Facial-Expression Recognition: an emergent approach to the measurement of tourist satisfaction through emotions

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Abstract

Purpose - The employment of facial-expression recognition to analyse emotions constitutes a potential instrument for the measurement of customer satisfaction in the tourism sector. The study aims to assess the functionality of Artificial Intelligence to measure tourists' emotions and hence their satisfaction with the quality of the service provided on a guided tour when visiting a UNESCO heritage site.

Design/methodology/approach - The methodology comprises the following stages. Firstly, the emotions are analysed through data recorded by using a software application on facial-expression recognition on a sample of tourists visiting a heritage site. Secondly, the tourists were asked to rate their overall satisfaction with the guided tour visit. Finally, a structural equation modelling approach is used to validate the strong relation between emotions and satisfaction.

Findings - The results achieved confirm that the information obtained from facial-expression recognition demonstrated that it is as valid an instrument as that offered by the self-administered questionnaires for the measurement of customer satisfaction. The findings from the application reveal that a change in the scientific and professional field is emerging in the measurement of customer satisfaction focused on the emotions from a digital approach.

Research limitations/implications - This research is mainly based on the use of specific software for facial-expression recognition with its intrinsic measurement of emotions with and in a specific heritage scenario. Other scenarios and software of a more sophisticated nature implemented in the tourism and hospitality industry are necessary for the in-depth comprehension of the significant role played by emotions in the improvement of service quality.

Practical implications - The recent application of recording emotions in the Tourism Industry provides practitioners with useful insights for the detection of deficiencies in their services and therefore the means to boost their reputation and destination image.

Originality/value- Artificial Intelligence presents a new paradigm in the measurement of satisfaction by substituting self-administered surveys with a method based on the use of innovative software that recognizes faces and detects emotions through facial expressions. The paper contributes to the literature by using an Artificial Intelligence approach to measure satisfaction through emotions in the tourism sector.

Keywords: Artificial Intelligence; Facial-expression recognition; Emotions; Satisfaction; PLS-SEM; Emotionalyser.

Paper type Research paper

1. Introduction

Traditionally, structural surveys have been employed to assess customer satisfaction in order to attain in-depth knowledge on the areas of potential improvement in the provision of a specific service (Coghlan & Pearce, 2010; Jacobs, Fehres & Campell, 2012; Walters, Sparks, & Herington, 2012; Oh and Kim, 2017). However, with the digital revolution, Artificial Intelligence (AI) tools are emerging through which the data collection process is greatly improved (Pittman & Reich, 2016; Lowe-Calverley et al., 2019). These innovative instruments are able to recognize faces, and to detect, via facial expressions, the emotions felt by users at the moment of the consumption of the service (Mauss & Robinson, 2009; Wang & Minor, 2008).

Bearing in mind that emotions have a significant impact on the majority of human activities and functions (Faria et al., 2017), facial-expression recognition has already begun to be implemented experimentally in certain hotel chains, such as that of the Bluebay Group (bluebayresorts.com). Thanks to its use, several of the less efficient features of the hotel could be identified, such as the service provided by the advertising leaflets, through the sensors placed on the shelf devoted to these leaflets. Recently, as a pioneering initiative in Spain, the Campanile hotel chain has been using sensors to recognize facial expressions of emotions to evaluate and improve its protocols in customer services (imotionanalytics.com). The method based on the recognition of facial expressions allows hoteliers to give an immediate response, make effective decisions, and act on the problems that arise on a daily basis. This technology appears to be an effective tool for managers to solve such difficulties in their hotels.

In addition, through facial-recognition technology, there is a reduction in the risk of bias in social desirability appearing in responses (Morin, 2011; Paulhus, 2002; Poels & Dewitte, 2006; Ravaja, 2004; Shanshi, Scott & Walters, 2014). With results of greater accuracy, practitioners can act more effectively by applying measures that optimize the quality of service delivery, or experience, and hence increase the perceived value and other variables that directly affect customer satisfaction.

Emotions play a fundamental role as antecedents of satisfaction (De Rojas & Camarero, 2008; Yuksel, Yuksel & Bilim, 2010; Walters, Sparks & Herington, 2012; González-Rodríguez, et al., 2019) and become the value-base object (measurement object) of facial-feature recognition (Lang, Greenwald, Bradley & Hamm, 1993; Tarnowski et al., 2017; Kirana et al., 2018). In this respect, negative emotions are related to a lack of satisfaction and tourists would perceive a negative experience either in the tourist destination or in the quality of the service provided. Conversely, the greater the accumulation of positive emotions, the higher the level of customer satisfaction. Knowledge regarding the causes of negative emotions, which enables dissatisfaction to be suitably addressed, can be gathered with the proper location of intelligent sensors. Hence, facial-expression recognition sensors can replace questions from self-administered questionnaires related to service quality, experience quality, and satisfaction in the tourism destination and hospitality sector (Li, Scott & Walters, 2015).

The unquestionable importance of feelings as an antecedent factor of satisfaction, together with the emergence of AI devices, form the basis of the present research devoted to the exploration of emotions through facial-expression recognition and their link with customer satisfaction measured by a self-administered questionnaire. The accuracy of how well emotions are related to customer satisfaction provides the validity of the technology used. Thus, the main aims of the present research, directly related to improving the perceived quality of a specific service offered on a UNESCO world heritage site are as follows: analyse customer satisfaction from the measurement of the emotions that are recorded from tourist facial expressions during the guided tour; and demonstrate the importance of emotions as a key antecedent of customer satisfaction, which in turn would help practitioners improve the quality of a service. The research strives to emphasise the use of artificial intelligence (AI) based on facial-expression recognition and emotions, and to reveal that the results provided by AI are sufficiently optimal to truly be considered as an effective instrument for the validation of or the combination with traditional surveys in order to better understand individuals' emotional responses (Critchley & Harrison, 2013; Kreibig, 2010; Lambie & Marcel, 2002; Mauss, Levenson, McCarter, Wilhelm & Gross, 2005; Mauss & Robinson, 2009).

In order to comply with the objectives above, a literature review has been carried out on emotions as an antecedent that influences the satisfaction with the quality of the service as perceived by the customers, and on the advantages and disadvantages of the application of self-report questionnaires to capture individual emotions. A powerful facial-recognition tool, Emotionalyser, has been employed to collect data on emotions. Structural equation modelling, PLS-SEM, has been applied in order to test the effectiveness of the facial-expression recognition used in the measurement of customer satisfaction, which in turn would provide information to practitioners regarding improvements to service quality.

2. Literature review

2.1. Satisfaction and emotions

Traditionally, studies on consumer satisfaction have been addressed from a cognitive perspective where satisfaction was generally modelled as the result of a process of comparison between the expectations and the perceived results after a consumption experience (Bigné et al., 1997a; Oliver, 1977, 1981; Oliver & Desarbo, 1988; Parasuraman, Zeithamal & Berry, 1985, 1988, 1994). However, a new trend in addressing satisfaction from a cognitive-affective approach emerged in the late eighties in the academic literature on customer behaviour (Bagozzi, Gopinath & Nyer, 1999; Bigné & Andreu, 2004; Dubé & Menon, 2000; Richins, 1997; Yu & Dean, 2001; González-Rodríguez et al., 2016). These authors claim that the cognitive component of satisfaction is insufficient to understand the consumer's response to a consumption experience since satisfaction is a process of cognitive evaluation that produces affective responses that influence a customer’s decision-making and therefore the subsequent consumer behaviour.

