V2P1-6. Approaches to emotion and sentiment analysis.

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1. Introduction

Emotions are central to how consumers respond to marketing stimuli, and how they go on to behave[1], both in the physical and the online environments. For instance, research has shown that warm physical environments elicit positive emotions and that these, in turn, increase customers' valuation of products (Zwebner et al., 2013); and that when Facebook users were exposed to posts that reflected a negative emotion, they were likely to go on to post content of a negative emotion, and that the opposite happened for positively charged posts (Kramer et al., 2014). In addition, exposure to emotionally charged content online can also have impact on the offline world, as demonstrated by Bigne et al (2018)'s analysis of the impact of social media reviews on purchase of low-cost airline tickets. Not only do emotions shape consumer behaviour online and offline, but messages with high emotional content (e.g., anger) spread quickly and widely, triggering emotional responses in others, and driving further sharing behaviour (Berger & Milkman 2012).

Given the importance of emotions in the outcome of marketing initiatives, and the ubiquity of digital and social media in everyday life, marketing scholars as well as marketing practitioners are interested in identifying and analysing online displays of consumers' emotions. This includes ad-hoc expressions of emotion, such as in social media conversations, as well as purposeful ones, such as crowd-sourced customer review platforms. The analysis of sentiment displayed in online content can assist marketers in anticipating consumer behaviour and, where pertinent, take remedial action. The latter goal is particularly relevant in the case of brewing social media crises, as these can have significant short, as well as long, terms effects on the brands at the centre of those conversations (Hansen et al, 2018).

This chapter outlines techniques for studying sentiment online, and is organised as follows. In the next section, we briefly clarify what we mean by sentiment analysis, and how it differs from the study of emotions more generally. Subsequently, we review the techniques for identifying and collecting sentiment data, at scale, in the digital environment. We illustrate their application in different marketing areas, and discuss their relative advantages and disadvantages. Then, in the following section, we turn our attention to techniques for analysing

[1] For a detailed discussion of the role of emotions on consumer behaviour, see Loewenstein & Lerner, 2003

digital sentiment data, in order to detect the sentiment valence and arousal level. We also consider the use of technological tools to process and classify digital sentiment data. Namely, we discuss how software can assist in processing the large volumes of data available online, depending on the goal of the analysis. This chapter concludes with a discussion of the challenges of conducting sentiment analysis, both those related to the study of sentiment per se, and those related to the use of technology to automate the analysis process.

2. Studying emotions vs. studying sentiment

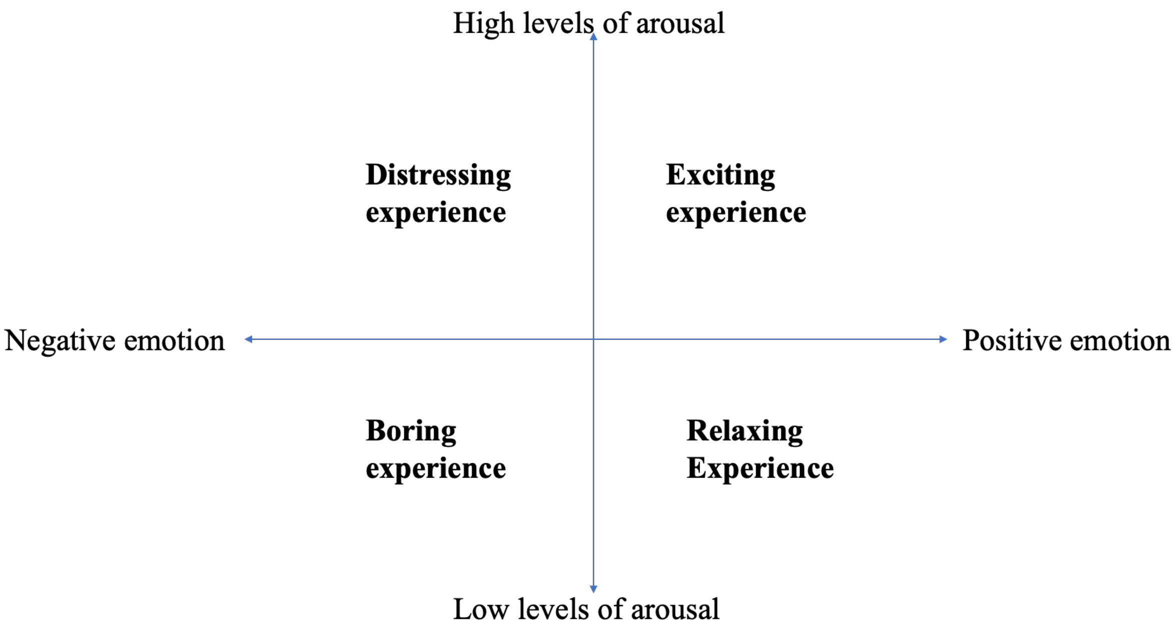
Although the terms "emotion" and "sentiment" are often used interchangeably, they actually refer to different psychological phenomena. The former is a socio-cultural expression of feelings, which occurs at the preconscious level, may be abstract and is fleeting in nature (Ullah et al 2016). In contrast, the latter is an emotional disposition, which occurs at the conscious level, is directed at an object, and develops over time (Ullah et al 2016). Zwebner et al's (2013) study of the effect of temperature on consumer behaviour, mentioned in the introductory section, focused on the abstract emotions elicited by warmth; while Bigne et al (2018)'s work, also mentioned in the introduction, considered the verbalised assessments made by customers of their experiences with specific airlines and was, therefore, focusing on sentiments.

But what exactly are we talking about when we talk about emotion or sentiment analysis?

By and large, most studies of consumers' emotion or sentiment focus simply on measuring the valence of the feelings – i.e., whether customers feel mostly positively or negatively (Kranzbühler et al 2020). However, focusing on valence, only, will offer an incomplete understanding of the observed behaviour. For instance, Gelbrich (2010) showed that customers complained when an experience resulted in negatively valanced emotions of anger, but not when it resulted in frustration and helplessness, which are also negative emotions. Conversely, Grappi and colleagues (2015) found that willingness to pay increases with the positively valanced emotion of gratitude, but not with happiness which, too, is a positive emotion. As these examples show, when studying emotions and sentiments, we should pursue a fine-grained understanding of customers, which goes beyond the valence (Rocklage et al, 2021).

