Retail managers' preparedness to capture customers' emotions: a new synergistic framework to exploit unstructured data with new analytics

Abstract. Although emotions have been investigated within strategic management literature from an internal perspective, managers ability and willingness to understand consumers emotions, with emphasis on retail sector, is still a scarcely explored theme in management research. The aim of this paper is to explore the match between the supply of new analytical tools and retail managers' attitudes towards new tools to capture customers' emotions. To this end, Study 1 uses machine learning algorithms to develop a new system to analytically detect emotional responses from customers' static images (considering the exemplar emotions of happiness and sadness), whilst Study 2 consults management decision makers to explore the practical utility of such emotion recognition systems, finding a likely demand for a number of applications, albeit tempered by concern for ethical issues. While contributing to the retail management literature with regard to customers' emotions and big data analytics, the findings also provide a new framework to support retail managers in using new analytics to survive and thrive in difficult times.

Keywords: retail management; customer behaviour; customers' emotion; emotional analytics; classifier machines; machine learning algorithms.

1. Introduction

Emotion has been an increasingly studied area in strategic management research (Daniels, 1998; Goss, 2008; Lewis, 2008; Delgado-Garcia et al., 2010), helping to build understanding of information processing and decision-making, employees' experiencing negative emotions in the working environment, leadership styles, etc. However, prior studies largely focus on the importance of emotion within the organization, almost ignoring the importance for managers of understanding also consumers emotional responses to certain organizational behaviours (e.g., service failure, reputation, green campaigns, etc.) (Schoefer and Diamantopoulos, 2009; Walsh et al., 2016; Kohli et al., 2021). However, understanding customers' experiences and engagement requires a deep insight into customers' emotions experienced during a service encounters (Schoefer and Diamantopoulos, 2009).

The need for the analysis of affective user generated content derives from previous research in cognitive vs affective experiences that suggests that affective experiences have a more significant role in influencing customer behaviour than do cognitive experiences (Dennis et al., 2014). For instance, customers expect organizations to respond proactively to their concerns, complaints and negative experiences, as well as to service failures by pushing them to find new solutions (Schoefer and Diamantopoulos, 2009). Thus, new forms of analytics have been employed to potentially improve organisations' competencies and add value by enhancing knowledge regarding various operations including the behaviour of customers (Paschen et al., 2020). Analytics help organisations in gaining insights useful to improve their performance in the market (Hajli et al, 2021) by optimizing the allocation of resources and by improving efficiency (Canhoto and Clear, 2020). Specifically, they utilise structured and unstructured data such as information about transactions and images respectively (Canhoto and Clear, 2020; Sheng et al., 2019; Balducci and Marinova, 2018). Indeed, the capability to analyse customers' unstructured data is considered to impart superior competitive advantage (Mikalef et al., 2019). Accordingly, recent research analysed user generated cognitive content focusing mainly on text posted on social media (Sheng et al., 2019; Srivastava and Kalro, 2019). Accordingly, the analysis of affective user generated content is rapidly acquiring scholars' attention (Li and Xie, 2020; Peng et al., 2019; Villarroel Ordenes et al., 2017). For instance, image analysis has been used in the past to assist employees with information processing facilitating a transition to delivering more creative work by using machine learning to classify images (Shrestha et al., 2021), or to understand if consumers' perceptions of a certain product/service are aligned with the company marketing campaigns (Giglio et al., 2020). However, different sectors might capture and produce value from these analytics differently (Mikalef et al., 2019), making investigation of these topics in the retail sector a promising area of research. The quantity of information generated by new forms of analytics makes its interpretation and understanding challenging (Calvard, 2016). However, organisations are not dealing effectively with privacy issues related to new data collection and analytics applications (Batistic and van der Laken, 2019; Aiello et al., 2020; Martin and Palmatier, 2020), and therefore the inefficiency of managing such risks tends to create a reluctance in the adoption of such technologies by managers (Canhoto and Clear, 2020).

Given the importance of emotions for service relationships (Schoefer and Diamantopoulos, 2009; Walsh et al., 2016), the potential contribution of new forms of analytics in the identification of customers' emotions while in retail settings as well as sensemaking and optimum utilisation of this information are key areas still to be explored. Of particular interest is whether managers and retail managers are able to exploit technology like artificial intelligence (including robotic companions and voice assistants) (Bertacchini et al., 2017; Mende et al., 2019; Vannucci and Pantano, 2019; Evanschitzky and Georgen, 2018; Grewal et al., 2020), to make a systematic correspondence between customers' emotions and service encounter.

The aim of this paper is (i) to explore the match between the supply of new analytical tools and retailers' demand for new tools to capture customers' emotions, and (ii) provide a new synergistic framework to exploit new analytics and new sources.

The methodological approach incorporates two studies to provide a holistic approach in analysing affective user generated content and exploring the practical implications respectively. Based on the findings, the research proposes a new machine learning approach, which has been used as an exemplary new tool for additional analytics of customers' behaviour. In doing so, paper insights would suggest a fairly novel approach to capture emotions into an area not yet widespread, retailing. Thus, our paper enhances our understanding of a fundamental aspect of retail management: how to exploit new sources and analytics to evaluate customers' emotions and to integrate into the service encounters.

While traditional analytical and statistical approaches are capable of investigating traditional marketing data, new approaches based on artificial intelligence and machine learning might be more suitable for understanding and predicting emergent trends (Pantano et al., 2019; Pantano et al., 2017; Shankar, 2018). One application of such techniques is in the more reliable detection of customers' emotions in specific retail settings. Similarly, recent studies call for new research in understanding how to extract visual information from customer generated contents shared online (Li and Xie, 2020). On one hand, this research responds to the recent calls for research into the role of new forms of analytics able to better support organizations to respond quickly to the environmental changes (Sena et al. 2017; Sheng et al., 2019), and on the other, it sheds light on the importance for managers of understanding consumers' emotions.

In the current paper, Study 1 contributes to retail management literature by proposing a new exemplar algorithm for emotional analytics, as part of new analytics to extract insights that can result in more efficient management strategies. The findings will demonstrate that it is possible to systematically detect customers' happiness and sadness when in retail stores (emotional analytics results). The main theoretical contribution, analysed later in the manuscript, suggest that hedonic responses can be evaluated as emotional reactions by using visual cues. This is a more logical approach compared to the use of cognitive cues in questionnaire surveys or systematic and simultaneous analyses of multiple sources (i.e., combination of tweets, posts on Facebooks and images on Instagram, etc.) employed in past literature on the topic, which we consider to be more appropriate to utilitarian rather than hedonic responses (e.g., Sheng et al., 2019; Srivastava and Kalro, 2019). The findings will enable researchers to reconceptualise the role of emotions and provide managers with new tools to enhance customer satisfaction. Mikalef et al. (2019) point out that even when managers have big data intelligence available, they might not use it in decision making, which constitutes a 'promising area of research' (p293). Accordingly, we carried out Study 2 with the aim of exploring the extent to which retail managers may use emotion recognition in decision making. Study 2 consults management decision makers to explore the practical utility of such emotion recognition systems, finding a likely demand for several applications, albeit tempered by concern for ethical issues.

The paper is structured as follows: the next section illustrates the theoretical background of the study, based on past research on customers' emotions measures in retail settings. Subsequently, the paper focuses on the method of research based on two studies (algorithm development and test, and retailers' response). Finally, results and implications for scholars and practitioners are discussed.

2. Theoretical background

Emotions have been conceptualized as positive or negative affect (Fredrickson and Losada, 2005; Nawijn, 2011), which has direct effects on an individual's thinking and behaviour (Fredrickson and Losada, 2005; Magids, Zorfas, and Daniel, 2015). Emotions are expressed through (i) subjective experience, (ii) expressive behaviour, and (iii) physiological changes (Ekman, 1992). Specifically, Bagozzi, Gopinath, and Nyer (1999, p. 184) defined emotion as "a mental state of readiness that arises from cognitive appraisals of events or thoughts; has a phenomenological tone; is accompanied by physiological processes; is often expressed physically (e.g., in gestures, posture, facial features); and may result in specific actions to affirm or cope, depending on its nature and meaning for the person having it". In the same vein, Isaac and Budryte-Ausiejiene (2015) claimed that emotions "are affective states characterized by occurrences or events of intense feelings associated with specific evoked response behaviours". Individuals are usually aware of their emotions, while their moods are more general and subtle, and often work beneath their consciousness (Goossens, 2000). In comparison with moods, emotions are more intense and associated with specific objects or events (Goss, 2008). Similarly, Malone, McCabe, and Smith (2014) claim that emotions are very subjective, and salient. For these reasons, researchers broadly agree on the key role played by emotions in experience formation (Brakus et al., 2019; Das et al., 2017; Dennis et al., 2014; 2017; Richins, 1997; Goss, 2008). Experience refers to emotions, sensations, feelings, cognitions, and behavioural responses evoked by, for example, a retailer (e.g., Brakus et al., 2019; Dennis et al., 2017). Goss (2008) further highlighted the importance of the social and cultural context where individuals display their emotions.

In the retail context, positive emotions usually lead to positive shopping approach behaviours such as satisfaction, willingness to pay, loyalty (Chou et al., 2016; Goldsmith et al., 2012; Sherman et al., 1997), attitudes towards the retailer/brand (Dennis et al., 2014; Brakus et al.,

2009), customers' evaluation of the product, service, and service encounters (Hasford et al., 2015; Hennig-Thurau et al., 2006; Mattila and Enz, 2002), as well as increased willingness to pay (Chou et al., 2016). On the other hand, negative emotions might lead to negative consumers' behaviours like product returns, limited engagement with the firm, diminished corporate reputation, etc. (Walsh et al., 2016; Kohli et al., 2021). However, positive emotions tend to have a stronger effect on behaviour than do negative emotions (Kranzbühler et al., 2020, Pappas et al., 2017).
The effect of emotions on shopping behaviour also informs store atmospherics literature which suggests that common retail practices employ, for example, music, scent, and appropriate colour schemes to evoke positive emotions in customers (Fuentes et al., 2019; Reynolds-McIlnay et al., 2017; Alpert et al., 2005). Past research examining customers' emotions in the context of shopping utilises traditional surveys, questionnaires, and observations (please see Table 1 for a review of studies published in academic journals in this area building on the review of the relevant literature by Gaur et al. 2014). In addition, retailers evaluate customers' experiences through methods including the employment of mystery shoppers (anonymous visitors to such businesses to check the extent to which they meet specific standards of cleanliness, speed, and quality of customer service, etc.). These practices may be subject to a number of limitations arising from interviewer/researcher bias and/or lack of depth of analysis, leading to a lack of understanding of customers' deeper feelings.