The understanding of the influence of emotions on individual responses such as satisfaction and behaviour has appeared as a recurrent theme in many disciplines, including travel and tourism. Emotions originally studied from consumer psychology have been understood as an antecedent driver of responses from consumers exposed to advertisements, service interactions, use of products, visiting experiences, or to certain environmental conditions, to name but a few. Although there is no standard definition for emotion, it is commonly accepted that “Emotions arise in response to events that are important to the individual's goals, motives, or concerns” (Frijda, 1988, p. 351). In an individual, emotions trigger affective, cognitive, physiological, and behavioural responses (Brave & Nass, 2002). In this vein, in behavioural science, it is argued that emotion is a key construct for understanding consumer preference with regard to consumption of products and services (Dai et al., 2015). Moreover, pleasant feelings and satisfying results are identified as emotion-related factors that determine consumption experiences (Stock, 2011). Accordingly, in the empirical research, the domain of emotion is divided into positive and negative emotions (Dai et al., 2015; Tarnowski et al., 2017).

In the literature, emotions have been generally measured through the self-report questionnaire method and observation techniques (Coghlan & Pearce, 2010; Isomursu, Tähti, & Kuutti, K., 2007; Lee & Kyle, 2012; Wang & Minor, 2008). While self-report techniques are mainly based on dimensional theories of emotions since they focus on cognitive aspects of a subjective or memorable experience, observation techniques are mostly related to categorical theories since they observe physiological and expressive responses derived from a stimulus.

Traditionally, in the tourism and hospitality fields, self-report methods based on previous measurement scales of emotion have been used to explore how travellers’ emotions experienced during a trip are strong predictors of satisfaction (Bigné & Andreu, 2004; Bigné, Andreu & Gnoth, 2005; Faullant, Matzler, & Mooradian, 2011; San Martin & del Bosque, 2008; González-Rodríguez et al., 2019) and behavioural intention (Bigné, Mattila, & Andreu, 2008; Donovan, Rossiter, Marcoolyn, & Nesdale, 1994; Machleit & Eroglu, 2000; Rodríguez Molina, Frías-Jamilena, & Castañeda-García, 2013; White & Scandale, 2005; Yüksel & Yüksel, 2007). A literature review on tourism and consumer behaviour reveals that the empirical approach for the measurement of emotions based on self-report questionnaires relies on either unipolar (San Martin, 2005) or bipolar items

(De Rojas & Camarero, 2008; Alegre & Garau, 2010; Žabkar, Brenčič & Dmitrović, 2010) to capture data concerning mainly valence and arousal. In the bipolar approach, emotions are conceived as bipolar states where extreme positions are mutually exclusive (Bagozzi et al., 1999; Oliver, 1997), such as happy/unhappy, entertained/bored. The use of bipolar measurement scales is not suitable when individuals experience the two extreme positions in the same experience. This situation could happen when the product or service provided presents multiple features leading the respondents to experience independent states of happiness and unhappiness, or when the service is provided over a period of time and hence the respondents might have both positive and negative experiences (Andreu, Bigne, Chumpitaz & Swaen, 2006). However, with the unipolar scales, the individual indicates the intensity or frequency with which each emotional state (positive and negative) is experienced by the respondent. The main limitation of the unipolar state is that the answers for positive and negative emotional states may be just the opposite and therefore redundant.

Self-report measures have been useful and widely employed in tourism mainly because they are simple and economical methods for the capture of emotions (Healey, Nachman, Subramanian, Shahabdeen & Morris, 2010; Micu & Plummer, 2010; Poels & Dewitte, 2006; Teixeira,Wedel & Pieters, 2012; Domínguez-Quintero et al., 2019). However, self-report questionnaires present major limitations when measuring travellers' emotions. First, the self-report methods may be biased towards providing socially acceptable answers (Brønn & Vidaver-Cohen, 2009; Podsakoff & Organ, 1986; Worthington, Ram & Jones, 2006), even when respondents have been assured confidentiality and anonymity. Second, the self-report measures may involve cognitive bias basically due to the respondents' conscious awareness of emotions (Clore & Ortony, 1988; Frijda et al., 1995; Kolodyazhniy, Kreibig, Gross, Roth & Wilhelm, 2011; Poels & Dewitte, 2006; Winkielman & Berridge, 2004; Wilhelm, Grossman & Mueller, 2012) and the ability to remember or explain the emotions they have experienced throughout the visit (Paulhus & Vazire, 2007; Poels & Dewitte, 2006; Wilhelm & Grossman, 2010). Third, a significant bias when measuring emotions involves the time elapsed between the moment travellers experience the emotion to the time those emotions are reported (Micu & Plummer, 2010; Urry, 2009). Mostly, in the tourism sector, emotions are considered as simple cognitive appraisals by being measured at a specific point in time and therefore represent the overall emotional assessments of the visit or trip (De Rojas & Camarero, 2008; Hosany & Gilbert, 2010). Furthermore, emotions are dynamic (Forlizzi & Ford, 2000) and a user can experience a variety of emotions while the service or product is being provided. Only a few studies measure emotions by asking respondents the same questions at regular intervals throughout the visit (Graham et al., 2008; Tussyadiah & Fesenmaier, 2009), although, for these studies, there is still a time lapse between the moment the emotion is experienced and the moment said emotion is reported (Kim & Fesenmaier, 2015). Fourth, other limitations have also been recognized as being related to the items utilised to identify emotions (Chamberlain & Broderick, 2007): certain measures grounded in emotions either contain terms which are not familiar to the respondents or ignore emotions which are part of people's daily lives. Furthermore, those measurements related to semantically differential items where the two anchor points are not clear opposites (e.g., bored and relaxed) are particularly confusing for respondents.

A growing interest in the collection of information on emotions through psychophysiological indicators has been stressed in the literature on tourism to overcome the limitations of the self-report measures (Bagozzi et al., 1999; Chamberlain and Broderick, 2007; Li, Shanshi, Scott, Noel, Walters & Gabbi, 2014; Li, Walters, Packer & Scott, 2018; Li, Walters, Packer & Scott, 2016; Shanshi, Scott & Walters, 2014). Psychophysiological measurements can be conducted continuously, thereby providing a vast number of measurements for the detection of the dynamism of emotions (Wang & Minor, 2008). Furthermore, since these measurements do not depend on verbal scales, they prevent users from experiencing any confusion with message processing (Ravaja, 2004) and require no cognitive effort or memory. The psychophysiological instruments available for the collection of data on emotions are essentially those that measure physiological reactions, such as sweating, and pupil dilation (Kreibig, 2010; Partala et al., 2000), or that measure expressions mainly based on facial or vocal expressions (Ekman & Friesen, 1978; Kaiser & Wehrle, 1994; Litman & Forbes, 2003).

