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# Non-verbal evaluation of retail service encounters through consumers' facial expressions

**Abstract**. Emotions have been largely acknowledged as important drivers of many consumers' behaviors. They are usually recognized through particular facial expressions, body language and gesture. However, the increasing integration of automatic systems in retailing is pushing researchers to understand the extent to which these systems can support employees to better understand consumers' shopping experience. In this vein, the present research aims at investigating the extent to which it is possible to systematically evaluate retail service encounters through consumers' facial expression. To this end, the research provides a machine learning algorithm to detect the six fundamental (human) emotions based on facial expressions associated with consumers' shopping experience in the 19 biggest shopping centers in UK, and (ii) investigates consumers' response to the usage of this system to automatically collect their evaluation of the retail service encounters. Findings reveal that a facial expression recognition system would uncover consumers' evaluation of retail service encounters, and that consumers would accept the usage of facial expression identification systems to automatically evaluate the retail service encounters.

**Keywords**. emotional intelligence; retail service encounters; emotions; emotional analytics; machine learning; facial expressions

## 1. Introduction

Recent studies (Huang, Rust and Maksimovic, in press.) have highlighted the shift of modern society towards the idea of Feeling Economy to embrace the emerging concept of feeling intelligence as the reply to the recent progress in artificial intelligence. Specifically, the authors (Huang, Rust and Maksimovic, in press) defined the Feeling Economy as "a new economy in which the feeling tasks of jobs, such as communicating/coordinating with others and establishing/maintaining interpersonal relationship, are becoming more important for human workers than the thinking tasks of jobs" (p.2). This new perspective may rely on the role of individual's emotions.

Emotions represent a mental state, manifested through particular gestures that are translated into specific actions (Bagozzi *et al.* 1999). These are an integrative part of daily life, and constitute an important component of the shopping experience (Babin et al., 2013; Kawaf and Tagg, 2017; Terblanche, 2018), since they influence consumers' behaviour, evaluation of products, purchase intention, loyalty, etc. (Frank et al., 2014; (Gardner 1985; Lajante and Ladhari, 2019; Kim et al., 2016b; Malik and Hussain, 2017; Ou and Vehroef, 2017; Das and Varshneya, 2017). Indeed, emotion exchange may affect consumers' brand attitudes, and evaluation of retail services (Wang 2009). While positive emotions might generate a positive consumers' attachment towards a brand, negative ones might result in negative behavior (i.e. switching, complaining, negative word of mouth, and so on) (Romani, Grappi and Dalli, 2012). For instance, anxiety and anger experienced during service consumption would lead to dissatisfaction resulting in avoidance behaviors of a certain store (Menon and Dubè, 2004; Otieno et al., 2005). Thus, distinguishing consumers' emotions (i.e., positive and negative emotions) would further result in a more effective prediction of the subsequent shopping behavior (Hooge, 2014; Romani, Grappi and Dalli, 2012). For these reasons, past studies further suggested to enhance practices to systematically evaluate consumers' emotion before and after entering the store (Kim et al., 2016b).

However, in modern retail settings, consumers are massively exposed to technology like digital assistants that might influence differently consumers' behavior (Vannucci and Pantano, 2019; Pantano and Gandini, 2017). Indeed, actual digital assistants are not fully able to execute feeling tasks (Huang, Rust and Maksimovic, in press). In particular, the interaction between machine and human, bounded by interaction protocols and restricted by the embedded information, may both create a different set of emotions that should be attended and challenge traditional consumer-salesforce interaction styles. Thus, new questions arise in the emerging competitive scenario:

*RQ1: How can technology support employees to better understand consumers' shopping experience?*

*RQ2: To what extent will consumers accept the usage of this system to automatically collect their evaluation of the retail service encounters?*

The aim of this paper is to understand the extent to which it is possible to systematically evaluate retail service encounters through consumers' facial expression. In this way, machines would support employees to better understand consumers' shopping experience and reply accordingly. To this end, the research provides a machine learning algorithm to detect the six fundamental (human) emotions based on consumers emotions in non-verbal expressions (i.e., facial expressions) associated with consumers' shopping experience in the 19 biggest shopping centers in UK, and (ii) investigates consumers' response to the usage of this system to automatically collect their evaluation of the retail service encounters.

The paper is organized as follows: the next section reviews the theoretical background. The subsequent part discusses the studies on emotion recognition. Then, the paper introduces the research method and approach. The paper concludes with the discussion of the main findings, while proposing some suggestions for future studies.

## 2. Theoretical Background

### 2.1 Emotion recognition research

Research in emotion recognition is not new. Russell and Mehrabian (1977) considered three independent dimensions as pleasure/displeasure, degree of arousal, and dominance-submissiveness to define individual's emotional state. Izard (1977) identified the ten fundamental emotions developing the Differential Emotions Theory: interest, joy, surprise, sadness, anger, disgust, contempt, fear, shame and guilt. Similarly, Ekman and Friesen (Ekman and Friesen, 1978; Ekman, 2003) identified the six fundamental human emotions through specific patterns of the faces (facial expression) as disgust, happiness, sadness, anger surprise, and fear. Plutchik (1980) identified through subjective language the same emotions as disgust, joy (instead of "happiness in Ekman' studies"), sadness, anger, surprise and fear, and added acceptance and expectation. These emotions do not vary across race, age and culture, and can be identified through the position of certain muscles in the face (Ekman and Friesen, 1978; Ekman, 2003).

Emotions can be displayed through verbal expressions (text) (Mehrabian and Russell, 1977) and non-verbal ones as body language and facial expressions (Sonderlund and Sagfossen, 2017; Ekman and Friesen, 1978; Ekman, 2003; Russell, 1994). In the online context, emotional analytics is a practice largely adopted to systematically evaluate consumers' opinions about brands, stores, etc. through the analysis of the verbal expressions (text mining of consumers' reviews and posts) (Malik and Hussain, 2017; Pantano, Giglio, Dennis, 2019; Zhou, Xu, Yen, 2019; Cracioun and Moore, 2019; Walasek, Bathia and Brown, 2018). Concerning the non-verbal expressions, facial expressions synthetize a non-verbal evaluation of certain situations, which are only partially beyond the individual's control, and can be exploited to measure the expressive emotional responses to certain stimuli (He et al., 2016). However, recently researchers have started considering also pictures as a valuable source of consumers' insights through the analysis of non-verbal expressions (Balomenou et al., 2017; Giglio et al., 2019; Giglio et al., in press; Humphreys and Wang, 2018; Rose and Willis, 2019).