As demonstrated by the seminal work of Russell (2003), customer behaviour is influenced not only by whether customers are pleased or displeased, but also how strong that emotion or sentiment are (referred to as "arousal level"). Namely, positive emotions and sentiments with high levels of arousal result in exciting experiences; whereas positive emotions and sentiments with low level of arousal result in relaxing ones. In turn, negative emotions and sentiments with high levels of arousal result in distressing experiences; while negative emotions and sentiments, with low level of arousal, lead to boring ones. See Figure 1.

Figure 1. Typology of consumer responses to emotionally charged events



In summary, emotion analysis provides researchers with a measure of the abstract, fleeting feelings that customers may experience as a result of marketing efforts; while sentiment analysis provides researchers with a measure of the specific, sustained emotional disposition towards a product, event or phenomenon (e.g., vaccination). However, for a complete understanding of consumer behaviour, we should go beyond valence, and also seek to identify whether the emotion or sentiment are active or passive (i.e., high or low arousal levels) and, if possible, the specific emotion or sentiment experienced by customers (Laros & Steenkamp 2005).

3. Collecting emotion and sentiment data

There are, broadly speaking, three approaches to collecting emotion and sentiment data online: 1) asking customers about emotionally charged episodes that they experienced in the past, via online interviews or questionnaires; 2) placing customers in emotionally charged situations via online experiments; or 3) observing customers when they experience an emotionally charged incident via online conversations. Each approach has its merits and limitations, as summarised in Table 1, and discussed next.

Table 1. Overview of methods for collection of sentiment data, online

Method	Advantages	Disadvantages
Online interviews and questionnaire	• Can direct participants to specific aspects of interest to the researcher. • Detailed understanding of causes (interviews), or the relationship between variables (survey). • Cost effective. • Suitable for participants that place a high value on their time, and for extended projects.	• Quality of insight relies on participants ability to verbalise emotions. • Participants may be unable to explain the causes and/or consequences of the emotion. • Participants may be unwilling to revisit emotionally charged memories. • Loss of non-verbal cues.
Online experiments	• Suitable to study emotions. • Simultaneous manipulation and measurement of variables. • Observations in real time. • Ability to testing relationship between emotions and behaviours, either directly (participant experiments) or indirectly (scenario-based experiments).	• Unsuitable to study sentiment. • Ethical concerns regarding mood induction and manipulation • Technical challenges of isolating independent and dependent effects; • Limited ability to produce realistic experiments. • Cost.
Online conversations	• Abundance of data already available (but certain online communities may require permission to use data). • Ability to study consumers at scale, in real time, and in a natural setting. • Low cost.	• Biased samples. • Unsuitable for sensitive topics. • Inability to confirm participants' profile. • Difficult to obtain informed consent. • Social desirability bias. • Limited control over content. • Complexity of data handling and analysis.

2.1 Online interviews and questionnaires

A common method used by marketing scholars and practitioners to collect emotion and sentiment data is to conduct online interviews or questionnaires, asking research participants to recall a situation that was emotionally charged, and then ask them questions about the phenomenon of interest to the researcher. In the former, the researcher obtains verbal accounts about the phenomena and behaviours of interest; whereas, in the latter, the researcher generates quantified, or quantifiable, data (Rose et al, 2014).

Interviews offer the researcher a detailed understanding of the observed behaviour, and their causes. For instance, Barnes and colleagues (2021) used online interviews to understand experiences of customer delight during the Covid-19 crisis. In turn, questionnaires can assist researchers in identifying relationships between the variables studied, or measure the effect of different factors on the phenomenon of interest. For instance, Wollebaek et al (2019) conducted an online survey to study how emotions such as anger and fear shape how people seek political information and debate political issues online.

In addition to the specific advantages of interviews and questionnaires, doing this type of data collection online can be very cost effective. It eliminates the need for travel, which saves time and money. It can also broaden the geographic reach of data collection, and makes it feasible to collect data across different time zones. The ability to conduct online interviews and questionnaires became particularly valuable during the Covid-19 pandemic, allowing researchers to continue collecting data despite the imposition of movement restrictions in many countries, to contain the spread of the virus. Rose et al (2014) recommend the use of technology-mediated interviews and questionnaires for collecting data from participants that place a high value on their time, such as managers, because it offers more flexibility than face to face interviewing; as well as for extended projects, or those aiming to capture the participants' views in real time. For high volumes of data collection, it is also possible to use artificial intelligence. Namely, chatbots with Natural Language Processing capabilities are being introduced to collect valuable sentiment information, in the context of customer support (Castillo et al, 2020) and job interviews (Kumar, 2020).

However, studying emotions and sentiment via online interviews and questionnaires has some limitations. Interviews and questionnaires rely on research participants being able to clearly express their emotions and sentiments, and to accurately identify the causes and/or consequences of those feelings (Cooke & Buckley, 2008). For instance, some research participants may not recognise that the use of social media impacts on their mental health, even though the former has been shown to impact the latter (Gao et al, 2020). Moreover, research participants may be unwilling to discuss emotionally charged memories (Cohen et al., 2008), especially those that caused distress. Indeed, researchers may find it difficult to obtain ethical clearance from their institutions' ethical boards to conduct interviews or surveys which may cause emotional distress in participants. More generally, conducting technology mediated interviews and questionnaires may result in the loss of important cues such as body language or mannerisms, which provide important information, to complement the words – particularly in terms of possible discomfort about the topic beings discussed, or the extent to which the research participant is being open about their emotions or sentiment (Rose et al, 2014).

2.2 Online experiments

In experiments we test research participants' emotional responses to specific scenarios. Given the nature of experiments, this approach is not suitable to study sentiment. The main advantage of experiments is that they allow for the manipulation and measurement of the impact of separate independent variables, on the phenomenon of interest. For instance, manipulating the temperature of a retail outlet to measure its impact on purchase behaviour (Zwebner et al, 2013). Unlike interviews and surveys, experiments do not rely on the research participants' ability or willingness to accurately recall or explain the emotion being studied. are commonly used in research, particularly in the fields of behavioural psychology and consumer behaviour.

Online experiments are, typically, done in one of two ways. One way of conducting online experiments is to place the research participants in situations where they are likely to experience a particular emotion. For instance, by manipulating the amount of emotional content displayed in Facebook's News Feed, researchers tested the extent to which research participants' emotions are influenced by observation of other Facebook users' expression of emotions (Kramer et al. 2014). This approach to online experiments has the advantage of directly testing the relationship between emotions on the one hand, and context or behaviour on the other. However, it presents some challenges in terms of the ability to manipulate moods (Cohen, Pham, & Andrade, 2008). There are also ethical concerns around the elicitation of negative emotions, and the obtaining of informed consent (Jouhki et al, 2016).