Study	**Method of research**	**Findings**
Brakus, Schmitt, Zarantonello, 2009	Quantitative (three surveys with 25, 267, and 193 university students respectively, and one survey with 150 customers)	New scale to measure brand experience based on four dimensions: sensory, affective, intellectual, and behavioural
Chou et al., 2016	Quantitative (survey with 230 college students in China)	Considering two services with two opposite valences (failure-success scenario and success-failure success scenario), findings demonstrates that when the priming information between two services increases (decreases) positive emotions the result is a raising (lowering) of willingness to pay
Das & Varshneya, 2017	Quantitative (survey with 346 customers)	Findings reveal the role of various social and promotional cues on customers' pleasure and arousal in shopping malls.
Dennis et al., 2014	Quantitative (survey with 437 customers)	Findings reveal that digital signage technology can evoke affective experience when impacting customers' experience.
Goldsmith et al., 2012	Quantitative (440 participants distributed in 6 independent studies)	Findings reveal the cognitive association between guilt and pleasure, thus priming the guilt increases the pleasure from hedonic consumption
Hennig-Thurau et al., 2006	Quantitative (223 customers)	Findings reveal the extent to which employees emotional labour display directly affects customers' emotional states.

Kidwell et al., 2020	Survey, experiments	When shopping, consumers with similar emotional ability experience significantly greater satisfaction in their interactions
Mattila & Enz, 2002	Mixed methods (observation and survey with 200 customers)	Findings suggest affect influences customers' responses to brief, nonpersonal service encounters
Pantano & Gandini 2018	Qualitative (in-depth interviews with 20 young customers)	Findings demonstrate the extent to which the shopping experience within stores can develop towards a new kind of experience based on the connection to a network of customers (shopping as a "networked experience")
Pappas et al., 2017	Quantitative (survey with 582 consumers)	Positive emotions have a greater effect on purchase intentions than negative.
Richins, 1997	Literature review	Provides a set of descriptors to measure emotions in consumption experience
Rick et al., 2014	Experiments	Shopping alleviates sadness
Sherman, Mathur, Smith, 1997	Quantitative (909 customers)	Findings suggest the emotional state of customers as driver of purchase behaviour
Schoefer & Diamantopoulos, 2009	Quantitative (two surveys with 189 and 154 respondents respectively)	Four distinct emotional response styles associated with perceptions of relationship quality

Table 1: Selected past research on customers' emotions.

Previous literature has also examined customer emotions in different settings and in different points of time of the customer journey, ranging from i) utilising machine learning to measure emotions in lab experiments (Yu and Ko, 2017) to ii) surveys while customers were shopping (Bustamante and Rubio, 2017) or iii) post-shopping where customers had to reflect on their shopping trip (Laros and Steenkamp, 2005; Adam, Krämer, and Weinhardt, 2012). Such methodologies demonstrate respectively three main disadvantages i) notwithstanding that they facilitate the collection of information about customer emotions in real time, the retail environments explored may be only simulated, ii) they rely on self-reported (rather than objectively measured) information, and iii) they rely on customers' perhaps-inaccurate recollections of their shopping experiences. Table 2 provides an overview of methods employed in past studies measuring customer emotions. This study aims to address these disadvantages by utilizing machine learning to collect information on customer emotions in real time as well as in a real physical retail space.

The constant drive to create memorable experiences for customers pushes retailers to adopt new solutions based on an ever-greater integration of technology (Inman and Nikolova, 2017; Vannucci and Pantano, 2019; Willems et al., 2017). Nevertheless, interaction with the new technology-enriched retail environments leads to emotional reactions and new shopping experiences (Dennis et al., 2017). For instance, this interaction might result in happier experiences gained from material purchases (Dennis et al., 2017). Indeed, technology can be based on mobile apps, digital signage, and smart mirrors (Dennis et al., 2014; Willems et al., 2017), humanoid shopping assistants (Bertacchini et al., 2017), contactless technologies, systems for fast payment, and so on to provide customers with access to additional information on products to support them in finding, comparing, locating, and buying goods, while enhancing their shopping experiences with relaxing and entertaining services.

For instance, systematic social media monitoring would facilitate the understanding of customer behaviour and engagement with companies (Li and Xie, 2020). In this sense, machine learning techniques would support the collection of online insights on customers, with emphasis on social media sources. However, they are still rarely explored in retail studies (Pantano et al., 2019). Therefore, finding new approaches to utilize social media content would help in understanding customers' shopping experiences and the associated emotions, while machine learning algorithms would analyse the collected data. Indeed, in analysing customer behaviour, previous literature has employed machine learning to explore the behaviour of individuals in the context of several marketing applications and channels to examine customer experiences. Previous studies vary both in terms of the type of data used in the analysis and in relation to the theoretical focus of the research. With regard to the former, machine learning has been employed to analyse text posted on review/ratings websites (Ahani et al., 2019; Peng et al., 2019; Sheng et al., 2019; Srivastava and Kalro, 2019), text posted on social media (Pantano et al., 2019; Kuhl et al., 2020; Pantano and Stylos, 2020; Villarroel et al., 2019; Lie and Xie, 2020), and images from various sources (Matz et al., 2019). In relation to the latter, existing studies have examined customers' emotions (Pantano et al., 2019; Srivastava and Kalro, 2019), customer needs (Kuhl et al., 2020), customer personality (Matz et al., 2019), customer segmentation (Ahani et al., 2019), customer engagement and contents of customer generated posts in social media (Li and Xie, 2020; Pantano and Stylos, 2020; Vermeer et al., 2019). Despite the potential of new technology to provide new customer solutions, competition in high streets is still critical. For instance, in the UK, traditional high street retailers are failing (The Guardian, 2018a, b), as retailers and shopping centres are losing business to online competition, while recent figures by KPMG report customers increasing expectations from retailers and retail experiences (KPMG, 2018). Thus, there is a need to shift emphasis towards experience in the face of competition from online, and therefore a deeper understanding of customer's emotions as drivers of positive shopping experiences in physical stores might play a key role.

Summarizing, past literature emphasises the importance of providing customers with positive shopping experiences, and the related tools to understand these experiences, while machine learning algorithms emerge as new powerful tools to support the elicitation of customers' insights. However, to the best of our knowledge, research on retailers' effective willingness to put into practice the new analysis and metrics and how to support them in doing so is still scarce. Therefore, this paper aims to develop a framework that bridges the gap between use of artificial intelligence and big data analytics in the retail environment and the managerial implications by developing a retail framework that can inform such decisions.

Table 2: Past applied methodologies measuring customer emotions

Emotions	Methods	Time of measurement	Reference
Happiness, anger, surprise and disgust	AI, FaceReader, an automatic facial expression recognition software	Virtual shopping experience in a lab	Yu and Ko, 2017
Arousal and pleasure	Survey utilising a self-reported questionnaire	Post shopping experience	Das and Varshneya, 2017
Pleasure, Arousal, Dominance, Joy, Sadness, Interest, Anger, Guilt, Shyness/shame, Disgust, Contempt, Surprise, Fear, Acceptance, Expectancy.	Survey utilising a self-reported questionnaire	Post shopping experience	Machleit and Eroglu, 2000
Elated, peppy, enthusiastic, excited, Strong, active	Survey utilising a self-reported questionnaire	Post shopping experience	Wang, 2009
Anger, fear, sadness, shame, contentment, happiness, love, pride.	Survey utilising a self-reported questionnaire	Post shopping experience	Laros and Steenkamp, 2005
Arousal, excitement	Self-reported questionnaire as part of a lab experiment	Post shopping experience	Adam, Krämer, and Weinhardt, 2012
Pleasure, arousal	Online survey	Virtual shopping experience	Cho and Lee, 2017
Joy, enthusiasm, calmness, excitement	Online experiment, survey	Virtual consumption experience	Borges, Herter, and Chebat, 2015
Contented, happy, optimistic, hopeful, enthusiastic, thrilled, surprised, amazed, astonished, delighted, fulfilled, encouraged, calm, unworried, discontented, frustrated, ashamed, tense	Survey	While Shopping	Bustamante and Rubio, 2017
Level of Arousal	electrodermal activity (EDA)	Real time experience	Kim and Fesenmaier, 2015
Joy	Survey	While Shopping	Bagdare and Jain, 2013
Anger, discontent, worry, sadness, fear, shame, envy, loneliness, love, peacefulness, contentment, optimism, joy, excitement, surprise.	Survey	Self-reported experience	Richins, 1997
Pleasure, arousal	Online experiment, survey	Virtual Shopping experience	Ainsworth and Ballantine, 2014
Arousal	Review of various studies employing EDA measures	Various settings both in labs and in retail outlets	Caruelle, Gustafsson, Shams, Lervik-Olsen, 2019
Pleasure, arousal	Survey	Real time experience	De Nisco and Warnaby, 2014

3. Method

3.1 Research design

Past studies in experimental psychology highlight the link between emotions and human facial reaction (expressions) (Eckman and Friesen, 1975, 1978). In other words, emotions can be revealed (and identified) through the facial expressions. Six distinctive fundamental emotions have been identified that are linked to facial expressions: anger, disgust, fear, happiness, sadness, and surprise (Eckman and Rosenberg, 1997; Kohler et al., 2004). Of these emotions linked to facial expression, we chose happiness and sadness as exemplars. Customer experience has become an important topic of study. Happiness conceptually contributes to positive experience (e.g., Brakus et al., 2009; Dennis et al., 2014) and, conversely, we expect that sadness will contribute to a negative experience as 'unhappy' and 'melancholic' (synonyms of 'sad') are opposite anchors to positive affect in environmental psychology scales. Interviews and surveys (usually collected sometime after the experience) are commonly used in retail research for identifying emotions (e.g., Dennis et al., 2014). Retail survey research often considers arousal (e.g., Das and Varshneya, 2017; Kim and Fesenmaier, 2015) and occasionally dominance and other emotions (e.g., Machleit and Eroglu, 2000) (Table 2) but happiness (reflecting pleasure) is central to affective experience and most clearly distinguished in facial expressions. As much emotion processing happens below the level of conscious awareness, interviews and surveys that involve conscious or self-reported techniques for evaluating emotional responses may not be the most reliable way to capture human's emotions (Marci and Murray, 2017). In contrast, the human face, which represents one of the most important non-verbal means of communication, can divulge unsolicited information about a person's emotions (Popa et al., 2017).