Eye tracking captures gaze direction (reflecting attention) and blink frequency (associated with mental load). Scan paths of the eyes reveals how people look at websites and advertisements: which parts of a web, an advertisement, or picture are actually noticed and how long people look at various items. Modern eye-tracking technology can easily collect this data, which makes it increasingly popular in behavioural studies. Recently, studies in tourism have used eye-tracking methodologies in a laboratory setting to explore visual attention distribution of consumers while navigating on an online interface (Espigares-Jurado et al., 2020), while looking at evocatively beautiful and emotional pictures, tourism advertisements, or hotel marketing images (Li, Huang and

Christianson, 2016; Scott, Green and Fairley, 2016; Scott et al., 2019; Wang et al., 2018). However, eye tracking is not without limitations: eye movements can be influenced by excessive blinking or tears and also by biases when participants have previous experience with eye-tracking applications. In this vein, the combination of eye tracking and facial-expression analysis with other physiological data to collect tourist emotional responses can take research to a higher level (Li, Scott and Walters, 2015).

Electrodermal activity analysis (EDA) measures the activation of the Autonomic Nervous System (ANS), which controls most of the organs and muscles and is responsible for arousal such as excitement and anticipation. When people are exposed to a stimulus, the ANS is activated leading to a change in skin conductivity. Skin conductance (SC) is a tool to measure EDA and therefore to capture emotion responses. EDA has also been used in tourism research to assess the emotional arousal experienced by participants in laboratory settings whilst observing stumuli (Babakhani, Ritchie & Dolnicar, 2017; Brodien Haparai, Walters & Li, 2018; Hadinejad, Moyle & Scott, 2019). The progress in technology regarding the availability of wearable and mobile physiological sensors offers researchers the opportunity to obtain tourists' physiological responses, such as electrodermal activity when exposed to a variety of cognitive, physical, and emotional experiences, in real time and throughout the entire experience (Kim & Fesemmaier, 2015; Shoval, Schvimer & Tamir, 2018). The major limitations of EDA are related to the sensitivity of the equipment used and the demand for accurate analysis since skin conductance levels (SCLs) differ across individuals (Li, Scott & Walters, 2015).

Facial-expression recognition techniques analyse the shapes and patterns of facial features as result of emotional responses when individuals are exposed to external and internal stimuli. Hence, the impact of any content, product, or service on how humans respond can be assessed by continuously observing the changes elicited in their emotional states as reflected in their facial features. Coding facial expressions during the time the individual is exposed to the stimuli can be employed to complement and enrich self-reports with quantified measures of emotional responses towards products or services that are of a more unconscious nature.

The majority of facial-expression recognition devices or applications that gather facial images using video or thermal imaging (Huopio, 1998) involve the following steps (Figure 1): face detection, that is, the position of a face in a video frame, which can be achieved by applying classifier algorithms; detection of facial landmarks or facial features (e.g., mouth corners, eyebrow corners). An internal face model, similar to an invisible virtual mesh, is placed onto the respondent's face and is adapted as the respondent's face moves or changes expression. The face model contains fewer facial features than those for the actual respondent's face but is sufficiently detailed to capture the shape of an emotionally indicative facial area. It detects both single landmark points (e.g., mouth corners, eyebrow corners, and eyebrows) and feature groups (entire mouth, entire eyebrows), and registers facial expressions and classifies emotions. Once the features are detected, they are used as inputs into the classification algorithms and translated into emotional states or affective metrics.

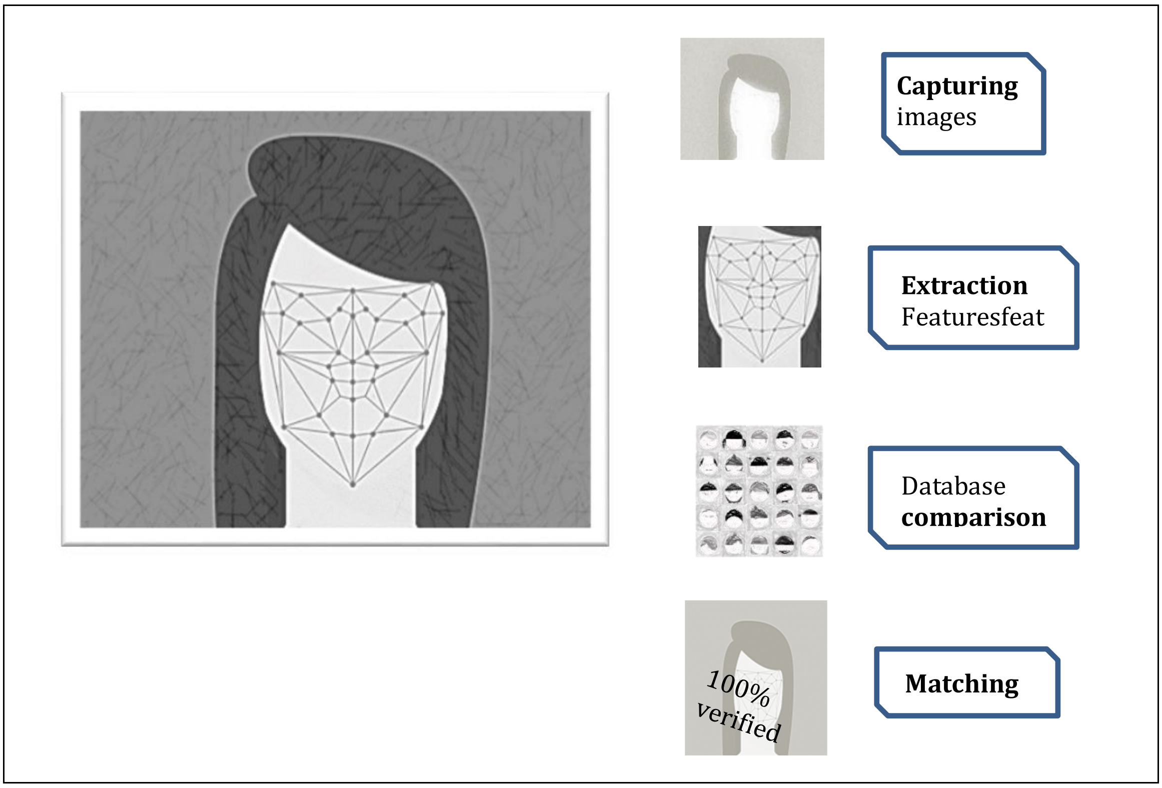

Figure 1. Procedure for facial-expression engines

Three methods have been used to measure facial expressions of emotion (Wolf, 2015): the facial electromyography (fEMG) method; the facial action coding system (FACS); and automated-based face recognition.