The other common way of using experiments to study emotions is by placing research participants in the role of witnesses of an emotionally charged situation, for instance, by reading a description or by watching a video. Sands and colleagues used this method to test the effect of different types of service interaction on consumers satisfaction with the customer service provided, by asking research participants to read different scenarios where they tried to solve a hypothetical problem with their laptops (Sands et al, 2021). While this approach addresses some of the ethical concerns previously mentioned, there are serious questions about the extent to which the scenarios are realistic and salient to the participants (Kaltcheva & Weitz, 2006); and the extent to which it is possible to induce the desired emotion simply by observing an exchange between third parties (Cohen, Pham, & Andrade, 2008).

Manipulation of individual variables requires over simplification of the situation. Namely, an experiment examining the impact of different types of service interaction on customer satisfaction can only consider one type of agent (e.g., Chatbot vs human) and one type of script (e.g., educational vs entertainment) at a time; whereas actual customer interactions maybe have a blend of all these characteristics, plus many others not considered in the Sands et al (2021) paper.

2.3 Online conversations

The third and final approach to collecting emotion and sentiment data is by observing online conversations. There are a vast number and range of digitised texts publicly available online, such as chat threads, social media posts, discussion forums, product reviews, and other consumer generated content which can be collected via data scraping software, or through simple coding applications. There are also private sources such as e-mails, apps, digital diaries and other forms of digital text. Not only are these resources in digital format, already, but a significant share of them contain expressions of emotion, or expression of sentiment about products and brands (Jansen et al, 2009), thus providing reach insight into the role of consumers' experiences. We can also observe how emotionally charged content spreads, both in time and across users, thus obtaining insight about new behaviours related to sentiment elicitation or amplification, such as "whispering" or "flaming" (Garcia et al., 2009). For instance, Liu (2019), found that messages posted by social bots are not only more likely to be negative than those posted by other users, but they are also significantly more likely to go viral.

These platforms are so popular and became such a part of consumers' lives, that they are now seen as a valuable mechanism for studying consumer behaviour at large scale in a natural setting (Kivran-Swaine et al, 2012), and in a non-intrusive manner (Murthy, 2008), thus obviating many of the limitations of online experiments. It has also been argued that when customers voice their emotions online, it's because the experience has been highly impactful (Rocklage et al, 2021). Moreover, because much of these data are generated in real time (Patterson, 2012), they also obviate the technical and ethical limitations of online interviews and surveys. Thus, it is no surprise that many marketing managers, as well as scholars, routinely use digital conversations as sources of insight about consumer sentiment (Shirdastian et al., 2019), as well as consumer emotion (Ullah et al, 2016).

In order to be able to collect such data, researchers need to be familiar with the usage practices and netiquette of the digital platform where the content is being collected from, such as relevant abbreviations, conventions and hashtags (McKenna et al, 2017), in order to understand the context of the conversations. In some cases, researchers will also themselves have to become members of the online community of interest, and engage in activities such as creating a profile or an avatar (Schultze, 2010), and posting content. Researchers also need to be aware that collecting digital texts from online communities (e.g., discussion boards in the parenting website, Netmums), and from within organisations (e.g., intranets) is likely to require special permission (McKenna et al, 2017).

Despite the many advantages, and the popularity, of using online conversations for studying consumer emotions and sentiment, there are some limitations, too. It is important to remember that the profile of digital platforms users differs from that of the general population. For instance, research by Hecht and Stephens (2014) suggests that, in most social media platforms, there is a skew towards urban users and urban perspectives. Hence, digital platforms are best suited for projects that investigate the behaviour, perceptions or attitudes of those platform users, as in the case of Liu (2019)'s study of virality on Twitter. They are not suited to study the general population or heterogeneous social groups. Moreover, they are not suited to study topics that require introspection, or which are of a sensitive nature, be it personal or commercial (Canhoto, 2014).

Moreover, there is less certainty about the identity, or even the profile, of the research participants than in interviews, surveys or experiments. For instance, it may not be possible to confirm whether online reviews were written by genuine customers; or indeed by a person at all. Social bots – i.e., software agents that mimic human communication – are widely present and active in many social media and other digital platforms (Liu 2019). In such cases, McKenna and colleagues (2017) advise developing research questions where the identity of participants is not important.

It is also challenging, or even impossible, to obtain informed consent. Many researchers believe that data that are in the public domain – such as social media - can be used without obtaining informed consent. However, in many discussion forums, intranets and other online communities, users may expect some level of privacy and control over their conversations, specially where the subject of analysis is contentious (Thelwall & Stuart, 2006).

In the case of public platforms, their open nature means that the content shared is open to scrutiny. Therefore, the users of those platforms may be inclined to say things or behave in ways that protect their ego, or that are socially acceptable, rather than in line with what they truly feel or think. For instance, Ke and colleagues (2020) found that users of review websites are more likely to post something after a friend has done a review, than after a stranger has done the same.

Furthermore, contrary to what happens with the other data collection approaches discussed in this chapter, researchers are likely to have limited control over the topic of discussion. The online conversations may not focus specifically on what the researcher is looking for (McKenna et al, 2017), even if they are broadly related to the topic. For instance, customer reviews may focus on the product, whereas the researcher is more interested in the packaging.

Finally, the large volume and variety of unstructured data collected creates complexity in terms of handling and analysis. For instance, a product review or a tweet post may have both text and image, or even an hyperlink to an external website, each requiring a different approach. The text may be analysed in terms of syntax or semantics; the images in terms of symbology or style (Villarroel Ordenes & Zhang, 2019); and the hyperlink in terms of site linked to, or impact on further sharing activity.

4. Analysing emotion and sentiment data

Once data have been collected using the relevant data collection tool, researchers can then analyse those inputs looking for ratings or other metrics of emotion or sentiment, in the case of surveys and experiments. Alternatively, they may look at terms, phrases or expressions that reflect sentiment as in the case of interview transcripts or online conversations. In the latter case, and given that the first purpose of emotion and sentiment analysis is to identify the valence of the underlying emotion, the data analysis process usually involves the conversion of qualitative data to quantitative one. For instance, terms associated with a positive emotion would be converted into “+1”, neutral ones into “0”, and negative ones into “-1”. This is followed by measuring the frequency with which each type of emotion is displayed.