Over the past few years, a stream of research has evolved demonstrating the technical aspect of operationalizing facial analysis in images and the development of successful ad-hoc software applications capturing individuals' emotional states via images (e.g., Kim and Stepchenkova, 2015). Although researchers have analysed images using machine learning (e.g., Matz et al. (2019), and customers' emotions in response to (e.g.,) ads (Teixeira, Picard and el Kaliouby, 2014; see Clark et al. 2020 for a systematic review), we are unaware of any retail studies that have evaluated customers' emotions by analysing facial characteristics. This is notwithstanding that machine learning has been acquiring attention as a new approach for complex analysis (e.g., big data analytics for marketing intelligence) (Ahani et al., 2019; Kuhl et al., 2020; Humphreys and Wang, 2018; Pantano et al., 2019; Bradlow et al., 2017; (Matz et al., 2019; Peng et al., 2019; Pantano and Stylos, 2020; Villarroel et al., 2019; Srivastava and Kalro, 2019).

Due to the exploratory nature of the present research, the methodology is based on a two-step approach that involves: (i) the development of a classifier machine able to recognize customers' expressions portrayed in pictures and understand the specific underlying emotions that they are presenting in terms of happiness or sadness, as an exemplar new tool for new analytics of customers' behaviours (Study 1); and (ii) interviews with retail practitioners to investigate the value that such a system can add to retail strategies and practices (Study 2). To this end, the research first builds and tests machine learning algorithms to detect the emotions from static images, then, second collects retailer managers' responses towards the use of this system. In other words, the research demonstrates to retailer managers the feasibility of the system as exemplar methods that they could put into practice and collects their responses in form of a set of in-depth interviews.

3.2 Study 1: Classifier machine development for emotional analytics

3.2.1 Classifier machine settings

The study starts with the collection of generic images of people to build, train and test the system, followed by its application on images taken by customers in a specific retail setting. In particular, the emerging classifier machine recognizes customers' faces on images and identifies two fundamental emotions (happiness and sadness). A specific machine learning algorithm that classifies/assigns the label 'happy' or 'sad' to each element of a certain set of data consisting of customers' pictures taken in a particular location (in this case, a specific large luxury department store in London, UK).
This study collected images from shoppers' own photos posted on the social media app Flickr, selecting this platform as pictures on this site are freely accessible to the public, including researchers.
Figure 1 explains the process we used to develop the classifier machine, from the image collection (for training and analysis) to the results (emotions in facial expressions detection).

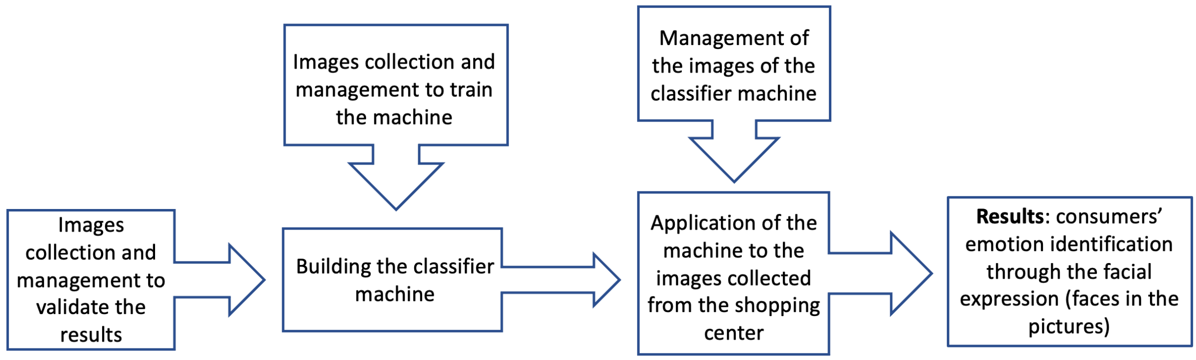

Figure 1: Classifier machine development

The images comprised a set of elements belonging to a set *I* which was the input to a classifier machine *m* that assigns a unique label to each element (continuous or discrete):

$$(1)\ m{:}I \to S$$

In other words

$$(2)\ i \epsilon I \to (i) \epsilon S$$

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

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

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

For this study, we also limit the identification of emotions to happiness or sadness, assigning the value 1 to “happy” and 0 to “sad”, in other words S={0,1} is the output of the system attributing the label of 1 or 0 (happy or sad) to each element (to each face included in the pictures composing the data set). Thus, the machine learning output would be a binary one able to identify the hyperplane in two regions, in order to guarantee that each element of the hyperspace that belongs to that set will get the unique label (each element will be assigned only to a specific region of the hyperspace).
For convenience, the present study uses only images with dimensions of 80x80 pixels, thus the matrix A of elements a_{ij} will have 80x80 elements (this means that the images will be reduced/enlarged accordingly):

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

Where a_{ij} represents a particular colour in RGB format.
Thus, the elements to be classified are $A\epsilon Z^{80x80}$.
This research employs a supervised machine, thus the set I whose elements already have a label can be used to train the classifier machine in order to assign to each element of Z^{80x80} the label (1 or 0).

3.2.2 Data settings

In order to analyse a large number of images containing different colours, brightness, and lighting and with one or more persons, the software *Wolfram Mathematica* allowed the automatic import of 400 pictures available freely on social networks (thus these pictures, not related to any specific location, comprise the initial database used only to test the algorithm). Subsequently, the function “FindFaces” facilitates the extraction of faces from each image. Wolfram Mathematica can use images as input and extracts all the faces of people through a set of boxes, while the function “ImageTrim” uses as input the output of “FindFaces” and compartmentalizes each face in a different image, by composing the data set (Figure 2).

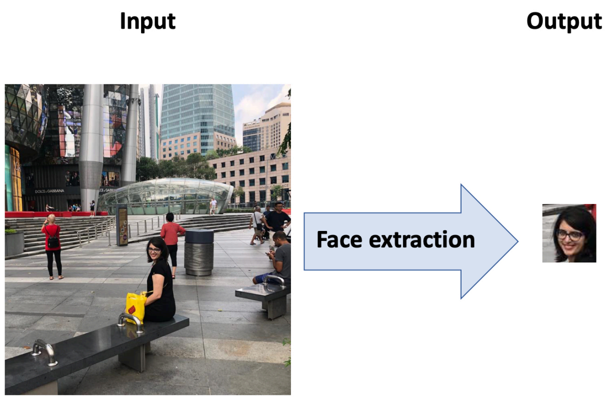

Figure 2: Example of photo extraction process (on the left-hand side the image, on the right the extracted face, no other faces are clearly recognizable in the figure).

Since the resulting images have different sizes, the images have been cut and adjusted in order to constitute a homogenous set of data (in this case the chosen format is 80x80 pixels). Drawing upon the work of Eckmann and Friesen (1975, 1978), who described happy and sad emotions through specific patterns of faces, the system extracted 467 faces from the initial data set; 150 of those images clearly portrayed happy faces and 150 sad faces. Thus, the emerging 150+ 150 faces formed the set Z^{80x80}.

3.2.3 Classifier machine building

Wolfram Mathematica creates a “table of rules” with the elements that should get the label 1 or 0 (Pantano et al., 2017), which consists of the faces. The software imports the “table of rules” and provides as output the classifier machine, developed through the command “Classify”. In particular, the system provides the following classifier function:

$$(5) \qquad m: Z^{80x80} \to \{0,1\}$$

In this case, the software selected the method “NearestNeighbors” (k-nearest neighbours algorithm) among the possible ones, as the most convenient one of the available algorithms, being one of the main systems used in pattern recognition (Datta et al., 2016).

3.2.4 Validation of classifier machine and results

To test the functioning of the classifier machine we created two sets of images with faces, ‘H’ including happy faces and ‘S’ including sad faces. Since the machine learning algorithm is supervised (in other words the machine learns to classify elements through training), researchers manually assigned labels to the faces and compared the results with the labels generated by the machine. In the case of H, the system properly identified the happy faces in 82% of the selected images, and in the case of S, 86%, which means that the overall reliability of the system is above 80%.

To further test the validity of the algorithm, we adopted the same procedure suggested in the validation of textual analysis (Humphreys, 2010). In other words, a stratified random sampling has been adopted to ensure that the classes (happy and sad) are reflected consistently across the faces dataset, by considering 10% to 20% of the total faces for each class (category). In this case, for each emotion 12% of the total number of faces was considered by three independent researchers (experts in consumer behaviour but not in psychology nor consumer science), and manually assigned a label to the faces and compared the results with the label generated by the machine by three independent researchers. The results confirmed the robustness of system prediction for sadness in 86% of faces, and happiness in 82%.