Many systems for automatic facial recognition have been mainly developed and used for medicine, robotics, animation, psychology, security monitoring (Kim et al., 2016a; Fasel and Luettin, 2003; Danelakis et al., 2016; Lv et al., 2019). For instance, these systems would be able to clearly identify individuals from different sources (i.e., CCTV cameras) for security monitoring in public areas, airports, and so on, to detect suspicious behavior (Kim et al., 2016a). In retail settings, the adoption of this kind of systems is still limited. To date, they have been employed as new payment systems to increase the security of the monetary transaction (Zhang and Kang, 2019; Tezuka et al., 2019).

Among the various measures of emotion of this kind of system, the present study focuses on Ekman's work (Ekman and Friesen, 1978; Ekman, 2003) to identify consumers' emotion and the subsequent retail service encounter evaluation. Literature to systematically map specific movements of facial muscles to determine the facial expression and related emotions are mainly based on Ekman's work (Danelakis et al., 2016).

## 2.2 Emotions as component of the shopping experience

To date, authors have shown the extent to which retail settings evoke emotional responses, leading consumers to perceive differently as a component of the in-store experience (Macheleit and Eroglu, 2000). In particular, negative emotions lead to negative consumer's behaviors as switching, complaint, store avoidance and so on (Romani, Grappi and Dalli, 2012; Menon and Dubè, 2004; Otieno et al., 2005; Macheleit and Eroglu, 2000). Therefore, understanding consumers' emotional dimension allows improving the shopping experience (Menon and Dubè, 2007). As a consequence, retailers need to constantly interact with consumers to understand their emotions (Pappas, 2018). However, literature has mainly focused on specific emotions taking a unidimensional approach (Pappas, 2018).

From an environmental perspective, in-store music, aroma, merchandise quality, price and service quality influence consumers' emotions in terms of arousal and pleasure allow for an improved shopping experience (Walsh et al., 2011). Similarly, employees are able to influence consumers' emotions in a sort of emotional contagion (Lin and Liang, 2011; Du, Fan and Feng, 2011; Verbeke, 1997; Sukhu et al., 2018; Elmashhara and Soares, 2019). In other words, if employees display certain emotions, consumers tend to react accordingly in the context of service encounters. For example, when employees show friendliness, consumers would replicate the same friendless in the shopping environment (Albrecht et al., 2017).

Emotions can be displayed beyond the verbal expressions, by including non-verbal expressions such as body language and facial expressions (Sonderlund and Sagfossen, 2017). For instance, if employees smile showing positive emotions, consumers react accordingly showing the same positive emotion, leading to the perception of overall satisfaction towards the experience at the service encounter (Andersson et al., 2016; Mattila and Enz, 2002; Bock et al., 2016). Indeed, employees expressing positive emotions in service interactions help increasing consumers' satisfaction (Grandey, 2003). For these reasons, past literature traditionally considered emotional intelligence as the ability to respond according to customer's positive and negative emotions as a fundamental part of retail workforce (McFarland, Rode and Shervani, 2016; Kadic-Maglajlic et al., 2017). Accordingly, emotional intelligence helps increasing consumer' satisfaction, by highlighting the causal relationship between salesperson, customer satisfaction and sales performance (McFarland, Rode and Shervani, 2016; Kadic-Maglajlic et al., 2017). In particular, emotional intelligence exploits four main abilities (Mayer and Salovey, 1997): (i) the ability to perceive emotions (in oneself and in others), (ii) the ability to facilitate desired thought processes, (iii) the ability to understand the transition from an emotional state to another, and (iv) the ability to manage emotions in terms of connecting or disconnecting from a certain emotion.

To support the ability to respond according to customers' emotions, some studies further provided frameworks to help the retailer to train sales personnel to provide a certain response to consumers' emotions to ensure a greater satisfaction (Menon and Dubé, 2000). However, this perspective solicited some controversial opinion, since empirical evidence in the analysis of this relationship generated unsatisfactory results (McFarland, Rode and Shervani, 2016).

Summarizing, creating anticipated emotions can influence subsequent consumers' behaviour (Pappas, 2018). Therefore, there is a need to develop new models that will describe how consumers' emotions evolve during the different phases of their shopping experience (Pappas, 2018).

### 2.3 Emotions in consumers' interaction with in-store technologies

The new retail settings (including atmospherics, arousal, layout, and so on) aim at fostering pleasant reactions by transmitting positive emotions, which ultimately result in more consumers' purchases. To this end, advanced interactive technologies have been introduced in stores (van Kerrebroeck et al., 2017; Bertacchini, Bilotta and Pantano, 2017; Rese et al., 2019). These retail technologies can be classified as (i) in-store technologies such as smart mirrors, robots, interactive displays (Bertacchini, Bilotta and Pantano, 2017; Rese, Schlee and Baier, 2019; Roggeveen, Nordfalt and Grewal, 2016; Vannucci and Pantano, 2020), (ii) out-store technologies such interactive storefront windows (Pantano, Priporas and Foroudi, 2019; Oh and Petrie, 2012), and (iii) pervasive/omnichannel technologies such as store or brand mobile apps that are not fixed to a certain location and "follow" consumers during their shopping experience before and after approaching the physical store (Li, Zhang and Tayi, 2020; Flavian, Gurrea and Orus, 2020; Fagerstrom, Eriksson, and Sigurdsson, 2020; McLean and Wilson, 2019). Consumers further tend to use the retail technologies based on their general attitude towards the technology (emotional reactions) and their mood (the affective state) (Karimi and Liu, 2020).