If our goal were to also identify strength of emotion in order to distinguish between different types of positive or negative emotion (e.g., sadness vs anger), then we would go a step further by attributing weights to particular attributes. For instance, the negative term “furious” would be weighted more heavily than the term “annoyed”, to convey that it refers to a high level of arousal.

This section provides an overview of the key elements of the process of analysing digital data related to emotion and sentiment. First, we highlight the importance of pre-processing the data. Then, we distinguish between top down and bottom up approaches, before considering the most popular methods in each.

3.1 Pre-processing

Before emotion and sentiment data can be analysed, it needs to be pre-processed – namely, cleaned and organised. If the main input is text (e.g., collected through online interviews or online conversations), then the input data will need to be organised into sentences, with the various forms of a word (e.g., like, likes, liked…) linked so that they can be processed as one[2]. Likewise, it is a good idea to convert negative sentences into their opposite, to ensure that we capture the right emotion or sentiment. For instance, "not good" would be converted to "bad", so that the phrase in question is accurately recorded as having negative valence (Villarroel Ordenes et al., 2019). In addition, we need to remove common but irrelevant words that work as pause or as connecting phrases words, such as "er" and "hum" or "a" and "the"; otherwise, we will end up with very high counts of terms that do not provide any insight regarding either the prevalent emotion, or sentiment, and its causes. Finally, we may want to classify key words according to some relevant attribute (e.g., noun, adjective, technical term, …), so that, later, we can filter the data according to those attributes (Tirunillai & Tellis, 2014).

If the data are in quantitative format (e.g., collected through online questionnaires or experiments), then we will need to look out for missing values (e.g., parts of the questionnaire that were not completed). If the values missing refer to a variable that is not part of the model (for instance, if location is not important), then we can simply ignore those answers. However, if there are missing inputs for important variables, then the missing data will have to be handled[3]. In the case of experiments, it is also customary to conduct manipulation checks in order to assess whether the respondent is engaged with the experiment, and reading the questions carefully and fully. Manipulation checks should also be used to assess whether the manipulated variable is producing the intended effect. For instance, whether watching a scary film trailer induces anxiety as intended, or, instead, induces boredom (Hauser et al, 2018). Finally, manipulation checks can be used to test for mediating effects, such as whether watching the scary movie produces a state of anxiety due to empathy with the main character as hypothesized by the researchers, or for some other reason.

It is also possible that the data will be in visual format. For instance, social media posts often include photos, gifs, videos, emojis and other non-text characters. As a first step in pre-processing these images, the researchers may want to classify the images in terms of type (e.g., photo vs video) to allow for similar types of images to be treated together. Another common

[2] In linguistics, this is referred to as "Lemmatisation".

[3] A detailed explanation of the methods for doing so falls outside of the scope of this chapter. Readers are directed to a research methods book, such as Rose et al. (2014).

step is to transform these image – e.g., resizing or rotating – in order to help with the visualisation of the image's content (Villarroel Ordenes & Zhang, 2019). In the case of emojis, it may be necessary to adjust for visual distortions induced by the operating system, or the social media platform where the image was collected. A study by Miller and colleagues found that classification of emojis as representing a positive, neutral or negative emotion could vary by as much as 25% depending on whether the image had been collected from an Apple iPhone or a Google Nexus phone (Miller et al, 2016), thus showing the need to consider such technical aspects, when analysing emojis to study the expression of emotions and sentiments.

In summary, pre-processing is a crucial – and, often, time consuming – step in the analysis of emotion or sentiment data, which can significantly impact the quality of the insight that can be generated.

3.2 Approaches to emotion and sentiment analysis

When conducting emotion or sentiment analysis, we can follow three approaches: a top down approach, a bottom up approach, or a combination of the two.

The top down approach starts with a list of terms that represent the constructs of interest (Thura, Na, & Khoo, 2010), such as 'happy' for a positive emotion vs. 'angry' for a negative one, or 'like' for a positive sentiment vs. 'unfavourable' for a negative one (Ullah et al, 2016). This is usually in the form of a word dictionary, but could also include other symbols, such as emoticons or quantitative ratings (Kronrod & Danzinger, 2013). For instance, in their analysis of customer reviews, Villarroel Ordenes and colleagues (2017), used the star ratings from the product review platform, the dictionary of emotion words from the LIWC program, and the emoticons dictionary from Pcnet.

The bottom up approach, in contrast, searches the dataset to identify the terms (words, symbols, etc.) that are commonly used to express emotions or sentiment, in that particular research context. This could be done, for instance, by using semantic network analysis tools like Leximancer; or by using machine learning. An example of this approach can be found in Tirunillai and Tellis (2014). These two researchers used unsupervised machine learning to identify how users of product review websites expressed product quality in different markets, from mobile phones to toys.

While published research on emotion and sentiment analysis tends to favour one approach or the other (Villarroel Ordenes & Zhang, 2019), it is also possible to combine both approaches. One example of such a combination is provided in Nisar et al (2020)'s investigation of the impact of online word of mouth on firms' reputation. The researchers used unsupervised machine learning (bottom up approach) to identify prevalent topics, followed by predefined dictionaries (top down approach) to classify the emerging topics into positive, negative or neutral sentiment (Nisar et al, 2020).

3.3 Popular emotion and sentiment analysis methods

This section provides a brief overview of popular emotion and sentiment analysis methods in management research. It is beyond the scope of this chapter to provide detailed technical descriptions of each method. However, examples are offered for each method, and these provide an opportunity for further reading. We start by discussing methods that follow a top-down approach, before considering those that follow a bottom-up approach.

Top down approaches aim to operationalise constructs within the specific setting of the research. For instance, we may want to understand the drivers of customer sentiment towards coffee. Following a top down approach, we take the expressions of such sentiment as the starting point, and then look for how they vary with the variables of interest, such as product features, the social context, the time of the day, or other parameters (Canhoto & Padmanabhan, 2015). Table 2 lists popular emotion and sentiment analysis methods that follow a top-down approach.

A common top-down method is the "predefined dictionary", whereby we use an existing word list or dictionary for specific emotions (e.g., the LWIC dictionary); and, then, essentially, search through the dataset (e.g., selection of product reviews, or interview transcripts) to count how many times the words on the list appear in the dataset. If the dataset consists of images, then, instead of words, we would use a dictionary of images commonly associated with each emotion (e.g., hearts, smiles or thumbs up, to denote positive emotions).