Considering this value as acceptable, the emerged classifier machine can be applied to customers’ images with particular characteristics, and the original database for building and testing the algorithm deleted.

We next built a new database consisting of the pictures referred to a specific location, a large luxury department store in London (UK). To this end, we wrote a web app in PHP and JavaScript format. To increase the speed of implementation of the web app through the usage of API we used a wrapper (written in PHP: phpFlickr available at https://github.com/dan-coulter/phpflickr) which allows the use of all the methods available through Flickr API (including visualization, uploading, downloading, etc.). Flickr API allows selection of the available pictures from a specific location (as each picture uploaded on Flickr includes the reference to the specific geographic position where taken). We collected 1,236[1] pictures, from which the system extracted 887 faces. When the classifier evaluates a face, it assigns to each

[1] Please, note that each image might include more faces, similarly some pictures might not include faces.

one a certain probability p of happy/unhappy. If p>0.5, the face is evaluated as happy, otherwise unhappy. Figure 3 shows how the algorithm recognizes the different points on the face to assign the label (happy/sad).

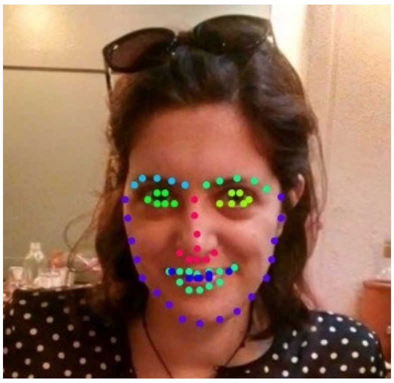

Figure 3. The points systematically detected on the face to assign the label of happy/unhappy.

The machine identified 67.9% as happy faces and 32.1% as sad faces. These results demonstrate that the algorithm can satisfactorily detect two fundamental emotions in customers (static) images. As expected from pictures voluntarily posted online, the majority of the faces were happy. The robustness of the results is further evaluated by the Accuracy Rejection Plot (Figure 4), which reports the accuracy of the results against the rejection rate. Specifically, if considering the accuracy of .78, the system identifies properly the 100% of the faces (rejection rate 0); while with the accuracy of 0.8 the system identifies properly the system identifies properly the 98.02% (rejection rate 0.08).

Figure 4. Accuracy Rejection Plot.

Although this system used a pre-built data base consisting of pictures posted online by consumers, thus implying a conscious emotional response to the retail environment, the input of an automatically generated database with pictures systematically extracted by internal camera would produce similar results, with the benefit of capturing non-conscious emotional responses. Thus, one additional algorithm would replace the input dataset with an automatically generated collection of pictures.

3.3 Study 2: Retailer managers' responses

3.3.1 Method

In order to explore the practical implications of the algorithm we carried out 13 in-depth interviews with senior retail managers and consultants in the UK. Respondents were selected via purposive sampling based on a snowballing approach and consisted of managers of major retail stores and shopping centres, plus consultants providing new technology solutions to major retail groups. Prior to the discussion, the interviewer presented to each participant the results of Study 1 to enhance their understanding of customers' emotions in general and the context of this study in particular, to facilitate the discussion on the topic with a particular focus of the practical implications of the results related to the collection of information regarding customers' emotions. Table 3 provides information regarding the profile of the interviewees. The interview protocol (Table 4) included four main areas of discussion, focusing on the operations of the retailers represented by the interviewees related to collecting customer information in general, and information regarding customers' emotions in particular; their beliefs and perceptions of the use of such information; the practicalities of using such systems; as well as the main advantages and disadvantages. A quantitative content analysis method was employed to analyse the transcriptions of the interviews, facilitated by QDA Miner with its WordStat extension. The documents were prepared for analysis by removing punctuation as well as words not relevant to the study. Co-occurrence analysis of two words, based on Jaccard's Index similarity, generated a concept mapping and proximity plot to visualise the relationships between the concepts whereas frequency analysis was carried out to show the importance of each topic, reported in a dendrogram (Figure 5). To validate the results of the study, invitations for follow up interviews were sent to respondents in order to discuss the interpretation of the results and their implications (Rowley, 2012; Longoni and Cagliano, 2018). Three of the respondents representing various roles and organisations (respondents 3, 6, 9 in Table 3) responded that they wish to participate in further discussion and therefore they were invited to an interview. Prior to the interview, respondents were sent a copy of the results and during the interviews they were invited to comment on the findings from the initial round of interviews.

	Role	Organisation
1	Retail Manager	High street retailer
2	Managing Director	Retail Research Intelligence
3	Director	Shopping Centre
4	Director of Strategy	Shopping Centre
5	Head of Customer Experience	Shopping Centre
6	Sales Operation Manager	Department Store
7	Director	Retail Consultant
8	Commercial and Digital Director	Shopping Centre
9	Retail Manager	Retail Consultant
10	Managing Director	Retail Consultant
11	Media Director	Department Store
12	Director	Shopping Centre
13	Digital Media Manager	Shopping Centre

Table 3: Participants Profile.

Topic	Questions
Opening question	Can you please explain to us the degree to which you collect data about customers? How do you use this data?
Retailer’s perception of algorithms recognising emotions to collect data	Do you collect any information about the emotional responses of your customers? Would you consider this area as important? If yes, why? (or if no, why not). Can you please provide your opinion about software collecting information about emotional responses similar to the ones that we use in this project? How would such systems be useful? To what extent do you consider that emotional responses of customers affect the positive image of the store and customers’ behaviours such as time and money spent shopping?
Usage of data collected with algorithms recognising emotions	To what extent would you use such systems in your store? How would you use data collected through such systems?
Wrap up	Do you have any other comments about such systems or the emotional responses of your customers that you would like to share with us? What are their benefits/drawbacks? Do you have any concerns about such systems?

Table 4: Interview Protocol.

Term	**Frequency**	**Number of cases**	**TF*IDF**
Customer	101	11	0.0
Customers	78	10	3.2
Experience	42	8	5.8
Feeling	40	8	5.5
Footfall	39	7	7.7
Emotion	28	6	7.4
Recognition	26	9	2.3
Service	24	7	4.7
CCTV	16	6	4.2
Twitter	14	4	6.2
Instagram	13	3	7.3
Mobile	11	4	4.8
Facebook	10	5	3.4
Sad	10	4	4.4
Privacy	10	4	4.4
Perception	10	3	5.6
Floor	9	6	2.4
Dwell	9	5	3.1
Follower	9	3	5.1
Purchase	8	5	2.7
Smile	8	4	3.5
Entrance	7	5	2.4
Trial	7	5	2.4
Interaction	7	4	3.1
Email	6	4	2.6
Feed	6	5	2.1
Happiness	6	5	2.1
Measurable	6	3	3.4
Utilise	6	1	6.2
Weekly	6	2	4.4
Busy	5	3	2.8
Complaint	5	3	2.8
GDPR	5	3	2.8
Honest	5	3	2.8
Incentivise	5	3	2.8
Promotion	5	3	2.8

Table 5: Frequency of the main concepts identified in the interviews.

3.3.2 Results and discussion

In the initial step of the analysis the interviews transcripts were cleaned to cancel potential noise in the results by removing common unrelated terms that participants mentioned during the interviews (e.g., words such as ‘the’, ‘is’ and so on) aiming to increase the validity of the subsequent text mining exercise) (Kobayashi et al., 2016). The analysis identified 36 concepts presented in Table 5 based on the frequency that these terms were mentioned during the discussions. The term frequency–inverse document frequency (TF*IDF) statistic was calculated to indicate the importance of each concept as raised during the discussions by the respondents (Qaiser and Ali, 2018; Pantano and Stylos, 2020). For reasons of brevity, Table 6 provides indicative quotes from the interviews representing the concepts.

Concept	Indicative quote
Busy	“I guess, to us is an ability to undertake large scale video analytics in very busy spaces”
Footfall	“What you also might do is decide that you’re gonna look at people’s reactions and people’s footfall to make decisions on where you might put your prime products, or prime brands”
Incentivise	“And I think actually understanding whether they’re happy, sad or indifferent wouldn’t be as important to us once they’re in the store because they’re in the store and then it’s down to the products, the branding and the staff in there to try and incentivise and encourage them to buy”
Utilise	“You could really monitor your immediate impact if someone walks past your store if you’ve got a really great window display and they stop you know that you’re onto something and you can then utilise that data to say why did that window display work brilliantly”
Sad	“How many of those people walked in again I don’t know if you’d be able to do it, happy, sad, indifferent”
CCTV - Entrance	“As long as it can be delivered without it costing an absolute fortune, as long as it’s got scalability, so, you know, if you are a department store, let’s say, as long as the cost just doesn’t become prohibitive and if you can feed it off existing technology. So, you know, many retailers have internal and entrance CCTV coverage. So, if you could build the solution from an existing technology base, then the only cost is in, really, the software and the analytics. So, it should become commercially viable”
Facial Recognition	“The other thing which we’re looking at from a security point of view is linking into facial recognition”
Emotions – Feelings	“Shopping is really a quest for pleasure and gratification, and it’s largely unmeasured at the moment, other than in a sort of anecdotal and qualitative way. But if it can be made more precise, then I think that could be proved, and that could be measured, one would be able to compare one product with another on a level of gratification which it delivered”
Measurable - Dwell	“Track eye contact [with products] … measure the number of seconds of eye contact”
Privacy - GDPR	“I would also be cautious of the disadvantages I mentioned such as public perception because I think once you start talking about analysing someone’s emotions it could become an intrusion of privacy to certain people”
Honest - Feedback	“In order to capture the responses of customers you’re not relying on self-reported comments, but you see their real reaction, their real-time reaction on things that are on display… eyes don’t lie”
Complaint	“We're always instinctively driven to trying to have a feedback loop to better improve, but there's nothing wrong with merely having another form of customer feedback, which might be an indirect one. As opposed to people actually looking at complaints coming through, a lot of people who are unhappy don’t take the step to actually physically complain. So, it could just be part of the KPI matric, that could be quite a valuable tool”

Table 6: Indicative quotes of the concepts and the potential practical implications emerging from the interviews.