However, these technologies, largely based on new self-service tools, have dramatically modified the service delivery process in the stores, by also replacing traditional human interactions (Pantano and

Gandini, 2017; Vannucci and Pantano, 2020). Indeed, the availability of interactive technology impacts consumer-employee interactions, by changing the communication between consumers and employees in terms of quantity and frequency of interpersonal contacts (Lee, 2015; Lee, 2017). Conversely, new computer-mediated retail settings impact differently on consumers' behaviour. Indeed, these technologies take over services that were traditionally executed by humans (employees), replacing these ones with automatic machine-provided services. Thus, they support consumers to access the service without any direct assistance of sales personnel. For instance, mobile apps for certain stores/brands assist consumers in finding product locations and retrieving additional information on favourite items autonomously. Hence, the new settings provide services that were traditionally provided by humans (employees) by transferring both employees' skills and organization's knowledge to a machine, which consumers can access instead of interacting with employees (Pantano and Vannucci, 2019). As a consequence, the customer experience shifts from the traditional consumer-employee interactions to a new experience emerging from the interactions across different (digital) touchpoints (Lemon and Verhoef, 2016; Rogeeveen, Nordfalt and Grewal, 2016). Summarizing, the introduction of these technologies decreases the number of interactions between consumers and employees, while increases the number of interactions between consumers and automated systems. Thus, this new computers-mediated interaction adds a new dimension to the service delivery process, by affecting the traditional emotion transfer between employees and consumers.

Nevertheless, communicating emotions through a technology has been argued as more difficult practice than face-to-face interactions (Derks et al., 2008). Humans can communicate emotions also through non-verbal expressions such as body language (including gesture, posture, facial expression), while others reply to these expressions. In the case of technology-enriched environment, the emotional experience as a result of the interaction with a computer may have the same quality, but lower intensity and duration if compared to face-to-face interactions (Derks et al., 2008).

Summarizing, consumers interact more with automated systems rather than employees. However, emotional intelligence as a human characteristic is important for improving retail services. Despite the large amount of research on the importance of emotions in service provision and on the utility of new technology for enhancing retail experience, there is still a lack of studies on the extent to which systematic "emotion evaluation" might be integrated into retail practices, and exploited to improve consumer's experience and retail service. Moreover, recent studies (Huang, Rust and Maksimovic, in press) further solicited for new forms of human complementarity with new technologies (with emphasis on artificial intelligence systems) to facilitate their collaboration. Therefore, there is a need of future studies investigating the extent to which the technology might support the employees to better understand consumers' shopping experience. This research aims to fill this gap, and to also understand consumers' acceptance of the usage of this kind of system to automatically collect their evaluation of retail service encounters.

## 3. Research design

The research is based on a two-step approach that involves (i) a machine learning algorithm for collecting and analyzing consumers' facial expressions, and (ii) consumers' appraisal of the usage of this system to automatically collect their evaluation of the retail service encounters. To this end, the research first develops and tests a machine learning algorithm to detect the six fundamental consumers' emotions based on facial expressions, secondly it collects consumers' response towards the possible retailers' usage of this system to automatically collect their evaluation of the retail service encounters. In other words, the research illustrates to consumers the proposed systems as exemplar software that retailers would put into practice in their physical points of sale and collect consumers' response in form of in-depth interview. To this end, consumers are especially informed about the process of data collection (how their pictures taken in the stores would be managed and the faces extracted and processed), and the typology of results.

Recently, different service providers like IBM, Google and Microsoft developed new tools to identify human emotions for a large set of applications in several industries (health, defense, etc.), while software suites make available existing machine learning algorithms within their platforms to improve and/or create the new ones such as Wolfram Mathematica and MATLAB. However, it would be possible to also use programming languages such as R, Python and C/C++ to develop machine learning algorithms (including training and testing). Table 1 lists systems most often used to support facial expression analysis, with main characteristics and limits.

| **Systems supporting facial expression analysis** | **Characteristics** | **Limits** |
|---|---|---|
| Amazon Web Services (AWS) – Amazon Rekognition, | It provides facial analysis and facial recognition, while analysing billions of images and videos using machine-learning algorithms. | Available through subscription, no information about the machine learning algorithms used. An input database is required. |
| Google Cloud Vision | API vision provides pre-trained machine learning algorithms through API REST and RPC to identify emotions in the images. Users can visualize the code used to perform the analysis | It is available with a subscription (free up to a maximum of 1,000 units per Feature Request per month). Machine learning algorithms are not customizable. The software provides the accuracy varies according to the picture (from 15% to 90% on average). An input database is required. |

| | | |
|---|---|---|
| IBM Watson Vision | It allows the creation and training of own classifier algorithms to detect images | Available with a license, no information about the machine learning algorithms used and related accuracy. An input database is required. |
| Imotions | It exports images from video and provide the probability values of the likelihood that the expected emotion is being expressed | Available with a license, no information about the machine learning algorithms used and related accuracy. It works only with images extracted from video. An input database is required. |
| MATLAB - Image Processing Toolbox | The image processing offers solutions to classify objects of interest included in the images | It is available with a license. The implementation of the code only through C/C++ code generation for desktop prototyping and embedded vision system deployment. An input database is required. |
| Microsoft Azure Face API | The software adopts cloud-based face algorithms to detect and recognize human faces in images | Available with a subscription (based on the analysis). Facial recognition systems should be embedded into an existing app recalling the FaceApi. The used algorithms are not customizable. An input database is required. It does not distinguish specific emotions. |
| Noldus | The image processing software (FaceReader) measures emotions included in faces (represented as a percentage of emotion) | Available with a license, no information about the machine learning algorithms used and related accuracy. It works only on Windows and Linux. An input database is required. |
| Wolfram Mathematica | It provides pre-trained machine learning algorithms to be implemented and customized within its platform or desk application (no additional codes required). Database can be automatically built and/or imported by different sources | It is available with a license. It requires a good knowledge of mathematical computation. |

Table 1: The systems most often used to support facial expression analysis.

