International Journal of Contemporary Hospitality Management, 34(7), 25972619-, DOI: https://doi.org/10.1108/IJCHM-101256-2021-.

90. Stylos, N., & Bellou, V. (2019). Investigating tourists' revisit proxies: The key role of destination loyalty and its dimensions. Journal of Travel Research, 58(7), 11231145-, DOI: https://doi.org/10.11770047287518802100/.

91. Stylos, N., Bigné, E., & Bellou, V. (2024). The affective impact of sightseeing bus tour experiences: using Affective Events Theory (AET) to examine length-of-stay and electronic word-of-mouth. Tourism Recreation Research, 49(4), 740756-, DOI: https://doi.org/10.108002508281.2022.2101273/.

92. Todorov, A., Olivola, C.Y., Dotsch, R., & Mende-Siedlecki, P. (2015). Social attributions from faces: Determinants, consequences, accuracy, and functional significance. Annual Review of Psychology, 66, 519545-, DOI: https://doi.org/10.1146/annurev-psych-113011143831-.

93. van Es, N., & Reijnders, S. (2016). Chasing sleuths and unravelling the metropolis: Analyzing the tourist experience of Sherlock Holmes' London, Philip Marlowe's Los Angeles and Lisbeth Salander's Stockholm. Annals of Tourism Research, 57, 113125-, DOI: https://doi.org/10.1016/j.annals.2015.11.017.

94. Verma, A., & Sharma, L. K. (2013). A comprehensive survey on human facial expression detection. International Journal of Image Processing, 7(2), 171182-.

95. Viglia, G., Adler, S., Miltgen, C.L., & Sarstedt, M. (2024). The use of synthetic data in tourism. Annals of Tourism Research, 108, art. 103819, DOI: https://doi.org/10.1016/j.annals.2024.103819.

رجب 1446هـ - ديسمبر 2024م
العــدد (170)

96. Wang, S. S., Moon, S. I., Kwon, K. H., Evans, C. A., & Stefanone, M. A. (2010). Face off: Implications of visual cues on initiating friendship on Facebook. Computers in Human Behavior, 26(2), 226234-, DOI: https://doi.org/10.1016/j.chb.2009.10.001.

97. Wang, X., Zheng, J., Tang, L. R., & Luo, Y. (2023). Recommend or not? The influence of emotions on passengers' intention of airline recommendation during COVID-19. Tourism Management, 95, art. 104675, DOI: https://doi.org/10.1016/j.tourman.2022.104675.

98. Xu, Y., Zhu, Q., Fan, Z., Qiu, M., Chen, Y., & Liu, H. (2013). Coarse to fine K nearest neighbor classifier. Pattern Recognition Letters, 34(9), 980986-, DOI: https://doi.org/10.1016/j.patrec.2013.01.028.