The facial electromyography method has been developed to recognize activation of facial muscles by using electrodes attached to the surface of the skin (Chamberlain & Broderick, 2007; Fridlund & Cacioppo, 1986; Mauss & Robinson, 2009; Tassinary, Cacioppo, & Vanman, 2007; Wang & Minor, 2008). Two major groups of facial muscles have been investigated: right/left corrugator supercilii ("eyebrow wrinkler") and right/left zygomaticus (major). The corrugator supercilii is a pyramidal muscle near the eyebrow that usually produces a vertical wrinkling of the forehead, and is associated with negative emotions such as disgust. The zygomaticus muscle extends from each cheekbone to the corners of the mouth and draws the angle of the mouth up and out, and is generally associated with smiling (Lang, Greenwald, Bradley & Hamm, 1993). Studies examining the effectiveness of using physiological emotion responses recorded by facial electromyography methods are rarely used in tourism research to detect consumers' spontaneous emotional responses. Li et al. (2018a) demonstrate the advantages of skin conductance and facial electromyography methods in tracking emotional responses over self-report emotions to destination advertisements. Studies carried out by Li et al. (2018b) and Li (2019) move beyond the methodological debate and analyse whether the influence of the emotional responses evoked by destination television advertisements on "attitude towards the advertisement", "attitude towards a destination", and visit intention may vary when collecting data from psychophysiological (facial electromyography (fEMG) and skin conductance (SC)) and self-report measures. According to this study, both measures reveal that emotions elicited by advertisements are relevant for subsequent cognitive and behavioural responses. The main disadvantage of the electromyography method is related to its technical complexity since it requires not only electrodes, cables, and amplifiers, but also expert biosensor processing skills. Furthermore, this method fails to allow the examination of facial expressions from real-life situations since the data is collected in laboratory settings (Wolf, 2015).

The Facial Action Coding System enables identification of emotions by analysing the changes in expression on a person's face. These changes can be observed either from real-life observations of a person or under laboratory conditions. This method is based on Ekman's' theory of six basic emotions (1992, 1999). Based on this approach, experts examine videotaped faces for image analysis and describe specific expression changes called "Action Units" (AUs). Thus, this method allows the identification of basic emotions over time (Wolf, 2015). While this is useful since FACS scores have high validity, the main disadvantage of this method is the time required for the analysis of the fixed images and therefore for its codification.

In order to overcome the limitations of the fEMG and FACS methods, fully automated technologies based on computer-vision algorithms have been developed and improved in quality over the years. The progress of automated technologies has been accompanied by developments in computer science, which has granted automated facial expressions more reliability and accessibility (Lewinski, den Uyl, & Butler, 2014). Examples of commercially available software largely used by researchers to classify emotions of facial expressions include FaceReader from Noldus, FACET, and AFFDEX from Affectiva. These algorithms differ in “the statistical procedures, facial databases, and facial landmarks to train the machine learning procedures and ultimately classify emotions” (Stöckli et al., 2017, p.5). FaceReader, software marketed by Noldus (www.noldus.com) automatically analyses facial expressions in terms of Ekman’s six basic emotions plus the neutral state. The analysis by FaceReader is based on FACS principles. FaceReader can recognize all changes in facial expressions based only on the basic emotions, although those emotions that are more complex cannot be analysed (Yu & Ko, 2017). Furthermore, FaceReader has evolved through the development of multiple face models, which work well under cultural and age differences (East-Asian Model, Baby Face Reader). FACET and AFFDEX are commercial toolkits that form part of a suite of software by iMotions (www.imotions.com). This iMotions’ software uses three databases of facial-expression pictures: WSEFEP, ADFES, and RaFD, which are validated to show FACS-consistent facial expressions of basic emotions. The FACET and AFFDEX algorithms categorize the facial expressions without integrating any contextual information and fail to detect non-prototypical emotions (Stöckli et al., 2017). While AFFDEX is currently one of the most widely used software development kits (SDKs) for classifying emotional states (Magdin, Benlo & Koprda, 2019), this is not the case in tourism research.

Recent studies in laboratory settings have shown that FaceReader is an efficient tool for the analysis of emotions with a range of accuracy rate between 88% (Lewinski et al., 2014) and 90% (Loijens & Krip, 2013). Stöckli et al. (2017) found similar results for iMotions automated facial-expression analysis modules: an accuracy rate of 70% and 96% for AFFDEX and FACET were obtained, respectively. Furthermore, technologies allow the examination of facial expressions of a person without the interference of technical recording equipment, such as electrodes, wires, and amplifiers. These technologies are consequently less intrusive for the subject, who therefore remains less aware of the measurements being taken.

In the analysis of facial expressions of emotions in the tourism literature, the studies obtain data from two different sources: FaceReader SDK, which is often complemented with other psychophysiological measurements; and a questionnaire that assesses the post hoc emotional states (Hetland, Vittersø, Fagermo, Øvervoll & Dahl, 2016; Kaiser, 2017; Söderlund & Sagfossen, 2017; Yu & Ko, 2017; Hadinejad, Moyle, Scott & Krali, 2018; Hadinejad, Moyle, Kralj & Scott, 2019). The main aims of these studies are twofold: to observe whether a stimulus triggers specific emotional responses and therefore whether these responses facilitate the prediction of tourist behaviour; and to uncover any differences or similarities between emotions derived from using FaceReader and post hoc self-reported emotional states. The studies all had similar findings: the physiological techniques provide objective measurements of emotion; the stimuli can be a powerful elicitor of emotions; and a combination of psychophysiological measurements and a self-report approach should be employed for a better and accurate understanding of emotional responses. However, these studies using FaceReader have been conducted in laboratory settings and therefore fail to capture emotions in real time and in real-world settings. With the development of mobile applications that support facial-expression algorithms, it has become possible to collect emotional responses under these circumstances, which constitutes a challenge for tourism research. In this vein, the following hypotheses are tested to confirm whether facial-expression recognition by using a mobile application constitutes a suitable instrument for the measurement of satisfaction:

H1: The expression of positive emotions measured through a facial-expression recognition method is positively related to Customer satisfaction measured through a questionnaire.

H1a: The influence of positive emotions on satisfaction is moderated by visitors' gender

H1b: The influence of positive emotions on satisfaction is moderated by visitors' age.

H2: The expression of negative emotions measured through a facial-expression recognition method is negatively related to Customer satisfaction measured through a questionnaire.

H2a: The influence of negative emotions on satisfaction is moderated by visitors' gender

H2b: The influence of negative emotions on satisfaction is moderated by visitors' age.

3. Methodology

The experiment took place on a UNESCO World Heritage Site that hosts guided tours, with the aim of determining customer satisfaction by means of the digital analysis of facial expressions. Over the course of the year 2018, 5 people from every tour group were photographed in various situations, throughout the entire length of each tour, by 5 different staff members. As a result, a wide range of facial expressions and emotions were captured and categorised according to age, gender, and nationality. Since we are interested in analysing the overall effect of emotions on overall satisfaction after the tour-guide service provided, aggregate scores (averages) per emotion and per tourist have been used. The average of each basic emotion has been employed as an indicator of the constructs involved in PLS-SEM. In order to comply with the Data Protection Act, all visitors were informed that facial photographs were being taken on the site with the sole purpose of complementing an ongoing academic study. In an attempt to minimise sample bias and maximise the likelihood of capturing spontaneous facial expressions, the consenting individuals were made aware that, at any point of their tour, only a few of the participants may or may not be photographed. In addition, they understood that only a small, randomised sample of the photographs obtained would eventually be taken into account. To moderate the enthusiasm to the greatest degree, the participants agreed not to be informed about whether their photographs were selected or not, which implied that there were zero personal benefits or losses involved in participating in the experiment.