## 3.1 Study 1: Collection and analysis of consumers' emotions

### 3.1.1 Data collection

Due to the exploratory nature of this research, we used pictures freely available and accessible online through Twitter to develop the system and achieve consumers' response. In contrast with other image-sharing networks like Pinterest and Instagram, users largely use Twitter as a tool to share evaluations about their experience with brands, products, and so on, rather than using the social medium to document their lives through pictures (Klostermann et al., 2018). In particular, when using social tags ("hashtags") in Twitter (space-free words and phrases that begin with "#" like #Gucci #Burberry #MichaelKors and so on), users mark content about a certain brand, indicating what concepts users associate with the brand (Klostermann et al., 2018). In addition to tags (multiple tags can be used in a single tweet), users add text and pictures. For this reason, Twitter has become a rich source of data for research in consumer behaviour (Aleti et al., 2019; Dindar and Yaman, 2018; Pantano, Giglio, Dennis, 2019; Walasek, Bhatia and Brown, 2018). Specifically, past authors argued that Twitter is characterized by users' scrolling in an ongoing search for something able to capture their attention and evoke emotions (Rose and Willis, 2019).

Since past studies also stated that the presence of consumers' information in social media like Twitter requires specific digital tools and resources for the related analysis (Rose and Willis, 2019), the present research is based on a machine learning approach. These kinds of algorithm support the analyses of huge volumes of data such as tweets (or pictures included in tweets) that are non-accessible by human coding to be structured and coded. Such methods can further track shifts in sentiment and other content categories (Hartman et al., 2019). In particular, the *Wolfram Mathematica* software allows the direct connection to TwitterAPI[1] to identify and download the pictures posted in tweets by unique Twitter users, by imposing the condition that each tweet should include a certain hashtag to build the face database. Simultaneously, it allows the exploitation of the already available pre-trained machine learning algorithms to analyse facial expression.

In order to ensure that we collected data related to identifiable retail settings, with bounded, definable attributes, we confined data gathering to shopping centers. To this end, we selected for the study 19 of the main shopping centers from across UK (Table 2) (selecting the largest ones in order to ensure sufficient numbers of tweets for the analyses).

| Shopping Centers | City/Town | Region | Dimensions (n. of shops) |
|---|---|---|---|
| Westfield London | Shepherd's Bush, London | Greater London | 404 |
| Westfield Stratford City | Stratford, London | Greater London | 322 |
| Bluewater | Greenhithe, Kent | South East England | 292 |
| Meadowhall | Sheffield | Yorkshire and the Humber | 287 |
| intu Metrocentre | Gateshead, Tyne and Wear | North East England | 247 |
| Manchester Arndale | Manchester | North West England | 224 |
| intu Lakeside | Thurrock, Essex | South East England | 202 |
| intu Trafford Centre | Trafford, Greater Manchester | North West England | 198 |
| intu Merry Hill | Dudley, West Midlands | West Midlands | 192 |
| Bullring Estate | Birmingham | West Midlands | 166 |
| intu Eldon Square | Newcastle | North East England | 143 |
| intu Braehead | Renfrew, Renfrewshire | Scotland | 136 |
| Liverpool One | Liverpool | North West England | 125 |
| Frenchgate Centre | Doncaster, South Yorkshire | Yorkshire and the Humber | 116 |
| Westgate Oxford | Oxford, Oxfordshire | South East | 113 |

[1]Twitter API is a set of URLs including some parameters. These URLs allow accessing the features of Twitter, such as creating, retrieving, deleting tweets, retweets and likes.

| Shopping Centers | City/Town | Region | Dimensions (n. of shops) |
|---|---|---|---|
| Trinity Leeds | Leeds | Yorkshire & The Humber | 108 |
| Highcross | Leicester | East Midlands | 107 |
| Queensgate | Peterborough, Cambridgeshire | East | 87 |
| Cabot Circus | Bristol | South West | 86 |

Table 2: The largest shopping centers in the UK in terms of number of shops.

Thus, the software was used to create the direct connection to Twitter API to identify and download the pictures posted in tweets by unique Twitter users, by imposing the condition that each tweet had include the hashtag related to one of the 19 shopping centers. This procedure allowed the collection of 28,481 pictures included in the posts uploaded by users in June and July 2019.

### 3.1.2 Emotion recognition procedure

Drawing upon the work of Ekman and Friesen (Ekman and Friesen, 1978; Ekman, 2003), *Wolfram Mathematica* (pre-trained) machine learning algorithms allow to (i) identify all the faces included in a picture and the portion of the picture which specifically includes the face (Figure 1), (ii) identify the characteristics of the faces (Figure 2), and (iii) assign a certain emotion to each set of face characteristics (formula 6). The present study adopts the machine learning algorithms already available in the software.

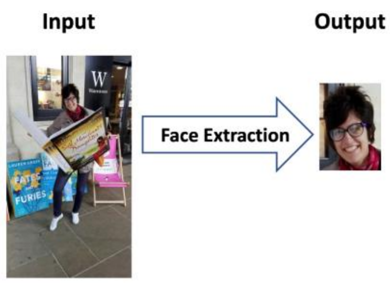


Figure 1: Faces extraction from users' pictures

Figure 2: System identification of the characteristics of the faces.

In other words, the machine learning algorithm "FindFaces" (already available in the software) extracts the images that build the set *I*, whose cardinality (number of elements consisting the set) is the number of faces. This algorithm extracted 42,140 faces.

Subsequently, we define a set *E* that includes the different emotions defined as:

$$E = \{\text{anger, disgust, fear, happiness, neutral, sadness, surprise}\}$$

$$(1)\ f: I \rightarrow E$$

So that:

$$(2)\ i \in I \Rightarrow f(i) \in E$$

Formula (2) associates a certain emotion to each face. Thus, the function *f* is a classifying algorithm with 7 values.