A cluster analysis based on the Jaccard similarity index grouped the concepts which were identified by the initial analysis based on the occurrence of the concepts in the interviews (Shikalgar and Dixit, 2014). The process generated a dendrogram which on the vertical axis has the concepts while the branches on the horizontal axis represent the clusters formed during the procedure (Figure 5). The clusters were respectively labelled: (i) Space Optimization, (ii) Profiling, (iii) Promotions, (iv) Privacy, (v) Shopping Behaviour, (vi) Customer Feedback and (vii) Customer Relationships, leading to the construction of a comprehensive customer emotions analytics practical implications index. The index represents the retail operations that can be enhanced by customer emotions analytics according to the retail professionals who participated in the study.

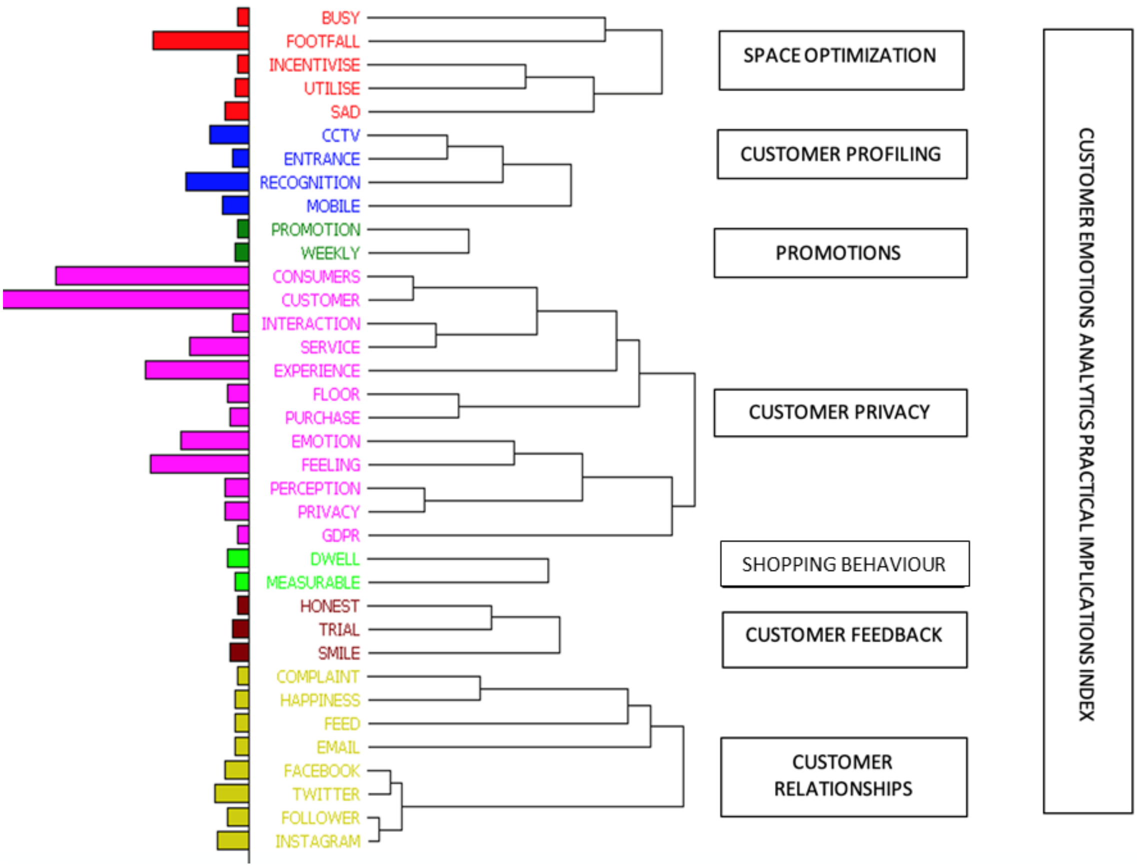

Figure 5: Customer Emotions Analytics Practical Implications Index.

Space Optimization

Space Optimization represents one of the main retail operations that can be facilitated by the classifier machine. According to the respondents, the algorithm can inform the design of a retail space by identifying the busy areas as well as areas in which customers may feel less happy based on their facial expressions. Therefore, the algorithm can facilitate the creation of a heatmap of a retail space and managers can take appropriate action to incentivize customers for a better use of such spaces.

Customer Profiling
Customer profiling is another retail operation that can be informed by the classifier machine as the algorithm can facilitate the identification and tracking of customers within a retail space. An appropriate positioning of a device utilising the algorithm at the entrance of a retail space (e.g., CCTV) can be used in order to evaluate customers' perceptions of a particular retail space or service (i.e., in front of the automatic cash desks or fitting rooms). This can provide a clearer picture to retailers about specific demographic characteristics of the customers such as gender and age as well as information about their emotions. Therefore, retailers can segment customers emotional reactions based on their demographic characteristics.
Shopping Behaviour
Shopping Behaviour research is a retail operation that can also benefit from the utilization of the classifier machine. The algorithm can be used to measure the dwell time as customers can be traced when they enter and leave a retail space and retailers can take appropriate actions to increase the time and subsequently the money that customers spent.
Promotions
The ability of the classifier machine to identify customers' emotions utilised in real time can inform the promotional strategy of a retailer. The information regarding customers' emotions can be used to trigger weekly promotions that may change customers emotional responses in times of the week which perhaps customers are less happy.
Customer Feedback
The classifier machine can also facilitate another major retail operation, namely the collection of customer feedback. The algorithm has the ability to collect spontaneous, unsolicited feedback about products or retail installations by capturing customers' emotional responses when they are exposed to them. Therefore, retailers do not need to rely on (possibly biased) self-reported questionnaires for the collection of this information. For example, a camera could be installed in an area where a product is sampled in order to assess the emotional response of the customers to a new product.
Customer Relationships
Customer relationships management is an additional retail operation that can be facilitated by the classifier machine. By using images that customers who follow retailers on social media such as Facebook, Twitter and Instagram upload on these platforms, retailers can assess their emotional reactions, which could help with addressing customers' complaints or enhancing communications with customers via asocial media or emails.
Customer Privacy
The utilisation of such classifier machines within retail spaces also highlights the need for careful design of retailer operations to protect customer privacy in general and address customers' perceptions of their privacy in particular. The discussions with the retail professionals revealed that protections of customer privacy should be at the core of any operation developed to facilitate interactions with customers aiming to enhance their experiences in the retail space, to collect information regarding their behaviour (e.g., purchases) or their attitudes towards a retailer. This issue has recently become very important with the introduction of related legislation such as the General Data Protection Regulation (known as GDPR) which has modernized laws across Europe that protect the personal information of individuals, was introduced into the EU in 2018 and remaining in UK law after Brexit.

Follow-up Interviews
The results were further discussed in follow-up interviews with three respondents aiming to increase validity. During the follow-up interviews, respondents highlighted the important role of the system in enabling retailers collecting information regarding the emotional response of customers to their shopping experience. Specifically, respondents highlighted the role of the emotional response of the customers based on the time spent in store as well as the areas of the store which are of particular interest for customers. This facilitates the better understanding of the information on how customers utilise the retail space which facilitates retailers' planning. Of particular importance for retailers was the implications on customer privacy and the compliance with the respective legislation.

4. Conclusion
4.1 Academic contribution
Building on the importance of emotion in strategic management research (Daniels, 1998; Goss, 2008; Lewis, 2008; Delgado-Garcia et al., 2010), with emphasis on the importance for managers of understanding consumers emotional responses to certain organizational behaviors (i.e., service failure, reputation, green campaigns, etc.) (Schoefer and Diamantopoulos, 2009; Walsh et al., 2016; Kohli et al., 2021), this study elaborates the importance of evaluating and managing emotions with new metrics that particular stakeholders (customers) might feel when interacting with the retail organization. Specifically, our research aims to explore the match between the supply of new analytical tools and retailers' demand for new tools to capture customers' emotions. In doing so, our study developed an exemplar system to examine particular kinds of visual information emerging from customers' generated images such as emotion identification as a result of facial recognition applications. Our findings reveal that the analysis of affective, emotional responses can be made more objective by avoiding the potential bias of self-reported behaviour. Indeed, our system can more accurately measure desired outcomes by using information produced by spontaneous reactions of customers. Our study can also access hedonic responses expressed as emotional reactions by using visual cues rather than cognitive cues such as text. This approach is more consistent in comparison with previous studies that have analysed large data sets of text in pursuit of the same outcome (Sheng et al., 2019; Srivastava and Kalro, 2019). Our findings confirm that emotion detection technology might help managers to understand customers' emotional states in retail settings, by synthetizing the nature of consumption experiences, and reply accordingly to improve retail service. In this way, this study responds to the recent calls for research into the role of new forms of analytics able to better support organizations to respond quickly to environmental changes (Sena et al. 2017; Sheng et al., 2019), with new emotional analytics.
The two studies also highlight the important wedge between the role of technology in understanding customers' emotion as tool to evaluate their experience, and effective managers preparedness to embrace this kind of technology. It is important to contrast the happiness/sadness emerging from the experience with retailers' abilities to react to positive/negative emotions to avoid backfire effects.
Despite a number of studies soliciting the adoption of new tools to measure customers' responses and their dramatic changes in marketing retail management (e.g., Ahani et al., 2019; Bradlow et al., 2017; Kuhl et al., 2020; Matz et al., 2019; Pantano and Stylos, 2020; Peng et al., 2019; Srivastava and Kalro, 2019; Villarroel et al., 2019), our findings suggest that retailers still experience reservations on adopting this kind of system. However, the involvement of retailers demonstrates the potential managerial implications of the adoption of such tools in

terms of (i) (retail) space, (ii) (customers') profiling, (iii) promotions, (iv) (risks to) customers privacy, (v) shopping behaviour, (vi) customers' feedback and (vii) customer relationships (see Figure 3). Thus, this research also emphasises the importance for managers of a rapid understanding of consumers' emotions, which would result in competitive advantages.