Alternatively, we can use the "customised dictionary" method, whereby we adapt or create a word list that is specific to the context of our research. For instance, the expression "salty" could refer to the amount of salt in the food, in one context; but be used to describe someone's bad mood, in another. So, before proceeding with data analysis, we would need to add "salty" to our dictionary, to signify the intended meaning. Alternatively, we could change the classification of words in a pre-existing dictionary, to reflect the fact that they reflect a different type of emotion or sentiment in the setting where we are conducting the research. For instance, "sick" is likely to refer to a negative emotion for adults, but a positive emotion for teenagers and young adults. Hence, if we are studying texts from the first group, this term receives a negative score. However, if we are studying inputs from the second group, this term needs to receive a positive score. Once the dictionary has been customised, we can use it to search through the dataset, and to count the frequency of appearance of different terms in the dataset.

A third common, top down method in emotion or sentiment analysis is the "rule based" method. Here, we combine various dictionaries, and classify the dataset based on the co-occurrence of terms from the dictionaries according to a specific set of rules. For example, Packard and Berger (2017), used a rule that flagged reviews containing a first-person pronoun, as well as words starting with "recomm" (e.g., recommend), "endorse" or "suggest". An example of the use of such a rule would be "I suggest this book for everyone". Once the rules regarding terms' co-occurrence have been defined, we search through the dataset, and count the frequency of rule occurrence in the dataset.

Table 2. Popular top-down analysis methods for construct operationalisation

Method	Description	Example
Predefined dictionary	Use an existing word list or dictionary (e.g., LWIC), to search through the dataset. Count occurrence of selected terms (words, images…) in the dataset.	Villarroel Ordenes et al (2017)
Customised dictionary	Create new terms' list, or adapt existing one to the research context (e.g., by changing classification of words). Then, use this dictionary to search through dataset, and to count occurrence of selected terms (words, images…) in the dataset.	Marinova et al (2018)
Rule based	Define rules for combining the dictionaries, and for searching the dataset. Then, count occurrence of the selected combinations in the dataset.	Packard and Berger (2017)

Adapted from Villarroel Ordenes & Zhang (2019)

Bottom down approaches can be used to operationalise constructs, too, though the terms are derived from classification of the dataset, rather than imposed form an external structure. There are two popular methods for doing this (see table 3). One common method to doing this is through "supervised machine learning". Using this method, we start by classifying the dataset according to emotion or sentiment (for instance, based on star reviews, or quantitative rating). Subsequently, we search the dataset to identify the terms (words, symbols, images…) associated with those emotions. Afterwards, the rules developed through this process can be used to predict emotion or sentiment in another dataset, based on the presence of the features identify through the supervised learning process.

Another bottom-up method for operationalising constructs is "deep learning". Here, researchers start with a dataset classified for relevant inputs. For instance, for restaurant reviews, the relevant inputs might be i) food, ii) service, and iii) price. Then, using an algorithm (for instance, convolutional neural network), the researchers extract the relevant classes among the dataset, and calculate the predictive power of each component[4]. Using this method, Zhang and Luo (2019) found that restaurant survival is more influenced by the availability of photos of the food, than the text reviews; and by the total volume of user-generated content than the valence of the sentiment expressed in that content.

Table 3. Popular bottom-up analysis methods for construct operationalisation

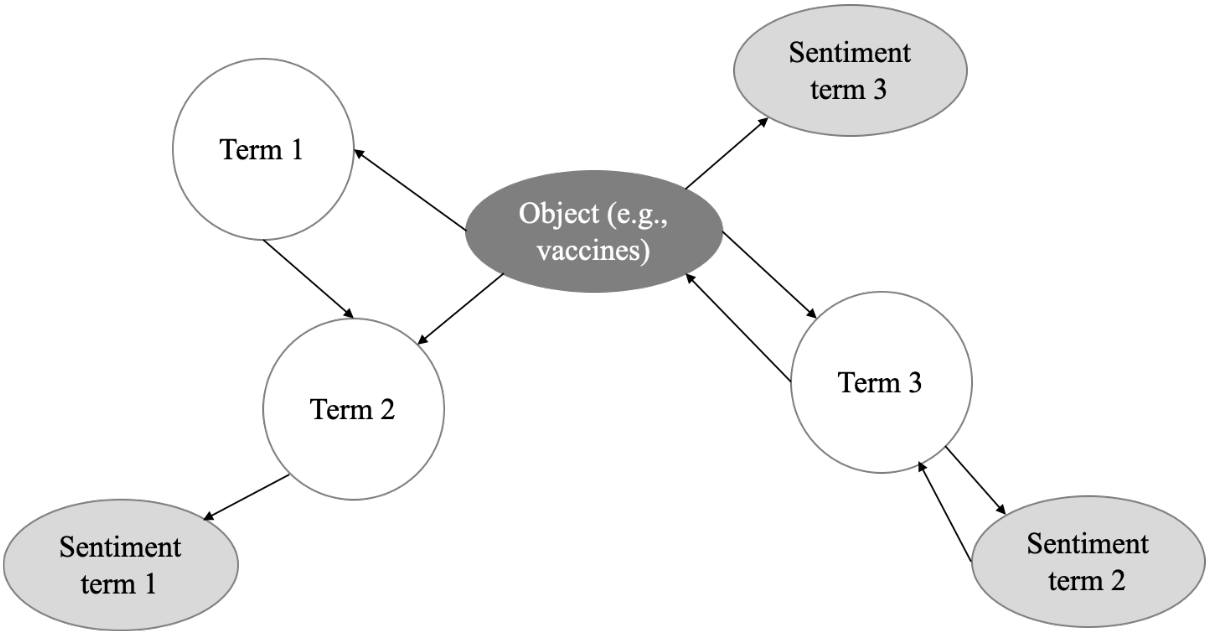
Method	Description	Example
Supervised machine learning	Classify the dataset according to the known outputs. Then, search the input dataset to identify the terms associated with those outputs, and the rules connecting inputs and outputs.	Shirdastian et al. (2019)
Deep learning	Classify the dataset for relevant inputs. Then, extract the relevant classes among the dataset, and calculate the predictive power of each component.	Zhang & Luo (2019)

Adapted from Villarroel Ordenes & Zhang (2019)

In addition to operationalising constructs, bottom up approaches can be used to identify latent topics. There are three popular methods for doing this (see table 4). The first such method is "Semantic network" which treats each term (e.g., word) as a node, and, then, analyses the dataset to identify common co-occurrences between nodes (Figure 2). These co-occurrences are referred to as links. This way, researchers can identify which target features are mostly associated with positive vs negative sentiment or emotions. They can also calculate the strength of the emotion or sentiment, by analysing the frequency of co-occurrence. Using this approach to study vaccine hesitancy, Kang and colleagues (2017) found that negative sentiment towards vaccination tended to be associated with generic topics such as the vaccine industry or doctors; whereas positive sentiment tended to be associated with specific diseases such as measles, HPV or meningococcal disease.