A classifier machine *m* includes as input a set of elements belonging to a set *I* (in this case a collection of pictures), and classifies each element (each picture of the set), in other words it assigns to each of them a unique label (continuous or discrete):

$$(3)\ m: I \rightarrow S$$

In other words

$$(4)\ i\epsilon I\rightarrow f(i)\epsilon S$$

If $S\subseteq\mathbb{R}$, where $\mathbb{R}$ includes real numbers, 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 discrete values. Thus, it is further possible to assign to each emotion a number:

$$S = \{0,1,2,3,4,5,6\}$$

If consider $S_i \subset$ I the set of elements of $I$ to guarantee $(x)=s_i$, $\nabla x\epsilon S_i$, thus the elements of $S_i$ will be part of $I$, in other words we have to impose that the classifier machine assigns a unique label to each element of $I$:

(5) $I=S_a\cup S_b\cup\cdots\cup S_n$

Where $S=\{0, 1\cdots 6\}$

In this way, the machine learning algorithm would be able to distinguish A hyperplanes (which is the mathematical representation of $I$) in seven regions , in order to ensure that each element of the hyperspace belonging to that set will get a unique label (each element will be assigned to only one specific region of the hyperspace). Formula (6) shows part of the code of the algorithm to finally assign the emotion to each face, with related characteristics

(6) In[1]: c= Classify["FacialExpression"]

Out[1]: = ClassifierFunction[ Input type: Image Number of classes: 7 ]

In[2]:= Information[c, "Classes"]

Out[2]:= {disgust, happiness, sadness, neutral, anger, surprise, fear}

### 3.1.3 Results

Table 3 summarizes the results of the analysis. Findings show that five out of the six main emotions (anger, fear, happiness, sadness, surprise and the additional one "neutral") have been identified for each shopping center, while disgust is the less displayed emotion. In particular, anger appears in 7% of the faces (almost no variation across the shopping centers), fear in 6% (almost no variation per shopping center), neutral in 26% (S.D. 3%), surprise in 2% (no variation per shopping center), while 19% is indeterminate (which means that the algorithm was not capable to identify any emotion). Happiness and sadness are the most frequent facial expressions. However, sadness seems to be identified in more faces if compared to happiness. On average, 15% are happy faces and 25% are sad faces (with a very limited variation per shopping center). For instance, in the case of Westfield, faces expressing sadness are much higher in number if compared to faces expressing happiness (414 and 28%, and 183 and 6% respectively). Findings reveal that the identified emotions in consumers' facial expression are almost constant in percentage across shopping centers.

| | **Anger** | **Disgust** | **Fear** | **Happiness** | **Neutral** | **Sadness** | **Surprise** | **Indeterminate** | **TOT** |
|---|---|---|---|---|---|---|---|---|---|
| Westfield London | 119 (8%) | 0 | 87 (6%) | 183 (12%) | 382 (26%) | 414 (28%) | 32 (2%) | 280 (19%) | 1,497 |
| Intu Metro Centre | 254 (7%) | 2 (0.05%) | 209 (6%) | 915 (25%) | 795 (21%) | 800 (22%) | 47 (1%) | 687 (19%) | 3,709 |
| Intu Trafford | 193 (6%) | 0 | 196 (6%) | 485 (16%) | 818 (26%) | 758 (24%) | 56 (2%) | 594 (19%) | 3,100 |
| Westfield Stratford | 87 (6%) | 0 | 97 (6%) | 270 (17%) | 410 (26%) | 367 (24%) | 27 (2%) | 299 (19%) | 1,557 |
| Blue Water | 82 (8%) | 1 (0.10%) | 63 (6%) | 104 (10%) | 244 (24%) | 257 (25%) | 21 (2%) | 237 (23%) | 1,009 |
| Manarndale | 173 (7%) | 2 (0.08%) | 193 (8%) | 397 (16%) | 741 (29%) | 541 (21%) | 44 (2%) | 453 (18%) | 2,544 |
| Bullring | 223 (6%) | 0 | 270 (8%) | 324 (9%) | 975 (28%) | 916 (26%) | 64 (2%) | 687 (20%) | 3,459 |
| Intu Merry Hill | 58 (7%) | 0 | 41 (5%) | 102 (13%) | 202 (26%) | 199 (25%) | 16 (2%) | 173 (22%) | 791 |
| Intu Lakeside | 14 (8%) | 0 | 12 (6%) | 18 (10%) | 62 (33%) | 49 (26%) | 0 | 31 (17%) | 186 |
| Liverpool One | 83 (6%) | 0 | 66 (5%) | 208 (16%) | 327 (25%) | 378 (29%) | 13 (1%) | 247 (19%) | 1,322 |
| Love Meadow Hall | 361 (7%) | 0 | 320 (6%) | 882 (17%) | 1,266 (24%) | 1,321 (26%) | 100 (2%) | 928 (18%) | 5,178 |
| Intu Eldon Square | 117 (7%) | 0 | 98 (6%) | 199 (13%) | 397 (25%) | 434 (28%) | 33 (2%) | 299 (19%) | 1,577 |
| CabotCircus | 226 (7%) | 1 (0.03%) | 212 (7%) | 375 (12%) | 796 (26%) | 817 (26%) | 60 (2%) | 634 (20%) | 3121 |
| Intu Braehead | 73 (7%) | 1 (0.1%) | 62 (6%) | 203 (19%) | 234 (22%) | 236 (23%) | 19 (2%) | 215 (21%) | 1,043 |
| Westgate Oxford | 67 (7%) | 1 (0.1%) | 82 (8%) | 115 (11%) | 274 (27%) | 274 (27%) | 19 (2%) | 198 (19%) | 1,030 |
| High Cross | 288 (6%) | 5 (0.1%) | 322 (7%) | 587 (12%) | 1,317 (28%) | 1,190 (25%) | 98 (2%) | 964 (20%) | 4,771 |
| Trinity Leeds | 131 (8%) | 0 | 97 (6%) | 310 (18%) | 406 (24%) | 456 (27%) | 30 (2%) | 286 (17%) | 1,716 |
| French Gate | 87 (6%) | 0 | 97 (6%) | 270 (17%) | 410 (26%) | 367 (24%) | 27 (2%) | 299 (19%) | 1,557 |
| Merriott Centre | 181 (6%) | 1 (0.03%) | 220 (7%) | 452 (15%) | 763 (26%) | 711 (24%) | 54 (2%) | 591 (20%) | 2,973 |
| **MEAN** | **148 (7%)** | **1** | **144 (6%)** | **337 (15%)** | **569 (26%)** | **552 (25%)** | **40 (2%)** | **426 (19%)** | **2,218** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **SD** | **91 (1%)** | **1** | **95 (1%)** | **245 (4%)** | **360 (3%)** | **343 (2%)** | **27 (0%)** | **264 (2%)** | **1,386** |

Table 3: The facial expressions identified for the main 19 shopping centers in UK, in terms of fundamental emotions.