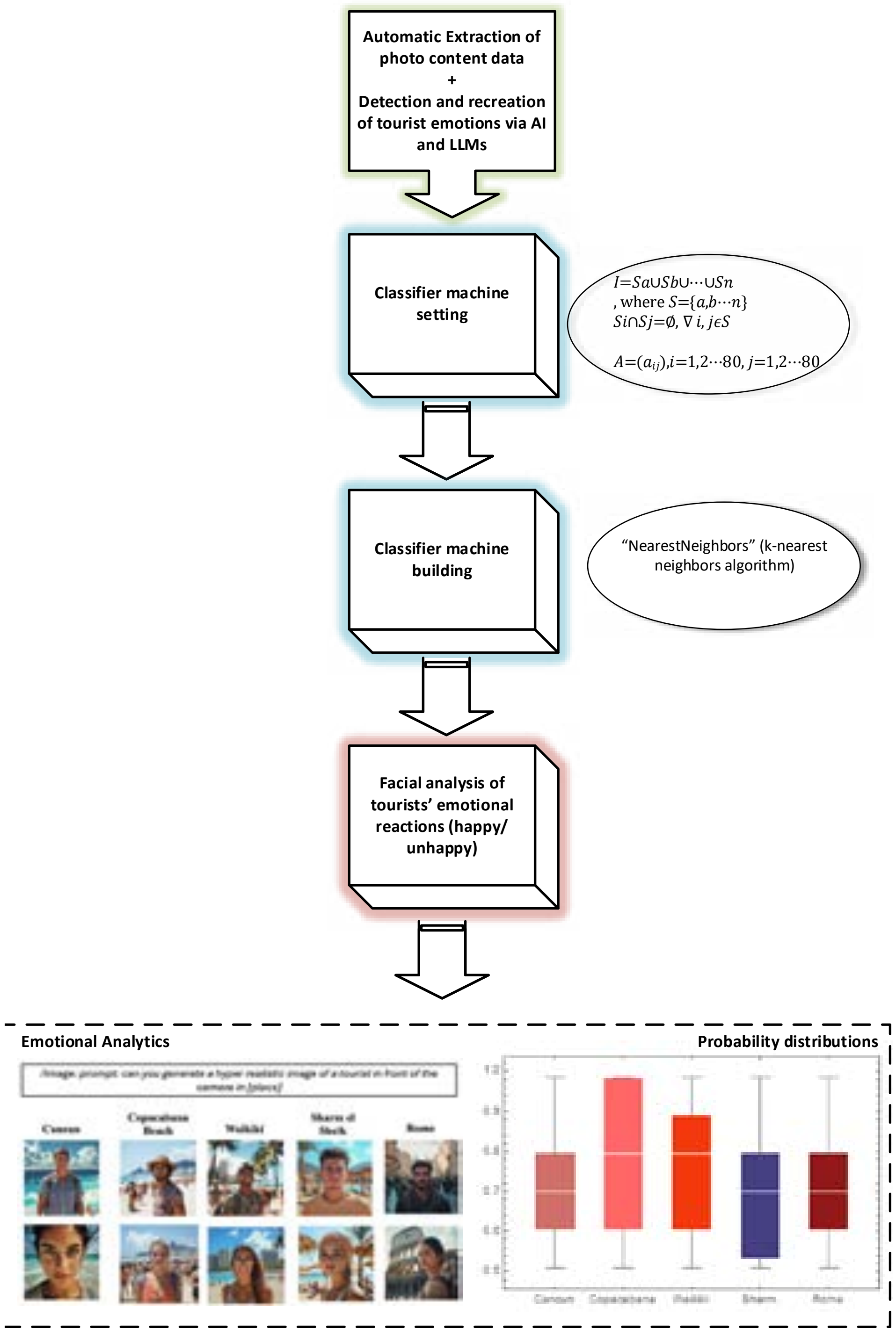
99. Xu, J., Zhang, W., Li, H., Zheng, X., & Zhang, J. (2024). User-generated photos in hotel demand forecasting. Annals of Tourism Research, 108, art. 103820, DOI: https://doi.org/10.1016/j.annals.2024.103820.

100. Zhao, C., Shang, Z., & Pan, Y. (2024). Beauty and tourists' sustainable behaviour in rural tourism: A self-transcendent emotions perspective. Journal of Sustainable Tourism, 32(7), 14131432-, DOI: https://doi.org/10.108009669582.2023.2238135/.

101. Zhao, X., Shi, X. & Zhang, S. (2015). Facial expression recognition via deep learning. IETE Technical Review, 32(5), 347355-, DOI: https://doi.org/10.108002564602.2015./1017542.

102. Zheng, Y., Gao, Y. L., Li, M., & Dang, N. (2023). Leadership styles and employee pro-environmental behavior in the tourism and hospitality industry: A cognitive-affective personality system perspective. International Journal of Hospitality Management, 113, art. 103509, DOI: https://doi.org/10.1016/j.ijhm.2023.103509.

103. Zhi, R., Cao, L., & Cao, G. (2017). Asians' facial responsiveness to basic tastes by automated facial expression analysis system. Journal of Food Science, 82(3), 794-806, DOI: https://doi.org/10.11113841.13611-1750/.