At the end of the visit, the photographed individuals were also invited to rate the satisfaction with the service received. The concept of satisfaction used refers to the judgment of a cognitive or affective nature that derives from the experience of the tourists after their guided visit (San Martín, 2005). Thus, tourists' satisfaction refers to the subsequent assessment of the tourist experience. In the academic literature on tourism, there are valid measuring instruments for satisfaction formed by a single item to collect the overall dimension of satisfaction with the provision of a service (Petrick et al., 2001; Bigné et al., 2001; Chi & Qu, 2008). The authors have adopted a single question to measure satisfaction since it is suitable for the research aim: *Overall, how satisfied were* *you with the tour guide service provided? Please rate from 1 (Not at all satisfied), to 7 (Very satisfied).* Those who were not in favour of being photographed refused to give their consent and were therefore exempt from all stages of the experiment.

Readily available commercial methods, especially mobile devices, have greatly improved in quality in recent years, thereby enabling the emotions of facial expressions to be analysed in real-life settings. This opens a spectrum of possibilities for the analysis of the emotions of facial expressions while people are enjoying themselves in a natural social environment.

While the Emotion API algorithm is available only for Smartphones (Emotionalyser App) and FaceReader toolkit is available only for desktop platforms, AFFDEX SDK is available across both major mobile (e.g., AFFDEXme) and desktop platforms (Windows, oIS). The three algorithms differ in their statistical procedures, facial databases, and facial landmarks for the classification of emotions. However, all three algorithms rely on the Discrete Emotion Theory which focuses on Ekman's six basic emotions.

For the purpose of the study, the freely available, user-friendly Emotionalyser App has been used. This application was developed by SN Creations and programmed with the Emotion API algorithm. The algorithm of the Emotionalyser App is also capable of identifying the gender, whether the person has facial hair, and/or whether he or she is smiling. This application detects ANGER (Anger), CONTEMPT (Disappointment), DISGUST (Aversion), FEAR (Fear), HAPPINESS (Happiness), NEUTRAL (Neutral), SADNESS (Sadness), and SURPRISE (Surprise). The most significant features of this application include its ability to recognize up to 64 faces in one single photo; there is also a wide dimensional range of facial-expression recognition, ranging from 36x36 pixels to 4096x4096 pixels, whereby faces outside those limits remain undetected. The results are enhanced with higher quality images; close-ups of faces photographed from the front improve the accuracy of the assessments (Figure 2). The ratings of each emotion are provided as percentages ranging from 0 to 100 that express the probability that the detected face expresses a certain basic emotion (Stöckil et al., 2019), whereby the sum of all the detected emotions for an individual is 100%.

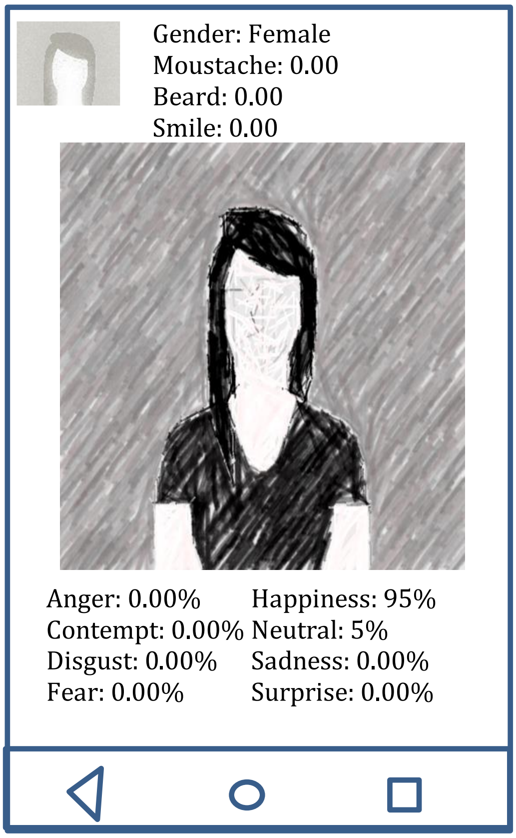

Figure 2. Facial-recognition expressions: mobile device application

All the images obtained during the visit were edited and fed into the application to obtain the data. Photographs were taken of 250 individuals. However, the final sample consisted of 230 individuals whose images were of a sufficiently high quality to be valid for their analysis by the software. For the final sample, 56% of the participants were female and 44% male. Of the participants, 30% were between the ages of 20 and 35, 48% were 35 to 55, and 22% were over 55 years old, while 42% were international tourists and a large percentage had higher or secondary education (67%). The data obtained was analysed to understand the pattern the sample in terms of emotions. In order to go into further depth in the analysis to confirm the validity of the facial-expression recognition application in its ability to measure satisfaction with the service provided, a structural equation model (SEM) was estimated by using Partial Least Squares (PLS-SEM). From the SEM model, the relevance of the emotions in the explanation of customer satisfaction was tested. To this end, the SmartPLS v3 software was used.

4. Results

4.1. First-Stage Analysis

A first analysis has been carried out in order to observe how the sample behaves in terms of emotions. For all respondents, different scores were given to the emotions (ANGER (Anger), CONTEMPT (Disappointment), DISGUST (Aversion), FEAR (Fear), HAPPINESS (Happiness), NEUTRAL (Neutral), SADNESS (Sadness), and SURPRISE (Surprise)). A person can present different emotions at the same time if these are similar emotions, such as Happiness and Surprise. A respondent with a high score in Happiness presents low scores in the negative emotions. Thus, the scores higher than 50% are the threshold for deciding the most predominant emotion in the individual. The descriptive statistics for the emotions are displayed in Table 1.

Table 1. Descriptive statistics

	Surprise	**Neutral**	**Fear**	**Sadness**	**Disgust**	**Anger**	**Contempt**	**Happiness**
Average	1.937	10.630	0.230	2.010	0.7836	0.951	0.592	77.272
Std. Deviation	3.920	23.874	1.033	3.389	3.001	3.021	1.695	20.394
Pearson's coeff.	2.024	2.246	4.492	1.686	3.829	3.176	2.863	0.264

From Table 1, it can be observed that Happiness is the emotion which has been detected as the most frequent emotion on the faces of participants while Fear was detected with the lowest frequency by the Emotionalyser App. Moreover, most of the emotions present high variability based on Pearson's Coefficient of variation (Fear, Disgust, Anger, Contempt, Neutral, Surprise), whereby the emotion Fear followed by Disgust and Anger are those with the highest variability, in contrast with Happiness which has the lowest variability.

The distribution of the emotion scores for each respondent is also observed in Figure 3. While most of their scores for Happiness remained above 80%, for neutral emotions most fell below 20%. With only a few exceptions, as observed in Figure 3, all the negative emotions plus that of Surprise most frequently present scores below 5%.