[4] A step-by-step example of classification of images, using deep learning techniques, is provided in https://engineeringblog.yelp.com/2015/10/how-we-use-deep-learning-to-classify-business-photos-at-yelp.html

Figure 2. Illustration of semantic network approach



Adapted from (Danwoski et al, 2021)

Another popular bottom-up method for latent topic elicitation is “unsupervised machine learning”. Here, researchers use training datasets without labels. It is then incumbent on the algorithm to identify the best way of grouping (or clustering) the data points (words, images…), and to develop rules for how the different terms may be related. As mentioned in section 4.2, this was the method used by Tirunillai and Tellis (2014) to analyse product reviews, leading them to conclude that customers used different ways to express sentiment depending on the type of product. In turn, Arefieva et al (2021) demonstrate the application of this method to the analysis of images.

A third, and final, method for latent topic elicitation is “word embeddings”. This method aims to identify, categorise and quantify words hat have the same meaning, or are used in similar ways, in the dataset – e.g., recommend, suggest, advise… It is these clusters of terms with semantic similarity (rather than individual terms) that are used to measure emotion or sentiment in the dataset. This methodology is illustrated in Tang et al’s (2014) analysis of 10 million tweets.

Table 4. Popular bottom-up analysis methods for latent topic elicitation

Method	Description	Example
Semantic network	Identifies key terms (the nodes) associated with a subject of interested, and the common co-occurrences between each term (the links).	Kang et al (2017)
Unsupervised machine learning	Identify clusters of different terms used to express sentiment, and develop rules for how the different terms related to each other.	Arefieva et al (2021)
Word embeddings	Identify clusters of terms with semantic similarity within a given dataset. Then, use these groupings to measure sentiment.	Tang et al's (2014)

Adapted from Villarroel Ordenes & Zhang (2019)

5. The challenges of emotion and sentiment analysis

The study of expressions of emotion and sentiment is a valuable, and increasingly popular activity, not just as a managerial practice, but also as a scholarly one. For instance, see Kumar et al (2021) for a review of popular text mining applications in the services management literature. However, it is not without challenges. In this section, we consider two types of challenges: those associated with the study of emotions and sentiments in themselves, and those associated with the use of technology to analyse emotion or sentiment data.

4.1 Expressions of emotion and sentiment

Emotion and sentiment analysis concern itself with capturing and measuring expressions of feelings. However, how people react to an emotional trigger, and express their emotion, can vary widely. People across the world reacted very differently to the Covid-19 crisis, and the public health measures adopted by governments, such as lockdowns or the use of contact tracing (Imran et al., 2020). The expression of emotions and sentiment can also vary over time, both in terms of the language's syntactic features and in terms of style (Abbasi et al, 2008). For instance, LOL started by being an acronym for 'lots of love', but now is also used as a replacement for 'laughing out loud'.

These expressions can also vary with where the emotion or sentiment is expressed. For instance, social media users tend to apply certain colloquialisms and abbreviations, that they might not use in an online product review, or an interview. It has also been observed that online reviews are not only mostly positive, but they tend to follow a J-shaped distribution, with many ratings, a few bottom ones, and very few in between (Rocklage et al., 2021).

Moreover, emotions and sentiment may be expressed through subtle elements, such as the use of exception or conditional clauses (Kim & Hovy, 2006), or even the choice of words and their placement (Davis & O’Flaherty, 2012). Emotions and sentiment can also be expressed through the use of irony and sarcasm. This is particularly prevalent in social media content (Maynard & Greenwood, 2014). An example of this is provided in Figure 3, via a Twitter conversation which alludes to the crisis faced by Samsung, when its Galaxy Note7 phones were found to overheat and catch fire.

Figure 3. Sarcasm and irony in social media conversations

Rory Cellan-Jones (@ruskin147)
10/10/2016, 09:27

Hi there - anyone got a Samsung Galaxy Note 7

Mike Harvey (@Tw0fl0wer)
10/10/2016, 13:19

@ruskin147 No but if you really need to start a fire I've got some matches around here somewhere.

New Normal Bot (@NormalBot)
10/10/2016, 10:06

@ruskin147 is anyone sure that it's the phone causing the explosions and not the batteries? Are those particular batteries in anything else?

Gavin Barrie (@jammach)
10/10/2016, 09:39

@ruskin147 hell no! pic.twitter.com/o4trhl6srE

Jeff Sutton (@iNdieboyjeff)
10/10/2016, 09:39

@ruskin147 the phone with built-in Russian Roulette mode? Thankfully not. I'm still attached to all my limbs!

Joseph (@SirJS)
10/10/2016, 09:37

@ruskin147 I used it to start a barbecue unfortunately.

---

langeydong (@langeydong)
10/10/2016, 09:34

@ruskin147 Yep

KBA IT (@KBA_IT)
10/10/2016, 09:34

@ruskin147 Momentarily... :-P

Chris Puttick (@putt1ck)
10/10/2016, 09:30

@ruskin147 waiting for mine :)

DisappointedOptimist (@rbp77)
10/10/2016, 09:29

@ruskin147 yes I left it in the ca- OH SH*T! pic.twitter.com/fvvfrFDPSV

Chris Field (@mrcfield)
10/10/2016, 09:29

@ruskin147 I know that @Rockbmi has one...

Stanley Pignal (@spignal)
10/10/2016, 09:29

@ruskin147 yes and I'm very happy with my Sams... aaAAAAAaaagh!! get that thing away from me!!! somebody call the fire department!

It is also possible for a single segment of text to express more than one emotion or sentiment. For instance, the author of a product review may judge the product positively, but express dissatisfaction with specific features. This type of situation creates uncertainty regarding the dominant feeling. In this example, whether the review should be classified as positive or negative depends on whether the focus of the analysis is the overall impression or the specific features, respectively. While this may be possible to do in large texts, such as interview transcripts, it is very difficult to achieve when analysing very short text segments, as is the case of short answer in surveys, or entries in popular social media platforms such as Twitter or Snapchat, where the short length or duration of the segment may hinder the identification of multiple foci within one segment of text. For instance, the short sentence "The early shift sucks. Oh well at least my latte is yummy :)" captures two different emotions, and refers to two separate objects, even though it only has 13 words, and 48 characters (Canhoto & Padmanabhan, 2015).