Automatic Extraction of photo content data
+
Detection and recreation of tourist emotions via AI and LLMs
Classifier machine setting
I=Sa∪Sb∪⋯∪Sn
, where S={a,b⋯n}
Si∩Sj=∅, ∀ i, j∈S
A=(aij),i=1,2⋯80, j=1,2⋯80
Classifier machine building
"NearestNeighbors" (k-nearest neighbors algorithm)
Facial analysis of tourists' emotional reactions (happy/unhappy)
Emotional Analytics
Probability distributions

”هل يمكننا معرفة: إذا كنتَ قد قضيتَ وقتًا ماتِعًا هناك؟“ الصور السياحية الحقيقية، والمُصنَّعة التي تكشف عن السعادة وعدمها من خلال الذكاء الاصطناعي والنماذج اللغوية الكبيرة

DOI: https://doi.org/10.63355/MrGf2346

إليونورا بانتانو (المؤلفة المراسلة)
البريد الإلكتروني: e.pantano@bristol.ac.uk

نيكولاوس ستايلوس
كلية إدارة الأعمال، جامعة بريستول، BS81SD بريستول، المملكة المتحدة
البريد الإلكتروني: n.stylos@bristol.ac.uk

المستخلص:

الهدف:
تهدف هذه الدراسة إلى استكشاف مدى إمكان استخراج البيانات من الصور تلقائيًّا المتعلقة بالعواطف البشرية المُضمَّنة، كالسعادة وانتفائها، ومعرفة إذا كان بالإمكان تحليل عواطف السُّيَّاح وإعادة إنشائها باستخدام الذكاء الاصطناعي والنماذج اللغوية الكبيرة.

المنهجية:
قُمْنَا ببناء وتدريب آلة تصنيف آلية لتحليل صور السُّيَّاح الحقيقيين في خمس وجهات سياحية دولية، ثم قمنا بمقارنتها بعينة اصطناعية من السُّيَّاح أُنشأت بواسطة الذكاء الاصطناعي والنماذج اللغوية الكبيرة.

النتائج:
تُوسِّع هذه الدراسة معرفتنا وممارساتنا في التعرف إلى مشاعر السُّيَّاح من خلال توظيف طرائق جديدة تعتمد إلى الذكاء الاصطناعي. كما تُظهِر مزايا الجمع بين تحليل تعابير الوجه لتحديد التفاعلات العاطفية للأفراد؛ ما يُوفِّر بديلًا عن التقارير الذاتية. فضلًا عن ذلك، تُقدِّم الدراسة أدلة إضافية على محدودية كفاءة النماذج اللغوية الكبيرة في ربط المعلومات المُستخرَجة من البيانات النصية (المطالبات) المقدَّمة.

الأصالة:
على حدِّ علمنا، تُعَدُّ هذه الدراسة أول بحث تجريبي يحاول تحليل وإعادة إنشاء عواطف السُّيَّاح باستخدام الذكاء الاصطناعي والنماذج اللغوية الكبيرة عبر بيانات اصطناعية مُستمَدة من عينة سياحية رقمية.

التطبيقات العملية:
توضح هذه الدراسة كيفية تقييم الحالة النفسية أو التفاعلات العاطفية للمُستهلِكين تجاه وجهة سياحية معينة باستخدام أدوات جديدة لا تعتمد بالكامل إلى تقارير السُّيَّاح الذاتية. بدلًا من ذلك، نناقش نهجًا جديدًا لالتقاط العواطف الحقيقية وقياسها؛ ما يسمح باستخلاص رُؤًى افتراضية عن تجارب وتفضيلات السُّيَّاح تجاه وجهات ومواقع سياحية محددة.

الكلمات المفتاحية:
سلوك السُّيَّاح، التحليلات العاطفية، البيانات الاصطناعية، العينة الرقمية، النماذج اللغوية الكبيرة، الذكاء الاصطناعي التوليدي، التعلم الآلي.

«هل يمكننا معرفة:
إذا كنتَ قد قضيتَ
وقتًا ماتِعًا هناك؟»
الصور السياحية
الحقيقية، والمُصنَّعة
التي تكشف عن
السعادة وعدمها
من خلال الذكاء
الاصطناعي والنماذج
اللغوية الكبيرة