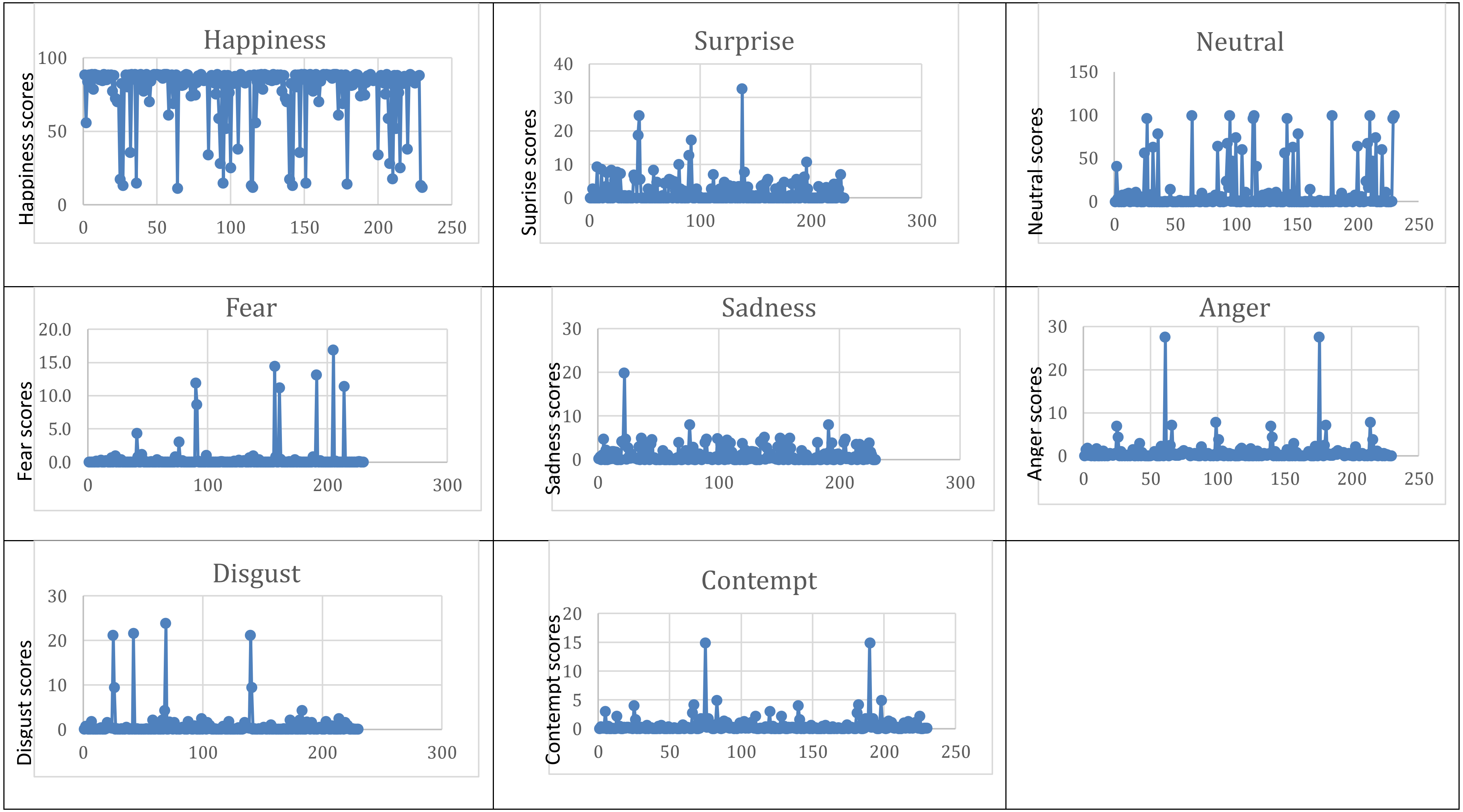

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Figure 3. Participants' Emotion distribution

4.2 PLS-SEM results

Partial Least Squares structural equation modelling (PLS-SEM) was employed to test the hypotheses. While PLS-SEM can be described as a composite-based approach that uses linear combinations of the indicator variables as proxies of the conceptual variables with a potential to explain the variance of the dependent variables, Covariance-Based SEM (CB-SEM) defines constructs as common factors that explain covariation between their indicators (Rigdon et al., 2017). Hence, the decision to use PLS-SEM is mainly made by setting the constructs for emotions in the model as composites defined as linear combinations of their indicators or dimensions (Becker, Rai & Rigdon, 2013; Henseler et al., 2014; Rigdon, 2012; Sarsted et al., 2016). The constructs for positive emotions (Happiness and Surprise) and for negative emotions (Disgust, Contempt, Fear, Anger, and Sadness) have been modelled as composites and estimated in Mode B (regression weights) since the existence of correlated items or internal consistency is not assumed for these latent variables. The weights provide evidence of the relative contribution of each indicator to their respective composite.

4.3. Measurement Model

In order to evaluate the measurement models in PLS-path modelling, it is necessary to distinguish between Mode A composites and Mode B composites. The Mode B composites (EC) for negative and positive emotion constructs were evaluated at the indicator level by assessing multicollinearity and regression weights (Hair et al., 2017). Unlike composites in Mode A, discriminant validity, composite reliability, and Average Variance Extracted are not applicable. First, to test the potential multicollinearity between items, the statistics of the variance inflation factor (VIF) were calculated for the two constructs. The VIF values obtained for the indicators were below the 3.3 threshold (Petter, Straub and Rai, 2007). Hence, no multicollinearity was observed between the items for the two B composites. Second, the significance of regression weights was addressed via the bootstrapping technique based on n=5,000 subsamples. Table 2 shows the VIF values and the statistical significance of the regression weights.

Table 2. Measurement model for Mode B composites: regression weights and VIFs

Mode B Composites	Weights	VIF	Bootstrapping 95% Confidence Intervals [BC]	
			Lower	Upper
Negative Emotions				
Contempt	0.227*	1.124	0.101	0.325
Disgust	0.427*	1.176	0.214	0.651
Fear	0.195*	1.280	0.092	0.320
Sadness	0.114*	1.037	0.05	0.321
Anger	0.109*	1.109	0.08	0.221
Positive Emotions				
Happiness	0.587*	1.563	0.285	0.653
Surprise	0.483*	1.734	0.258	0.514

Notes: BC: Bias-Corrected. 5,000 bootstrap samples; * $p<0.05$ (two-tailed t-distribution)

4.4. Structural Model

In order to assess the structural model, potential multicollinearity between constructs has been checked. The VIF values for the exogenous constructs indicate that multicollinearity is not an issue in our research model since the VIFs remain below 3.3. Table 3 shows the main effects of the negative, positive, and neutral emotion constructs on satisfaction. To test for the significance of the path coefficients, the Bootstrapping procedure has been applied with 5,000 samples. It provides t-values and confidence-interval bias corrected at a 95% confidence level for the assessment of the statistical significance of the path coefficients (Hayes & Scharkow, 2013; Roldán & Sánchez-Franco, 2012). From Table 3, it is observed that positive emotions have positive and significant effects on satisfaction (β=0.557), whereas a negative relationship between negative emotions and satisfaction has been found (β=-0.322) as expected. Hence, hypotheses H1 and H2 are confirmed. It is also interesting to notice that the contribution of positive emotions is greater than that of negative emotions on satisfaction.