However, one of the main disadvantages identified by retailers regarding the use of images to analyse customers' emotions concerns privacy, in particular after the introduction of tighter restrictions in Europe and the UK (GDPR) and reinforced by the Centre for Data Ethics and Innovation in the UK that highlight similar concerns. Hence, our study builds on a stream of literature focusing on customer privacy (Batistic and van der Laken, 2019; Aiello et al., 2020; Hilken et al., 2017; Martin and Palmatier, 2020), by highlighting the need for retailers to consider this aspect in their operations, and by suggesting that data privacy initiatives should be proactively incorporated into retail strategies. Our study suggests that by taking the necessary actions to protect customer privacy when incorporating face recognition systems in strategies, retailers can gain important information that can shed light on the overall customer journey building upon relevant calls in past literature (Martin and Palmatier, 2020). Indeed, our work also contributes to the current discussion on data privacy by introducing an additional dimension, i.e., data privacy issues related to information about customer emotional responses in stores as past research on customer privacy focuses on information related to transactional data that organisations collect during purchases.

4.2 Implications for retail managers

From a practical point of view, our system automatically distinguishes consumers' positive/negative emotions from face detection, without the need for tedious, potentially biased, human input. Results should be more realistic than those obtained through simulations, self-reported or after-the-event questionnaires. Our findings suggest important implications for retailers who can implement emotion analytics in their management strategy, as outlined in the framework in Figure 6.

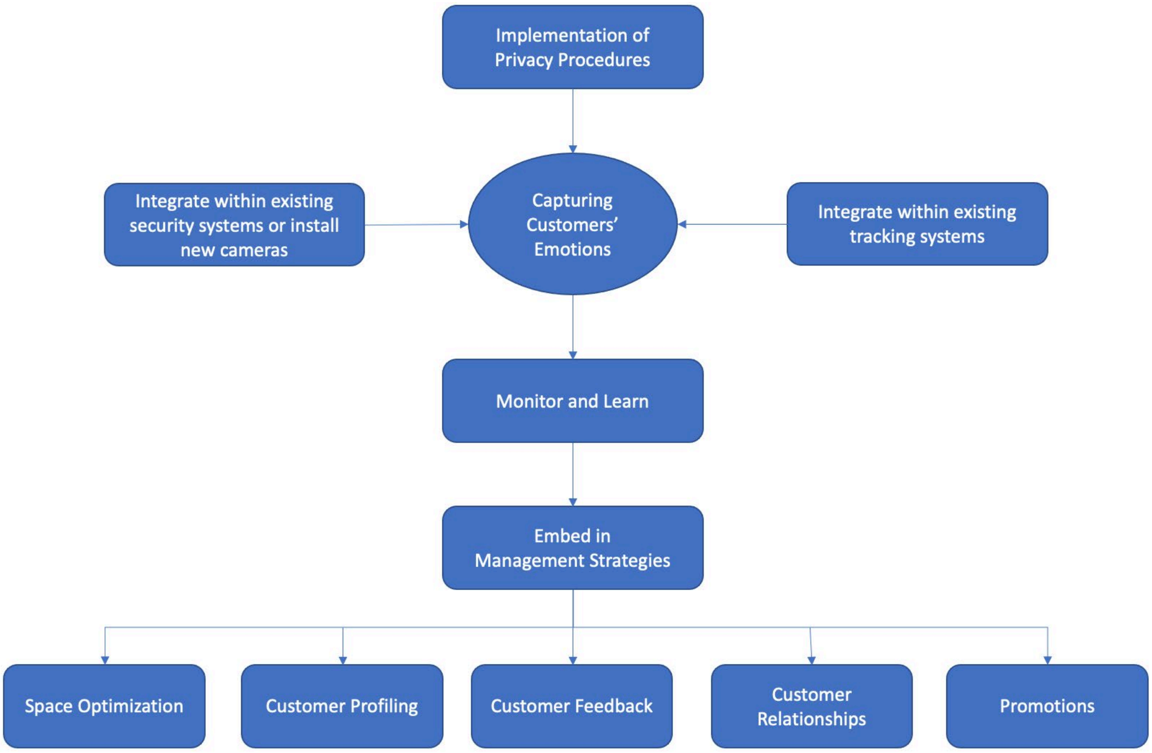

Figure 6: Implementation process for retailers: a new framework to integrate consumers' emotional analytics.

Specifically, the system for emotion analytics should be integrated with existing security systems and tracking systems, and privacy procedures. In other words, to address the 'Privacy' cluster and concerns, retailers should not retain individuals' data from emotion tracking, as retaining such data could be construed as retaining customers' personal information. Rather, the algorithms utilized should, as in the case demonstrated in this paper, measure only limited dimensions of facial characteristics that are not identifiable as an individual. These should be aggregated in real time rather than stored, so that the data stored contains only the probability of customers in the specific context having the specific emotional state, rather than data concerning any specific individual(s). Similarly, Current systems are available that capture data on customer characteristics. For example, some digital signage installations contain a system cam, as with the emotion-recognition system explored in this paper, measure limited dimensions of facial characteristics, which are used to predict the likelihood of the viewer being a particular gender, ethnicity, and age range. Similar to our suggestions for emotion recognition, the system does not store data on any specific individuals. We therefore propose that retailers can amend the algorithms of such systems to include emotion recognition in the analysis and output. To this end, managers can integrate and combine a suitable processor with the existing internal security or customer tracking cameras, these could be used to gather and aggregate data on customer emotions. Indeed, as customers are familiar with being observed by security cameras, custom 'cameras' can be placed around the store. These can be placed at specific locations for testing the efficacy of experimental shopping environment tactics such as décor, lighting, colour, aroma, or music. Some retailers have custom 'cameras' around the store to measure footfall and dwell time in specific areas, which may be similarly utilizable.
Results from emotion analytics would help retailers to monitor consumers' variations in emotions (from happy to sad and vice versa) and understand (learn) the specific circumstances

leading to these changes. This process should help define the strategies able to get more "happy customers". Finally, this process will result in better 'Space Optimisation'. Indeed, the data produced could inform marketing communications such as social media campaigns. For example, communications could play up merchandise categories, linking to positive emotions, or alternatively, help to address and ameliorate negative emotions, related to the 'Promotion' and 'Customer Relationships'. Also, measuring customers' (aggregate) positive and negative emotions at specific parts of the store/atmospheric experiences or to specific merchandise provides objective, unsolicited 'Customer Feedback'.

All of the above data-gathering suggestions could be extended to gather aggregate information on customer characteristics such as age, gender, and ethnicity, associated with the 'Profiling' cluster.

5. Limitations and suggestions for future research

Our study proposes just one system as example of how to take into consideration two emotions out of the six fundamental ones identified by Eckmann and Friesen (1975, 1978) as happiness, sadness, disgust, surprise, fear, and anger. Future studies might focus on the development of new machine learning algorithms for the identification of a larger spectrum of emotions, in order to provide more detailed insights to support retailers. Similarly, future studies might consider neuromarketing and neuroscience approaches to understand what stimuli lead to certain emotions, by analysing the cognitive process inside human brain driving a certain facial expression. Also, other forms of non-verbal communications as gesture and body language might be considered, and triangulated with verbal communications as consumers' ratings and rankings of a specific experience. Moreover, our system works only with static images, measuring a certain emotion in a specific moment of the shopping experience. Future studies might improve our systems in order to consider more images to show the changes in the facial expressions and provide a more comprehensive overview of the full shopping experience.

Our research extracted customers' emotions from facial expressions from pictures posted voluntarily online, thus it limits the analysis in this paper to only conscious emotional consumers' responses. However, the real-time access to non-conscious emotional response can link in to the retailer's internal cameras system (e.g., CCTV or customer tracking) or ad hoc cameras located in certain areas of the store (e.g., on the storefront window, or in front of the cash desks, etc.). Future studies might embrace the emerging privacy issues, and understand under what circumstances customers would be willing to accept this kind of data collection, and if the usage of this data collection would change consumers' attachment to the retailer.

Finally, our study does not distinguish retailer managers in different subsectors; future studies might explore the extent to which retailers' willingness to adopt certain systems might vary according to the specific subsectors (i.e., luxury, grocery, etc.).

References

Adam, M. T. P., Krämer, J., and Weinhardt, C. (2012). 'Excitement up! price down! Measuring emotions in Dutch auctions', International Journal of Electronic Commerce, 17(2), pp. 7-40.

Ahani, A., Nilashi, M., Ibrahim, O., Sanzogni, L. and Weaven, S. (2019). 'Market segmentation and travel choice prediction in Spa hotels through TripAdvisor online reviews', International Journal of Hospitality Management, 80, pp. 52-77.

Aiello, G., Donvito, R., Acuti, D., Grazzini, L., Mazzoli, V., Vannucci, V., and Viglia, G. (2020). 'Customers' willingness to disclose personal information throughout the customer purchase journey in retailing: the role of perceived warmth', Journal of Retailing, 96(4), pp. 490-506.

Ainsworth, J., and Ballantine, P. W. (2014). 'That's different! How consumers respond to retail website change', Journal of Retailing and Consumer Services, 21, pp. 764–772.

Alpert, M.I., Alpert, J.I., and Maltz, E.N. (2005). 'Purchase occasion influence on the role of music in advertising', Journal of Business Research, 58(3), pp. 369-376.

Bagdare, S., and Jain, R. (2013). 'Measuring retail customer experience', International Journal of Retail & Distribution Management, 41(10), pp. 790-804.