To test the validity of the algorithms, we used the same procedures adopted in the validation of textual analysis (Humphreys, 2010), in other words, a stratified random sampling has been adopted to ensure that the classes are reflected consistently across the faces dataset, by considering 10% to 20% of the total faces for each category (class). In this case, for each emotion 12% of the total number of faces was considered, and manually assigned a label to the faces and compared the results with the label generated by the machine. The results meet those expected for Anger in 86% of the cases, Disgust in 83%, Fear in 80%, Happiness in 88%, Neutral in 81%, Sadness in 88%, Surprise in 83%.

### 3.2. Study 2: Consumers' response

#### 3.2.1 Data collection procedure

Study 2 employs a qualitative approach as part of an inductive design, as it is commonly adopted for theory generation (Hackley, 2005), based on face-to-face semi-structured interviews with 24 consumers recruited in Bristol, UK in August 2019. Each interview lasted approximately 45 minutes. The study involved a non-probabilistic convenience sample, where members of the target population met the criteria of easy accessibility, geographical proximity, availability at a given time, willingness to participate voluntarily, and same age group (Etikan et al., 2016). In particular, visitors of Cabot Circus shopping center were approached and asked to be the subject of an interview. Data were collected at the same time (between 10.00 a.m. and 1.00 p.m. for three weeks), through a common interview guide (Appendix 1), while each interview was recorded along with the authorization of the interviewee, and was subsequently transcribed by researchers to facilitate the analysis. During the interview, respondents were further informed about the functioning of the system, in terms of what kind of information it collects (pictures and faces extraction as in Figure 1), how it analyses (procedures to assign a certain emotion to each extracted face, as in Figure 2), and the resulting outputs (as the number of faces expressing each emotion).

The names of the interviewees have been omitted for anonymization purposes. A copy of the transcription was forwarded to interviewees to confirm their authenticity and to ensure the reliability (Moustakas, 1994).

In total, the sample consists of 24 consumers, 15 females and 9 males, aged between 27 and 35 years old (average 30). Concerning the frequency of purchase in a physical shop, 6 participants purchase at least once per month, 15 participants once a week, and 3 participants 2-3 times per week, with an average time spent of 30 minutes (3 participants less than 10 minutes, 16 participants half an hour, and 5 participants about one hour). Finally, concerning the frequency of visiting shopping centers, 3 participants declared that they usually do not visit shopping centers, only 4 participants visit once a week, and the majority (17 participants) usually once per month.

The data were subsequently analyzed through thematic analysis. Drawing from the research questions, we identified the main codes to code the text (as shopping experience, service evaluation, interaction, automatic collection), and the resulting themes associated with the codes in each interview, as suggested by Braun and Clarke (2006).

### 3.2.2 Consumers' perception of the new system

Results have been organized into two main standpoints: (i) willingness to evaluate the service, and (ii) willingness to base the evaluation on disclosed emotions.

*Willingness to evaluate the service*

Many interviewees showed a positive willingness to provide an evaluation of the service. First, the possibility to leave feedback is perceived as an opportunity to provide a personal evaluation of the service. Consumers pay attention to the tools provided by retailers to collect their feedback. Even if this practice is scarcely adopted by consumers who prefer giving the feedback just after the experience, they appreciate the possibility on the retailer's website to complete an ad hoc form indicating specifically the date/time of the visit to the store, the level of satisfaction, suggestions for future improvements, and eventually the name of the salesperson. Often, retailers provide a unique code on the receipt of purchase to access the online forms. In this case, benefits such as discounts on the next purchase, or possibility to win some prizes are the most common strategies to incentivize consumers' participation. Secondly, the possibility to leave the feedback is perceived as a tool to show that the retailer takes into account the opinion of the single consumer. When retailers provide this tool (in any form), they make a sort of declaration that they want to have consumers' opinion, and they are open to consumers' evaluation. Thus, independently of the access to the forms (either offline or online), consumers expect retailers to provide tools to collect their feedback. Accordingly, a respondent declared:

*"When retailers give me the opportunity to provide my opinion, I have the feeling that my opinion is important for them. So, I usually give my feedback whenever they allow me to do with any tools (i.e., forms/questionnaires). Afterwards, I like returning to the store to see if they improved/changed something"* (participant #12).

While another one said:
*"I tend to give my feedback especially when I don't like the service, so that they can improve. If there are no tools in this sense, I use Facebook. Unfortunately, in this moment I noticed that only a limited number of stores give the possibility to evaluate their service, while museums and exhibitions always give this possibility. I think that this is a good tool to improve the service, or an award for retailer if consumers say that the service is already excellent. I would like to see more stores with the opportunity to provide a frank evaluation*" (participant #8).

Also, some respondents assume that the possibility to leave the feedback pushes retailers to adjust somehow the strategy accordingly. For this reason, they might feel forced to visit the store again to evaluate the extent to which the suggested proposals have been taken into account. However, some others showed doubts regarding the effective usage of the provided feedback, considering the forms to fill just a practice to meet their expectation rather than a suggestion for improvements to be effectively explored:

*"I think retailers pay attention to our expectations and needs, because if they satisfy us we will make more purchases. However, I'm not sure that they will effectively explore our responses. Our suggestions might require time and money, and probably retailers are already satisfied with their service without understanding our suggestions to improve the service"* (participant #3).