A high value for the coefficient of determination (R-square) has been obtained, which reveals the great explanatory power of emotions regarding satisfaction (Hair et al., 2011; Henseler et al., 2009). Thus, 68.89% of the variability of satisfaction is explained by the respondents' emotions. The model has also been assessed through the analysis of the cross-validated redundancy index (Q2) for the dependent variable of satisfaction. A Q2 value of 0.348 (greater than 0) implies that the model shows satisfactory predictive relevance. The high explanatory power and predictive relevance achieved in the research model might indicate that the algorithm of the Emotionalyser App is a very powerful tool for the explanation of satisfaction through facial-expression recognition. Finally, to evaluate the goodness of fit of the research model, the standardized root mean square residual (SRMR) (Henseler et al., 2014) has been obtained. The SRMR is of 0.067, which lies below the thresholds of 0.10, and the more conservative threshold of 0.08 (Hu & Bentler, 1999).

Table 3. Hypotheses testing, path, and confidence interval

		Bootstrapping 95% confidence interval BCa	
	Path coefficients	Lower	Upper
H1: Positive Emotions →Satisfaction	0.557** *(8.891)	0.297	0.672
H1a: Positive Emotions*gender→ Satisfaction	0.073* (2.256)	0.004	0.187
H1b: Positive Emotions*agegroup1→Satisfaction	0.004 (0.978)	-0.031	0.978
H1b: Positive Emotions*agegroup2→Satisfaction	0.0061 (0.1553)	-0.0825	0.0748
H2: Negative Emotions → Satisfaction	-0.322***(4.133)	-0.523	-0.185
H2a: Negative Emotions*gender→Satisfaction	0.087 *(2.246)	-0.007	-2.011
H2b: Negative Emotions*agegroup1→Satisfaction	0.0032 (0.098)	-0.0004	0.147
H2b: Negative Emotions*agegroup2 →Satisfaction	0.007(0.831)	-0.0023	0.876

Notes: BCa, Bias-Corrected and accelerated. 5,000 bootstrap samples. *p<0.05;**p<0.01, ***p<0.001 (based on t-statistics, one-tailed test).

+Gender=1 for female and Gender=0 for male;

+agegroup1=1 for age between 20 and 35, and agegroup1=0 for age between 35 and 55 (this being the reference group);

+agegroup2=1 for age over 55, and agegroup2=0 for age between 35 and 55.

Having considered the possibility of heterogeneity being caused by demographic variables such as age and gender in the relationships analysed by hypotheses H1 and H2, the article employs those variables as moderating factors. The results shown in Table 3 demonstrate that there are no significant differences expressed by different age groups regarding the relation between positive emotions and satisfaction and the relation between negative emotions and satisfaction. Hypotheses H1b and H2b are therefore not supported. However, by considering gender as a moderating variable, the relation between positive emotions and overall satisfaction is shown to be stronger for female participants, whereas the relation between negative emotions and overall satisfaction is stronger for male visitors. Hypotheses H1a and H2a are consequently confirmed.

5. Discussion and Conclusion

The aim of the study is to analyse individuals' immediate emotional responses when an on-site tour-guide service is provided in a heritage place. We assume that the emotional responses are good indicators of the perception of the quality of the service provided. To support this assumption, the paper provides a literature review on research which focuses on the role of emotions in the measurement of tourist satisfaction.

In order to test the hypotheses that emotions detected via individuals' facial expressions influence satisfaction, participants were also invited to comment on their overall satisfaction with the service at the end of the guided visit, and structural equation modelling was used that was estimated by means of PLS. The study found that Happiness, with its scores higher than those of other emotions, was the most frequent emotion response. Happiness and Neutral emotions present more variability in comparison to negative emotions. Positive and neutral emotions exert a positive and significant influence on overall satisfaction, whereas negative emotions have a negative and significant influence on overall satisfaction. This study concludes that emotional responses as coded by the facial-expression recognition device, Emotionalyser, constitute a good indicator for overall satisfaction derived from the service provided on a tourist heritage site. The findings achieved are supported by the academic literature that shows empirical evidence of emotions playing a relevant role in the customer experience in tourism (Lee & Kyle, 2012; Mcintosh & Siggs, 2005; Prayag, Hosany & Odeh, 2013; Yuksel, Yuksel & Bilim, 2010) and therefore in behaviour intention (Bigné et al., 2005; Prayag, Hosany & Odeh, 2013; Tsaur, Chiu & Wang, 2007). The moderating influence of gender on the relation between emotions overall satisfaction is also supported by previous studies in the tourism literature (Wu et al., 2016; Yan & Wu, 2018), since positive emotions are more commonly associated with women and neutral and negative emotions are more frequent in men.

5.1. Theoretical Implications

In the last decade, scholars have claimed the need to employ real-time and real-world settings to attain physiological measurements (Hunziker, Buchecker & Hartig, 2007; Walls et al., 2011). However, a few studies applying psychophysiological metrics have been found in the literature and the most frequent methodology to measure emotions in tourism is through surveys via either open-ended questions (Prayag, Hosany & Odeh, 2013; Walters, Sparks & Herington, 2012) or self-report methods (Chamberlein & Broderick, 2007; Jacobs, Feheres & Campell, 2012; Wang & Minor, 2008). However, self-report questionnaires are not exempt from limitations since they are subject to a bias towards social desirability, the scale of measurement employed, or seek responses regarding emotional experiences of which respondents remain unaware. Measuring emotions through facial-expression recognition is still in its infancy in the tourism sector (Kim & Fesenmaier, 2015; Mills, Meyers & Byun, 2010), and has largely been applied in the fields of marketing and publicity (Lee, Broderick & Chamberlein, 2007; Micu & Plummer, 2010) and salient organizations and large-scale governmental programs (Mills, Meyers & Byun, 2010). It is broadly recognized that researchers and managers should understand the major role of emotions in customer experiences in the tourism destination and in the hospitality industries (Li, Ashkanasy, & Ahlstrom, 2014). Our study responds to a claim in the literature on tourism with respect to recording facial-expression recognition spontaneously rather than in a laboratory (Matsumoto & Hwang, 2015).

Furthermore, this paper combines both psychophysiological measures and self-report questionnaires as a hybrid approach towards confirming the potentiality of the application of AI in the tourist sector. The combination of these methods provides a potential direction for future research in the tourism industry at a time when artificial intelligence instruments (facial-expression recognition, eye tracking, etc.) are continuously improving in their ability to detect emotions while the subjects remain unaware of the spontaneous measurements being taken.

5.2. Managerial Implications

In recent decades, major efforts have been made in information technology that enable a better understanding of people's emotions and their influence on behaviour (Blaters & Steirnert, 2015; Campellone, & Kring, 2013; Firmin, Luther, Lysaker, Minor & Salyers, 2016; Lerner, Li, Valdesolo, & Kassam, 2015). For over forty years, the facial-expression recognition method has been under development for the collection of accurate information regarding emotional responses to a stimulus (Wilhelm & Grossman, 2010). However, artificial intelligence is starting to be more widely appreciated in the tourism industry since it can improve business by measuring customer experience through the codification of emotional experiences (Kim & Fesenmaier, 2015). Since the user experience is dynamic (Forlizzi & Ford, 2000), the accurate measurement of emotions provides Destination Marketing Organizations (DMOs) and practitioners with valuable insights regarding the perception of the experience by the customers in real time. In general, tourist destinations and the hospitality industry strive to provide tourists with memorable experiences that go beyond mere satisfaction. Emotional responses might therefore be used not only to improve the quality of the services in tourist destinations and in the hospitality industry, but also to design attractions, activities, and hotels, and to allocate resources more efficiently. The facial-coding approach provides the tourism industry with a means to measure the impact of the service regarding retaining customers, and to attract new customers by creating a differential value based on the customers' emotional experiences, and therefore to improve its ability to provide customers with a personal guest experience. Thus, the provision of high-quality service would lead to an increase in customer satisfaction and loyalty (Berry & Parasunaman, 1991). Furthermore, unlike surveys, facial-expression recognition as a customer-experience measurement system might have the capacity to detect any problem while the service is provided and to measure satisfaction continuously and in a non-intrusive way. At the same time, obtaining information continuously in real time would allow companies and DMOs to make changes in their business strategies in order to continue improving and to achieve a sustainable competitive advantage. In fact, psychophysiological methods can capture "emotional peaks" during the customer's exposure to a stimulus when visiting a destination, thereby offering valuable information to DMOs and hospitality managers to make improvements in the image of the destination.