Lastly, sentiment about an object may be expressed in an indirect form, such as through comparisons. For instance, the expression "100 copies of Ghosts sold overnight means a definite Starbucks run this morning. Possibly coffee out twice this week! Maybe even sushi!!" lacks any emotionally charged words (e.g., celebrate, success) that clearly indicate whether the person expressing this sentiment is feeling positively or negatively towards the drink (Canhoto & Padmanabhan, 2015). Instead, the researcher needs to draw on contextual knowledge to understand the complexity of meaning in this conversation (Kozinets 2002).

The challenges associated with the expression of emotion and sentiment are summarised in Table 5.

Table 5: Challenges associated with the expression of emotion and sentiment

Type	Description	Impacts
Form	Way of expressing emptions changes with culture, time and platform	Syntax and style
Source	Use of exception, conditional clauses, irony and sarcasm to express emotion	Nuance
Focus	Multiple sentiments and/or objects mentioned in the same segment	Uncertainty
Context	Emption is expressed by comparison or reference to context	Domain knowledge

4.2 Automated analysis of emotion and sentiment

The large volume of digital data available (for instance, on social media) and the ability to collect data easily online (e.g., via MTurk surveys) often result in very large datasets for analysis. Thus, increasingly, both managers (e.g., Davis & O'Flaherty, 2012) and researchers (e.g., Nunan & Domenico, 2013) turn to technology that enables the automated tracking and analysis of digital emotion and sentiment data.

Using specialist software for data analysis, such as those mentioned in section 4.3, can help with the manipulation of big datasets, and either the application or the generation of codes related to emotions and sentiments. Using data analysis software can also improve the credibility of the research, even if it does not change the rigour of the analytical work done, or the outcome of the analysis (Ryan, 2009). However, as illustrated in section 4, the different approaches to analysing emotion and sentiment data, and the various specific methods, are best suited for some types of data and for specific research goals. Hence, it is crucial to carefully assess the suitability of the selected approach and method for the project at hand. Unfortunately, research (e.g., Canhoto, 2021) shows that this choice (for instance, the choice between unsupervised machine learning vs. semantic network, in the case of latent topic elicitation) is often influenced by pragmatic factors, such as the type of software that the analyst has access to, or the experience of the researcher.

It is also evident that, even though software can accelerate the analysis of the data, researchers still need to be actively involved throughout the process – for instance, deciding what data to retrieve and collate (Basit, 2003), or labelling data for the training dataset (Villarroel Ordenes & Zhang, 2019).

The researchers also need to carefully verify the accuracy of the classification, as content analysis software has limitations in terms of discerning nuances in meaning, resulting in the partial retrieval of information, only (Brown et al., 1990). This validation is particularly difficult when using off-the-shelf analysis tools, as the working of the underlying algorithms are strongly guarded by the commercial organisations that sell these applications (Beer & Burrows, 2013).

In summary, while technology can accelerate the process, and enable the analysis of large datasets, there are a number of vulnerabilities, which may affect the researcher's ability to correctly detected and classify emotion or sentiment in a dataset. These challenges are summarised in Table 6.

Table 6: Challenges associated with the automated analysis of emotion and sentiment

Type	Description	Impacts
Tool selection	Choice of approach and method	Fit with current project
Data preparation	Selection of data and creation of training dataset	Accuracy of classification
Tool evaluation	Assess accuracy of results	Confidence in the results

6. Concluding thoughts

Emotions are key to understand, explain and anticipate consumer behaviour. Digital technology, in particular, offers many opportunities for practitioners and scholars to researching, measuring and describing those emotions or sentiments. However, as noted in this section, the analysis of emotion and sentiment is neither a simple nor a straightforward process. Instead, it is a process embedded in nuance, subjectivity and variability.

It should be emphasised that techniques and technology are constantly evolving, being updated and improved. Therefore, some of the problems highlighted in this chapter may soon be addressed by new methodologies or technical solutions. For instance, dictionaries can be improved, and new techniques can be implemented. However, ultimately, the study of emotions and sentiment needs to be guided by rigour, sensitivity, and criticality – from the point of deciding which method to use to collect data, to the validation of the results of automated analysis, and even the reporting.

References

Abbasi, A., Chen, H., & Salem, A. (2008). Sentiment analysis in multiple languages: Feature selection for opinion classification in Web forums. *ACM Transactions on Information Systems*, 26(3), 1-34. doi 10.1145/1361684.1361685

Arefieva, V., Egger, R. & Yu, J. (2021). A machine learning approach to cluster destination image on Instagram. *Tourism Management*. 85, 104318. https://doi.org/10.1016/j.tourman.2021.104318

Basit, T. N. (2003). Manual or electronic? The role of coding in qualitative data analysis. *Educational Research*, 45(2), 143-154. DOI:10.1080/0013188032000133548

Beer, D., & Burrows, R. (2013). Popular Culture, Digital Archives and the New Social Life of Data. *Theory, Culture & Society*, 30(4), 47-71. doi: 10.1177/0263276413476542

Berger, J. and Milkman, K.L. (2012), What makes online content viral?, *Journal of Marketing Research*, 49(2), 192-205.

Bigne, E., Andreu, L., Hernandez, B. & Ruiz, C. (2018) The impact of social media and offline influences on consumer behaviour. An analysis of the low-cost airline industry, *Current Issues in Tourism*, 21:9, 1014-1032, DOI: 10.1080/13683500.2015.1126236

Brown, D., Taylor, C., Baldy, R., Edwards, G., & Oppenheimer, E. (1990). Computers and QDA - can they help it? A report on a qualitative data analysis programme. *The Sociological Review*, 38(1), 134-150. DOI: 10.1111/j.1467-954X.1990.tb00850.x

Canhoto, A. I. (2014). Issues to consider when using Social Media to collect qualitative data. In K. Woodfield (Ed.), *Social Media in Social Research*. London: NatCen Social Research.