Similarly, another respondent said:
*"I think that the stores who really evaluate the collected feedback are few. Probably, they provide the forms to fill because consumers expect to see them, but at the end of the day the majority of retailers ignore the results*" (participant #15).

Nevertheless, consumers' willingness to provide their feedback does not automatically result in an effective evaluation due to time constraints. Indeed, the stores that provide evaluation tools request that questionnaires are filled immediately after the experience (by hand or online), by accessing the long link provided on the bill. This generates frustration on consumers who consider the evaluation as a waste of time. Accordingly, a respondent said:

*"I would like that the process for collecting my feedback would be as fast as possible. If I have to read pages and pages, I would waste too much time just to evaluate the service. I would be bored immediately and leave the questionnaire half blank*" (participant #20).

Hence, consumers expect retailers to provide tools for collecting their feedback, however questionnaires, which are the most common tool, are considered to take too long. However, when stores do not provide any tool to collect consumers evaluation, respondents believe that retailers do not really care about receiving consumers' feedback, and do not show any willingness to improve the service based on their comments.

*Willingness to base the evaluation on disclosed emotions*

Analysis of interviews shows consumers' willingness to provide their feedback on retailers' service, and the expectation to have the possibility to evaluate the service providers' performance. Some respondents even leave the feedback through social media when questionnaires to clients are not available. Also, some said that the idea to select an emoticon representing their level of satisfaction from the physical totem (as the ones largely used in the airports) should be adopted also by retailers, because it is something intuitive, user-friendly and fast. However, traditional techniques, such as questionnaires or totem with a set of buttons do not emerge as particularly effective. Similarly, these techniques are not able to deeply understand consumers' emotion when at the service encounter, since they do not completely integrate the emotional dimension into service provider. Instead, we proposed that respondents use a system able to identify their non-verbal expression to understand the emotion at the moment of service delivery, as a tool to collect their feedback. The system is based on the algorithm for emotions identification through the analysis of facial expression. A respondent said:

*"This system would be useful for retailers, because it allows to link consumers' evaluation of the store service with the real feelings/emotions. The facial expression would tell more than any judgment expressed by pressing a button with an emoticon!"* (participant #11).

Although respondents considered the new system something to try and exciting, the majority expressed some doubts about the privacy issues that might emerge from the effective retailers' usage of the collected data. Accordingly, one respondent declared:

*"I would use this system, but I would like to understand how the retail will ensure my privacy. What if s/he will use my picture for other purposes? How can I be sure that the retailer will use the picture exclusively to improve the service? What if s/he will give all the pictured to third parties or to develop ad hoc advertising campaigns, and so on?"* (participant #1).

While another said:

*"Will they collect the picture of my face and keep a track of this in their records? I would suggest them to ask a picture that we choose to provide, rather than one automatically taken by them. Many like being photographed and tend to take unnatural poses. Will this really help retailers to improve the service? However, I don't like being photographed. Why don't use gesture rather than pictures? Would it be possible? I would prefer this kind of system"* (participant #9).

Consumers associate pictures they take with the need to show themselves in a certain way, without paying attention to the fact that only a limited sets of points distributed on the face will be tracked (see Figure 2). Indeed, the system does not memorize the faces of consumers, since each face is represented by a set of distributed points. However, when used in real contexts, consumers would need to be reassured that retailers would effectively use the pictures in this way. Thus, there is no need to care about poses of looks, since the system does not keep track of these elements.
Finally, one respondent expressed curiosity to see the different facial expression of a client paying at a cashier and of a client paying at an automatic cash-desk, to understand effectively the reliability of evaluating the different facial expressions at diverse retail service encounters. Hence, the respondent is the one going beyond the picture as a tool, to focus more on what elements of the picture can be effectively used without violating consumers' privacy. Thus, consumers' response towards the system would solicit new practices and strategies that retailers should adopt to protect consumers' privacy, which constantly emerges as a very sensitive issue in modern retail settings.

## 4. Discussion

The aim of this paper is to understand the extent to which it is possible to systematically evaluate retail service encounters through consumers' facial expression. To this end, the research investigated the extent to which emotion recognition systems (through non-verbal expression) can be used by retailers to better understand consumers' shopping experience, and the extent to which consumers accept this kind of systems in their shopping journey. Since consumers show positive emotions as the synthesis of the positive experience at the service encounter (Andersson et al., 2016; Mattila and Enz, 2002; Bock et al., 2016), the results of our study support our assumption that an automatic system can be employed to help the retailer in this sense. Indeed, the system, based on machine learning algorithms, would identify human emotions, and can be used to recognize consumers' emotion as a tool to evaluate the service encounters, which consumers would be willing to accept under certain circumstances (i.e., guarantees of not disclosure of pictures, etc.). In this sense, the contributions of our study are manifold. First, it shows the extent to which service encounters enriched with our system would be able to identify human emotions through the analysis of non-verbal expressions as the facial expressions in terms of anger, disgust, fear, happiness, neutrality, sadness and surprise. In this way, our research extends previous retail studies focused on few emotions (Pappas, 2018) with a multidimensional approach, taking into account all the six fundamental emotions. Specifically, Pappas (2018) demonstrated the extent to which past studies mainly focused on the evaluation of effects of positive or negative emotions. Similarly, a large deal of research pointed out the greater influence of especially negative emotions (as anger and anxiety) (Menon and Dubè, 2004; Otieno et al., 2005). Our results show the simultaneous evaluation of both positive (happiness) and negative emotions (anger, disgust, fear, and sadness), confirming the different experiences lived by diverse consumers in the same retail settings. Drawing upon the Ekman and Friesen's six fundamental emotions (Ekman and Friesen, 1978; Ekman, 2003), our findings also highlight the extent to which negative emotions such as sadness are more dominant than happiness (appearing in the 25% and 15% respectively) in shopping centers. This would push retailers to consider that a huge number of visits would result in negative behaviours such as dissatisfaction.