The growing interest in measuring customer satisfaction with AI is evident in the tourism sector, especially in the hotel sector, due to the implantation of facial-expression recognition sensors. Thus, a pioneering initiative in this regard is found in the Campanile chain, which, through an agreement with the start-up iMotion Analytics, has installed a sensor that combines video with infrared to detect the emotional reaction of its guests. Subsequently, the information is processed and an assessment of the customer experience in the hotel is obtained. This allows the company to evaluate and improve its customer service protocols (imotionanalytics.com). Expedia has also applied a similar experience by analysing the facial emotions of its users through a series of sensors to improve their portals and services.

One type of visual monitoring to detect emotions in contrast to other devices such as Emotionalyser, is the iMotions Facial-Expression Analysis Module, which integrates automated facial-coding engines, such as AFFDEX. This module, by using a webcam, directly synchronizes facial emotions expressed with stimuli in real-time in the iMotions software. It displays 20 facial-expression measures (action units): 7 core emotions (joy, anger, fear, disgust, contempt, sadness, and surprise) and provides values on the expected emotion (imotionanalytics.com).

In recent years, controversy has grown over whether facial expressions faithfully reveal an individual's emotions. While accurate identification of emotional facial expressions is essential for practitioners, the limitations of the algorithms employed for the detection of emotions with accuracy has been subject to certain debate over the last two decades. Kim et al. (2005) recognized a skin-colour bias due to the illumination conditions when an image is extracted. To overcome this limitation, a fuzzy classifier algorithm was proposed for the detection of the skin colour by using a fuzzy colour filter to extract the face region. The fuzzy classifier was adopted to recognize emotions from extracted features. The experiment results show that the proposed algorithm detects emotion well, specifically with an accuracy of emotion detection of 74%. The recognition accuracy of the five emotions (Happy, Sad, Angry, Disgust, and Surprise) ranges between 69.9% (Sad and Disgust) to 78.5% (Happy). Barrret et al. (2019) investigated how people move their faces to certain emotions, concluding that it is very difficult to say precisely how someone feels only from their facial expression. According to this study, people do many other things with their faces when they are happy or sad. A smile can be mocking or ironic. Behaviours vary greatly depending on cultures and situations, and context plays a major role in the way expressions are interpreted. In addition, facial-recognition systems might generate extremely inaccurate results, especially for races other than the white race as noted by the National Institute of Standards and Technology (NIST, 2019) (https://www.nist.gov/). These biases make it necessary to train artificial intelligence algorithms that incorporate details of images that include other aspects, such as skin tone, culture, race, and improved facial geometry. Barret et al. (2019) concluded that it is even more important than technology development for scientists to consider emotions in a more complex fashion. The expressions of emotions are varied, complex, and situational, and therefore "simply 'reading out' people's internal states from an analysis of their facial movements alone, without considering various aspects of context, is at best incomplete and at worst entirely lacking in validity, no matter how sophisticated the computational algorithms".

With the advent of disruptive technologies, concerns regarding security and privacy issues have emerged and appear to be more pronounced over the past decade by being widely discussed in academia, the media, and the courts. However, the legal systems, in most countries, have failed to address these concerns properly and fully (Shoval, Schvimer and Tamir, 2018). The EU General Data Protection Regulation (GDPR) considered “biometric data” as a special category of personal data that cannot be processed without first satisfying established permission and/or exceptions. However, broader regulation of emotional information is required since the EU GDPR provides no specific regulation for emotion tracking under those situations in which the emotion analytics prohibit identification of the individuals. However, Privacy laws should be revised to regulate not only issues related to biosensed data that is not considered biometric, but also those issues related to group privacy (Sedenberg and Chuang, 2017).

Emotion AI technology is a helpful tool to obtain competitive advantages for a firm when used correctly, thus avoiding harm related to consumer privacy and security issues. With the growing interest in implementing emotion AI technology in hospitality and tourism businesses, customers could evolve social norms or behavioural adaption to address certain risks associated to this use (Senderber & Chuang, 2017) which would render emotion analytics unreliable. Thus, practitioners, rather than waiting for revised and highly developed laws, should move one step ahead by developing mechanisms to maintain the highest standards of security and privacy to ensure transparency. Practitioners could use a Privacy Impact Assessment (PIA) prior to the processing of personal data so that they may attain an insight on the privacy risks, thereby enabling the organization to take suitable measures to prevent any impact on consumers’ privacy. The hotel could make this document visible to guests so that they are informed about the risks to privacy when they stay at the hotel.

5.3. Limitations of the Study and Future Research

This paper presents certain limitations that indicate future avenues of research. Although this paper has striven to encourage research into measuring emotions through facial-expression recognition codification as an alternative in the measurement of customer-experience satisfaction, further research into this topic is needed. At present, facial-expression recognition applications are not exempt from limitations, as they depend on the specific dimensions of the emotions considered. In particular, the mobile application device employed in this paper uses the basic emotions by Ekman (1999) to detect emotions through facial-expression recognition software. Other scenarios and software of a more sophisticated nature implemented in the tourism and hospitality industry are necessary to fully comprehend the significant role played by emotions in the improvement of service quality. It is expected that further research work will be performed in the future in this direction, which in turn will benefit from the growing improvement in the facial-expression recognition software. In the case of this particular research, the respondents' images were inherently subject to self-reported biases, since the participants were made aware that staff were taking pictures during their visit, which may have influenced their behaviour and the validity of their emotional expression under the given circumstances. Since visitors have to be informed about such activities due to the Data Protection Act being in place, this drawback is inevitable. However, in order to reduce self-reported biases, this experiment was designed to collect photos of only a small number of participants. Those involved were aware of the randomness and the absence of personal benefit for the participants; this potentially normalised the unnatural atmosphere of the experiment and reduced the possible bias issues with the obtained images. Moreover, repeated photos of each person were taken because the aim of the study was to capture how overall emotions during the visit influenced overall satisfaction. In this vein, aggregate data (averages) of each emotion and per person were used in the empirical analysis. As future avenues of research, the study could be extended to also analyse the dynamic changes in emotions during the visit as well their influence on each dimension of satisfaction related to the various attributes of the services offered. To this end, the study might be completed by also using wearable and mobile physiological sensors to obtain tourists' emotional responses throughout the entire experience in real time.

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