Bagozzi, R. P., Gopinath, M., & Nyer, P. U. (1999). 'The role of emotions in marketing', Journal of the Academy of Marketing Science, 27(2), 184-206.

Balducci, B., and Marinova, D. (2018). 'Unstructured data in marketing,' Journal of the Academy of Marketing Science, 45(4), pp. 557-590.

Bastiaansen, M., Lub, X.D., Mitas, O., Jung, T.H., Ascencao, M.P., Han, D.-I., Moilanen, T., Smit, B. and Strijbosch, W. (2019). 'Emotions as core building blocks of an experience', International Journal of Contemporary Hospitality Management, 31(2), pp. 651-668.

Batistic, S., and van der Laken, P. (2019). 'History, evolution and future of big data and analytics: A bibliometric analysis of its relationship to performance in organizations', British Journal of Management, 30, pp. 229-251.

Bertacchini, F., Bilotta, F., and Pantano, P. (2017). 'Shopping with a robotic companion', Computers in Human Behavior, 77, pp. 382-395.

Borges, A., Herter, M. M., and Chebat, J. C. (2015). 'It was not that long!": The effects of the in-store TV screen content and consumers emotions on consumer waiting perception', Journal of Retailing and Consumer Services, 22, pp. 96-106.

Bradlow, E. T., Gangwar, M., Kopalle, P., and Voleti, S. (2017). 'The role of big data and predictive analytics in retailing', Journal of Retailing, 93(1), pp. 79-95.

Brakus, J.J., Schmitt, B.H., and Zarantonello, L. (2019). 'Brand experience: what is it? How is it measured? Does it affect loyalty?', Journal of Marketing, 73, pp. 52-68.

Bustamante, J. C., and Rubio, N. (2017). 'Measuring customer experience in physical retail environments', Journal of Service Management, 28(5), pp. 884-913.

Calvard, T. S. (2016). 'Big data, organizational learning, and sensemaking: Theorizing interpretive challenges under conditions of dynamic complexity', Management Learning, 47(1), pp. 65-82.

Canhoto, A. I., and Clear, F. (2020). 'Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential', Business Horizons, 63, pp. 183-193.

Caruelle, D., Gustafsson, A., Shams, P., and Lervik-Olsen, L. (2019). 'The use of electrodermal activity (EDA) measurement to understand consumer emotions – A literature review and a call for action', Journal of Business Research, 104, pp. 146-160.

Cho, J. Y., and Lee, E. J. (2017). 'Impact of interior colors in retail store atmosphere on consumers' perceived store luxury, emotions, and preference', Clothing and Textiles Research Journal, 35(1), pp. 33-48.
Chou, T.-J., Chang, E.-C., Zheng, Y., and Tang, X. (2016). 'What makes consumers believe: the impacts of priming and sequential service experiences on consumer emotions and willingness to pay', Journal of Services Marketing, 30(1), pp. 115-127.
Clark, E. A., Kessinger, J., Duncan, S. E., Ann Bell, M., Lahne, J., Gallagher, D. L., and O'Keefe, S. F. (2020). 'The facial action coding system for characterization of human affective response to consumer product-based stimuli: A systematic review', Frontiers in Psychology. Frontiers Media S.A. https://doi.org/10.3389/fpsyg.2020.00920
Daniels, K. (1998). 'Towards integrating emotions into strategic management research: trait affect and perceptions of the strategic environment', British Journal of Management, 9, pp.163-168.
Das, G. and Varshneya, G. (2017). 'Consumer emotions: determinants and outcomes in a shopping mall', Journal of Retailing and Consumer Services, 38, pp. 177-185.
Datta, S., Misra, D. and Das, S. (2016). 'A feature weighted penalty based dissimilarity measure for k-nearest neighbor classification with missing features', Pattern Recognition Letters, 80, pp. 231-237.
Delgado-Garcia, J.B., De La Fuente-Sabaté, J.M. and De Quevedo-Puente, E. (2010). 'Too negative to take risks? The effect of the CEO's emotional traits on firm risk', British Journal of Management, 21(2), pp. 313-326.
Dennis, C., Bourlakis, M., Alamanos, E., Papagiannidis, S. and Brakus, J.J. (2017). 'Value co-creation through multiple shopping channels: the interconnections with social exclusion and well-being', International Journal of Electronic Commerce, 21(4), pp. 517-547.
Dennis, C., Brakus, J.J., Gupta, S. and Alamanos, E. (2014). 'The effect of digital signage on shoppers' behavior: the role of the evoked experience', Journal of Business Research, 67, pp. 2250-2257.
De Nisco, A., and Warnaby, G. (2014). 'Urban design and tenant variety influences on consumers' emotions and approach behavior', Journal of Business Research, 67, pp. 211-217.
Ekman, P. (1992). 'An argument for basic emotions', Cognition & Emotion, 6(3-4), pp. 169-200.
Eckman, P. (2003). 'Darwin, deception, and facial expression', Annals of the New York Academy of Sciences, 1000, pp. 205-221.
Eckman, P. and Friesen, W. (1975). Unmasking the Face: A Guide to Recognizing Emotions from Facial Clues. Englewood Cliffs, NJ: Prentice Hall.
Eckman, P. and Friesen, W.V. *Facial Action Coding System (FACS): A Technique for The Measurement of Facial Action*. Palo Alto, CA: Consulting Psychologists Press (1978).
Eckman, P. and Rosenberg, E.L. (1997). What the Face reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System. New York, NY: Oxford University Press.
Evanschitzky, H., and Goergen, M. (2018). 'Looking forward, looking back: British Journal of Management 2000-2015', British Journal of Management, 29(1), pp. 3-9.
Fredrickson, B. L. (2000). 'Extracting meaning from past affective experiences: the importance of peaks, ends, and specific emotions', Cognition and Emotion, 14(4), pp. 577-606.
Fredrickson, B. L., and Losada, M. F. (2005). 'Positive affect and the complex dynamics of human flourishing',.American Psychologist, 60(7), pp. 678-686.

Fuentes, C., Hagberg, J. and Kjellberg, H. (2019). ‘Soundtracking: music listening practices in the digital age’, European Journal of Marketing, 53(3), pp. 483-503.
Gaur, S.S., Herjanto, H. and Makkar, M. (2014). ‘Review of emotions research in marketing, 2002–2013’, Journal of Retailing and Consumer Services, 21, pp. 917-923.
Goldsmith, K., Cho, E.K. and Dhar, R. (2012). ‘When guilt begets pleasure: the positive effect of a negative emotion’, Journal of Marketing Research, 49(6), pp. 872-881.
Goossens, C. (2000). ‘Tourism information and pleasure motivation’, Annuals of Tourism Research, 27(2), pp. 301-321.
Goss, D. (2008). ‘Enterprise ritual: a theory of entrepreneurial emotion and exchange’, British Journal of Management, 19(2), pp. 120-137.
Grewal, D., Noble, S.M., Roggeveen, A.L., and Nordfalt, J. (2020). ‘The future of in-store technology’, Journal of the Academy of Marketing Science, 48, pp.96-113.
Hajli, N., Shirazi, F., Tajvidi, M., and Huda, N. (2021). ‘Towards an understanding of privacy management architecture in big data: An experimental research’, British Journal of Management, 32, pp. 548-565.
Hasford, J., Hardesty, D.M. and Kidwell, B. (2015). ‘More than a feeling: emotional contagion effects in persuasive communication’, Journal of Marketing Research, 52(6), pp. 836-847.
Hennig-Thurau, T., Groth, M., Paul, M. and Gremler, D.D. (2006). ‘Are all smiles created equal? How emotional contagion and emotional labor affect service relationships’, Journal of Marketing, 70(3), pp. 58-73.
Humphreys, A. (2010). ‘Semiotic structure and the legitimation of consumption practices: The Case of Casino Gambling’, Journal of Consumer Research, 37(3), pp. 490–510.
Humphreys, A. and Wang, R. J.-H. (2017). ‘Automated Text Analysis for Consumer Research’, Journal of Consumer Research, 44(6), pp. 1274–1306.
Inman, J.J. and Nikolova, H. (2017). ‘Shopper-facing retail technology: a retailer adoption decision framework incorporating shopper attitudes and privacy concerns’, Journal of Retailing, 93(1), pp. 7-28.
Isaac, R. K., and Budryte-Ausiejiene, L. (2015). ‘Interpreting the emotions of visitors: a study of visitor comment books at the Grūtas park museum, Lithuania’, Scandinavian Journal of Hospitality and Tourism, 15(4), pp. 400-424.
Kidwell, B., Lopez-Kidwell, V., Blocker, C. and Mas, E.M. (2020). ‘Birds of a feather feel together: Emotional ability similarity in consumer interactions’, Journal of Consumer Research, 47, pp. 215-236.
Kim, H. and Stepchenkova, S. (2015). ‘Effect of tourist photographs on attitudes towards destination: manifest and latent content’, Tourism Management, 49, pp. 29-41.
Kim, J., and Fesenmaier, D. R. (2015). ‘Measuring emotions in real time: Implications for tourism experience design’, Journal of Travel Research, 54(4), pp. 419-429.
Kobayashi, V., Mol, S. T., Berkers, H. A., Kismihok, G., and Den Hartog, D. N. (2018). ‘Text mining in organizational research’, Organizational Research Methods, 21(3), pp. 733-765
Kohler, C. G., Turner, T., Stolar, N. M., Bilker, W. B., Brensinger, C. M., Gur, R. E. and Gur, R.C. (2004). ‘Differences in facial expressions of four universal emotions’, Psychiatry Research, 128(3), pp. 235-244.
Kohli, G.S., Yen, D., Alwi, S. and Gupta, S. (2021). ‘Film or film brand? UK consumers’ engagement with films as brands’, British Journal of Management, 32(2), pp. 369-398.
KPMG (2018). ‘Annual Retail Survey 2018’. Retrieved March 23, 2020, from kpmg.com/uk/retailsurvey2018.