Secondly, our system simplifies the emotions communication between consumer and technology, which has been argued to be more difficult than the face-to-face interaction, due to the capability of interpreting non-verbal expression as facial expressions, in a more honest appraisal if compared to the evaluation provided via others (i.e., filling a form provided by an employee) (Derks et al., 2008). For instance, consumers may express disgust towards the service without being concerned with the impression they make on employees, and consequently they may feel less vulnerable to express certain emotions. Indeed, the present form of consumer-computer interaction and emotional transfer from consumer to the system would include the emotional embodiment that is usually excluded in this context.

Thirdly, in study 1 our research evaluates the emotional analytics through facial expression. In doing so, the research adds new knowledge to the methods of systematically evaluating consumer's emotions (Malik and Hussain, 2017; Pantano, Giglio, Dennis, 2019; Zhou, Xu, Yen, 2019; Cracioun and Moore, 2019; Walasek, Bathia and Brown, 2018). To do so, the present research shows that facial expression analysis can reveal important information about consumer's state in addition to the traditional methods based on the text analysis. Thus, the system goes beyond the linguistics and content analysis of texts, by offering additional value and insights into consumers' behavior.

## 5. Conclusion and future research

The study provides a set of algorithms to support employees to better understand consumers' shopping experience and reply accordingly. As solicited by recent studies (Huang, Rust, and Maksimovic, in press), the present research describes a new form of human complementarity with technology able to facilitate the human-computer collaboration that would be accepted by consumers. From a practical point of view, our research provides retailers with a new practice to be used to constantly evaluate clients' emotions at the service encounter as a measure of appraisal of the service. Based on the emotion, retailers might change the service accordingly. This system represents a new application of emotion recognition through facial expression in retail settings, which used emotion recognition only to increase the security of the payment systems (Zhang and Kang, 2019; Tezuka et al., 2019).

Finally, the present study used pictures shared only by consumers, thus these pictures might not show spontaneous emotions since consumers might have decided what kind of emotion they want to portray before sharing. Also, these pictures have been taken in a certain moment of the shopping experience, thus, the results do not provide an evaluation of how the emotions changed across the experience. Accessing the internal/external cameras (i.e. CCTV) rather than consumers' pictures would provide more spontaneous consumers' expressions, which would result in a better overview of the real emotions in the different phases of the shopping experience and retail servicer encounters.

Consumers might associate emotion recognition with a loss of privacy, believing that this procedure would collect also data on age, sex, race and gender. Thus, retailers should adopt new practices in order to reassure consumers about the exact data to be collected and their usage, while avoiding the collection of sensitive data. Indeed, systems such as the one presented in this study only information from some points on the face of individuals, and the space between these points in order to identify an emotion. As a consequence of the new practices, retailers would be able to solicit consumers' willingness to adopt the system, to share their service evaluation through the facial expression analysis.

Despite the contributions of the study, some limitations impact the generalizability of results. The first one relates to the sample of the study, which mainly focuses on a specific age (ranging between 27 and 35 years old). Although this age range has been chosen due to the extensive use of technology of people falling in this group, responses of older or younger consumers may differ in terms of perceived benefits of the system, and willingness to use. Similarly, studies in psychology provided evidence that emotion norms apply differentially to men and women due to gender roles (Craciun and Moore, 2019). However, this research does not differentiate between females and males, using the data only in aggregate form. Thus, we encourage future research on the effect of emotions gender bias. Second, the study does not specify how the system might react according to the detected emotion. Future studies may highlight the diverse possible reactions to positive or negative feelings to increase the emotional intelligence of the system. Presumably, one category has a greater effect on the subsequent buying decision. Third, the study does not consider a specific retail service encounter (i.e., self-service cash desk, contactless payments systems, interactive totem displays, and so on) or retail sector (i.e., grocery, luxury, and so on), while the emotions experienced by consumers may vary according to the different store in which they shop; further research could compare the present findings in different stores at different service encounters. Indeed, the different kind of encounters might solicit diverse emotions, not only related to the quality of interactions (influenced by ease of use or usefulness of the technology), but also related to the technology typology (i.e., do self-service cash desks solicit more positive responses if compared to interactive touch screen displays?). Therefore, future studies might examine what are the specific characteristics of each technology leading to a certain purchase behaviour (i.e., the level of interactivity). Fourth, some respondents elicited issues related to the privacy, since they expressed some doubts in retailers' usage of data only for improving the service. Additional studies could investigate the best practices to push consumers to voluntarily adopt this kind of system, as well as the forms of collaboration that might help consumers to be more positive towards the system.

Finally, our study adopted the machine learning algorithms already available in Wolfram Mathematica that still generate a 19% of indeterminate faces, while they are able to successfully recognize the emotion from the facial expression in between the 81% and the 88% of the cases (according to the specific emotion). However, new progresses in computer sciences and machine learning might develop new algorithms able to reduce the number of indeterminate faces, and increase to 90% the percentage of successful recognition, in order to give retailers more accurate information.

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## Appendix 1: Interview guide

| Topic area | Question/s |
|---|---|
| Opening question | Can you please explain to us your willingness to provide an evaluation of the in-store retail service? How do you like providing this evaluation? Why? |
| Consumers' perception of our system to evaluate retail service | Would you consider evaluating in-store retail service as important? If yes, why? (or if no, why not). Can you please provide your opinion about such a system to collect your evaluation about the service that you have experienced? Would be this system worth for you? To what extent do you consider that your emotional responses is important for retailers to improve the service? Why? |
| Effectiveness of the new system to evaluate retail service | To what extent would you appreciate this system to evaluate the retail service? How would you like retailers use the data collected through this system? |
| Wrap up | Do you have any other comment about the system or the emotional responses when you are in the stores that you would like to share with me? What are benefits/drawbacks of this system?  Do you have any concerns about this system? Do you think it would be useful?  Would you tell other about this system? |