Kranzbühler, A.M., Zerres, A., Kleijnen, M.H.P. and Verlegh, P.W.J. (2020). ‘Beyond valence: a meta-analysis of discrete emotions in firm-customer encounters’, Journal of the Academy of Marketing Science, 48, pp. 478-498.
Kuhl, N. Muhlthaler, M. and Goutier, M. (2020). ‘Supporting customer-oriented marketing with artificial intelligence: automatically quantifying customer needs from social media’, *Electronic Markets*, 30, pp. 351-367.
Laros, F. J. M., and Steenkamp, J. B. E. M. (2005). ‘Emotions in consumer behavior: a hierarchical approach’, Journal of Business Research, 58, pp. 1437-1445.
Lewis, P. (2008). ‘Emotion work and emotion space: using a spatial perspective to explore the challenging of masculine emotion management practices’, British Joula of Management, 19 pp. S130-S140.
Li, Y. and Xie, Y. (2020). ‘Is a picture worth a thousand words? An empirical study of image content and social media engagement’, Journal of Marketing Research, 57(1), pp. 1-19.
Longoni, A. and Cagliano, R. (2018). ‘Sustainable innovativeness and the triple bottom line: The role of organizational time perspective’, Journal of Business Ethics, 151, pp. 1097-1120.
Machleit, K. A., and Eroglu, S. A. (2000). ‘Describing and measuring emotional response to shopping experience’, Journal of Business Research, 49, pp. 101-111.
Magids, S., Zorfas, A., and Leemon, D. (2015). ‘The new science of customer emotions’, Harvard Business Review*,* 76, pp. 66-74.
Malone, S., McCabe, S., and Smith, A. P. (2014). ‘The role of hedonism in ethical tourism’, Annals of Tourism Research, 44, pp. 241-254.
Marci, C. and Murray, B. (2017). ‘Emotions’. In Cerf M. & Garcia-Garcia M. (eds), Consumer Neuroscience, pp. 151-176. The MIT Press.
Martin, K.D. and Palmatier, R.W. (2020). ‘Data privacy in retail: Navigating tensions and directing future research’, Journal of Retailing, 96(4), pp. 449-457.
Mattila, A.S. and Enz, C.A. (2002). ‘The role of emotions in service encounters’, Journal of Service Research, 4(4), pp. 268-277.
Matz, S.C., Segalin, C., Stillwell, D., Muller, S.R. and Bos, M.W. (2019). ‘Predicting the Personal Appeal of Marketing Images Using Computational Methods’, Journal of Consumer Psychology, 29(3), pp. 370-390.
Mende, M., Scott, M.L., van Doorn, J., Grewal, D. and Shanks, I. (2019). ‘Service robots rising: how humanoid robots influence service experiences and elicit compensatory consumer responses’, Journal of Marketing Research, 56(4), pp. 535-556.
Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019). ‘Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment’, British Journal of Management, 30(2), pp. 272-298.
Pantano, E. and Gandini, A. (2018). ‘Shopping as a “networked experience”: an emerging framework in the retail industry’, International Journal of Retail & Distribution Management, 46 (7), pp. 690-704.
Pantano, E., Giglio, S. and Dennis, C. (2019). ‘Making sense of consumers’ tweets: Sentiment outcomes for fast fashion retailers through Big Data analytics’, International Journal of Retail & Distribution Management, 47(9), pp. 915-927.
Pantano, E., Priporas, C.V. and Stylos, N. ‘You will like it!’ (2017). ‘Using open data to predict tourists’ response to a tourist attraction’, Tourism Management, 60, pp. 430-438.
Pantano, E. and Stylos, N. (2020). ‘The “Cinderella” moment: exploring consumer’ motivations to engage with renting as collaborative luxury consumption mode’, Psychology and Marketing, 37(5), pp. 740-753.

Pappas, I.O., Kourouthanassis, P.E., Giannakos M.N. and Chrissikopoulos, V. (2017). 'Sense and sensibility in personalized e-commerce: How emotions rebalance the purchase intentions of persuaded customers', Psychology & Marketing, 34(10), pp. 972-986
Paschen, U., Pitt, C., and Kietzmann, J. (2020). 'Artificial intelligence: Building blocks and an innovation typology'. Business Horizons, 63, pp. 147-155.
Peng, L., Cui, G., Chung, Y., and Li, C. (2019). 'A multi-facet item response theory approach to improve customer satisfaction using online product ratings', *Journal of the Academy of Marketing Science*, 47, pp. 960-976.

Popa, M. C., Rothkrantzy, L. J. M., Wiggers, P. and Shan, C. (2017). 'Assessment of facial expressions in product appreciation', *Neural Network World,* 27(2), pp. 197-213.
Qaiser, S. and Ali, R. (2018). 'Text mining: Use of tf-idf to examine the relevance of words to documents', International Journal of Computer Applications, 181(1), pp. 25-29.
Rand, W., Rust, R.T. and Kim, M. (2018). 'Complex systems: marketing's new frontier', AMS Review, 8, pp. 111-127.
Reynolds-McIlnay, R., Morrin, M. and Nordfält, J. (2017). 'How product-environment brightness contrast and product disarray impact consumer choice in retail environments', Journal of Retailing, 93(3), pp. 266-282.
Richins, M. L. (1997). 'Measuring emotions in the consumption experience', Journal of Consumer Research, 24, pp. 127–46.
Rick, S.I., Pereira, B. and Burson, K.A. (2014). 'The benefits of retail therapy: Making purchase decisions reduces residual sadness', Journal of Consumer Psychology, 24(3), pp. 373-380.
Rowley, J. (2012). 'Conducting research interviews', Management Research Review, 35(3/4), pp. 260-271.
Schoefer, K. and Diamantopoulos, A. (2009). 'A typology of consumers' emotional response styles during service recovery encounters', British Journal of Management, 20(3), pp. 292-308.
Sena, V., M. Demirbag, S Bhaumik and A. Sengupta (2017). 'British Journal of Management Special Issue 2019 – Call for Papers: Big Data and Performance', British Journal of Management, 28 (3), pp. 551–553.
Shankar, V. (2018). 'How artificial intelligence (AI) is reshaping retailing', Journal of Retailing, 94, pp. vi-xi.
Sheng, J., Amankwah-Amoah, J., Wang, X. and Khan, Z. (2019). 'Managerial responses to online reviews: a text analytics approach', British Journal of Management, 30(2), pp. 315-327.
Sherman, E., Mathur, A. and Smith, R.B. (1997). 'Store environment and consumer purchase behavior: mediating role of consumer emotions', Psychology and Marketing, 14(4), pp. 361-378.
Shikalbar, N. R. and Dixit, A. M. (2014). 'JIBCA Jaccard index based clustering algorithm for mining online review', International Journal of Computer Applications, 105(15), pp. 23-28.
Shrestha, Y. R., Krishna, V., and von Krogh, G. (2021). 'Augmenting organizational decision-making with deep learning algorithms: Principles, promises, and challenges', Journal of Business Research, 123, pp. 588-603.
Srivastava, V. and Kalro, A. D. (2019). 'Enhancing the helpfulness of online customer reviews: The role of latent (content) factors', Journal of Interactive Marketing, 48, pp. 33-50.
Teixeira, T., Picard, R., and el Kaliouby, R. (2014). 'Why, when, and how much to entertain consumers in advertisements? A web-based facial tracking field study', Marketing Science, 33(6), pp. 809–827.

The Guardian (2018a). ‘Embattled high street retailers call for help as closures soar’. Retrieved March 20, 2020, from https://www.theguardian.com/business/2018/nov/09/embattled-high-street-retailers-call-for-help-as-closures-soar.
The Guardian (2018b). ‘No end in sight to UK high street retailers’ troubles: shops and restaurants face a tough 2019, with the malaise of failing sales spreading online’. Retrieved March 20, 2020, from https://www.theguardian.com/business/2018/dec/28/no-end-in-sight-to-uk-high-street-retailers-troubles.
Vannucci, V. and Pantano, E. (2019). ‘Digital or human touchpoints? Insights from consumer-facing in-store services’, Information Technology and People, 33(1), pp. 296-310.
Vermeer, S.A.M., Araujo T., Bernritter, S.F. and van Noort G. (2019). ‘Seeing the wood for the trees: how machine learning can help firms in identifying relevant electronic word-of-mouth in social media’, International Journal of Research in Marketing, 36(3), pp. 492-508.
Villarroel Ordenes, F., Ludwig, S., Grewal, D. and Wetzels, M. (2017). ‘Unveiling what is written in the stars: analysing explicit, implicit, and discourse patterns of sentiment in social media’, Journal of Consumer Research, 43, pp. 875-894.
Villarroel Ordenes, F., Grewal, D., Ludwig, S., De Ruyter, K., Mahar, D. and Wetzels, M. (2019). ‘Cutting through content clutter: how speech and image acts drive consumer sharing of social media brand messages’, Journal of Consumer Research, 45, pp. 988-1012.
Walsh, G., Albrecht, A.K., Kunz, W. and Hofacker, C.F. (2016). ‘Relationship between online retailers’ reputation and product returns’, British Journal of Management, 27, pp. 3-20.
Wang, E. S. T. (2009). ‘Displayed emotions to patronage intention: consumer response to contact personnel performance’, The Service Industries Journal, 29(3), p. 317-329.
Willems, K., Smolders, A., Brengman, M., Luyten, K. and Schöning, J. (2017). ‘The path-to-purchase is paved with digital opportunities: An inventory of shopper-oriented retail technologies’, Technological Forecasting and Social Change, 124, pp. 228-242.
Yu, C. Y., and Ko, C. H. (2017). ‘Applying FaceReader to recognize consumer emotions in graphic styles’, Procedia CIRP 60, pp. 104-109.