Canhoto, A. I. (2021). Leveraging machine learning in the global fight against money laundering and terrorism financing: an affordances perspective. *Journal of Business Research*, 131, 441-452 DOI: https://doi.org/10.1016/j.jbusres.2020.10.012

Canhoto, A. I. & Padmanabhan, Y., (2015). We (don't) know how you feel – a comparative study of automated vs. manual analysis of social media conversations. *Journal of Marketing Management*, 31(9-10), 1141-1157. DOI: 10.1080/0267257X.2015.1047466

Castillo, D., Canhoto, A. I & Said, E., (2020). The Dark Side of AI-powered Service Interactions: exploring the process of co-destruction from the customer perspective. *The Service Industries Journal* DOI: https://doi.org/10.1080/02642069.2020.1787993

Cohen, J. B., Pham, M. T., & Andrade, E. B. (2008). The nature and role of affect in consumer behavior. In C. P. Haugtvedt, P. Herr & F. Kardes (Eds.), *Handbook of consumer psychology* (pp. 297-348). Mahwah, NJ: Lawrence Erlbaum

Cooke, M., & Buckley, N. (2008). Web 2.0, Social Networks and the Future of Market Research. *International Journal of Market Research*, 50(2), 267-292.

Danowski, J.A., Yan, B. & Riopelle, K. A (2021) Semantic network approach to measuring sentiment. *Quality & Quantity*, 55, 221–255. https://doi.org/10.1007/s11135-020-01000-x

Davis, J. J., & O'Flaherty, S. (2012). Assessing the Accuracy of Automated Twitter Sentiment Coding. *Academy of Marketing Studies Journal*, 16(Supplement), 35-50.

Gao J, Zheng P, Jia Y, Chen H, Mao Y, Chen S, et al. (2020) Mental health problems and social media exposure during COVID-19 outbreak. *PLoS ONE* 15(4): e0231924. https://doi.org/10.1371/journal.pone.0231924

Garcia, A., Standlee, A., Bechkoff, J., & Cui, Y. (2009). Ethnographic approaches to the Internet and computer-mediated communication. *Journal of Contemporary Ethnography*, 38, 52–84.

Gelbrich, K. (2010). Anger, frustration, and helplessness after service failure: coping strategies and effective informational support. *Journal of the Academy of Marketing Science*, 38, 567–585.

Grappi, S., Romani, S., & Bagozzi, R. P. (2015). Consumer stakeholder responses to reshoring strategies. *Journal of the Academy of Marketing Science*, 43, 453–471.

Hansen N, Kupfer A-K, Hennig-Thurau T. (2018). Brand Crises in the Digital Age: The Short- and Long-term Effects of Social Media Firestorms on Consumers and Brands. International *Journal of Research in Marketing*. 35(4), 557-574. https://doi.org/10.1016/j.ijresmar.2018.08.001

Hauser, D.J., Ellsworth, P.C. & Gonzalez, R (2018) Are Manipulation Checks Necessary? *Frontiers in Psychology*, 9, 998. doi: 10.3389/fpsyg.2018.00998

Hecht, B., & Stephens, M. (2014). A Tale of Cities: Urban Biases in Volunteered Geographic Information. *Proceedings of the International AAAI Conference on Web and Social Media,* 8(1). Retrieved from https://ojs.aaai.org/index.php/ICWSM/article/view/14554

Imran, A. S., Daudpota, S. M., Kastrati, Z. & Batra, R. (2020). Cross-Cultural Polarity and Emotion Detection Using Sentiment Analysis and Deep Learning on COVID-19 Related Tweets. *IEEE Access*, 8, 181074-181090. doi: 10.1109/ACCESS.2020.3027350.

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter Power: Tweets as Electronic Word of Mouth. *Journal of the American Society for Information Science and Technology*, 60(11), 2169-2188.   DOI: 10.1002/asi.21149

Jouhki, J., Lauk, E., Penttinen, M., Sormanen, N., & Uskali, T. (2016). Facebook's Emotional Contagion Experiment as a Challenge to Research Ethics. *Media and Communication*, 4 (4), 75-85. doi:10.17645/mac.v4i4.579

Kaltcheva, V.D. and Weitz, B.A. (2006), When should a retailer create an exciting store environment?, *Journal of Marketing*, 70(1), 107-118.

Kang, G. J., Ewing-Nelson, S. R., Mackey, L., Schlitt, J. T., Marathe, A., Abbas, K. M., & Swarup, S. (2017). Semantic network analysis of vaccine sentiment in online social media. *Vaccine*, 35(29), 3621–3638. https://doi.org/10.1016/j.vaccine.2017.05.052

Ke, Z., Liu, D. & Brass, D. (2020). Do Online Friends Bring Out the Best in Us? The Effect of Friend Contributions on Online Review Provision. *Information Systems Research*, http://dx.doi.org/10.2139/ssrn.3607468

Kim, S.-M., & Hovy, E. (2006). Automatic Identification of Pro and Con Reasons in Online Reviews. *Paper presented at the COLING/ACL*, Sydney

Kivran-Swaine, F., Brody, S., Diakopoulos, N., & Naaman, M. (2012). Of joy and gender: emotional expression in online social networks. Paper presented at the 2012 *Conference on Computer Supported Cooperative Work Companion*, New York.

Kozinets, R. V. (2002). The Field Behind the Screen: Using Netnography for Marketing Research in Online Communities. *Journal of Marketing Research*, 39(February), 61-72. DOI 10.1509/jmkr.39.1.61.18935

Kramer, A. D. I., Guillory, J. E., Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences of the United States of America*, 111, 8788–8790

Kranzbühler, A-M, Zerres, A., Kleijnen, M. H. P. & 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, 478-498, https://doi.org/10.1007/s11747-019-00707-0

Kronrod, A & Danziger, S. (2013), 'Wii Will Rock You!' The Use and Effect of Figurative Language in Consumer Reviews of Hedonic and Utilitarian Consumption. *Journal of Consumer Research*, 40(4), 726–39.

Kumar, P. (2020). Using online interviews for recruitment & selection. Times of India. https://timesofindia.indiatimes.com/readersblog/farsightthinking/using-online-interviews-for-recruitment-selection-26677/ Last accessed 12 March 2021

Kumar, S., Kar, A. K. & Ilavarasan, P. V. (2021). Applications of text mining in services management: A systematic literature review. *International Journal of Information Management Data Insights*. 1(1). https://doi.org/10.1016/j.jjimei.2021.100008

Laros, F. J. M., & Steenkamp, J.-B. (2005). Emotions in consumer behavior: a hierarchical approach. *Journal of Business Research*, 58, 1437–1445.

Liu, X. (2019). A big data approach to examining social bots on Twitter. *Journal of Services Marketing*, 33(4), 369-379. https://doi.org/10.1108/JSM-02-2018-0049

Loewenstein, G. & Lerner, J. S. (2003). The role of affect in decision making. *Handbook of Affective Sciences*. Davidson, R. J., Scherer, K. R. & Goldsmith, H. H. (Eds). Oxford, Oxford University Press: 619-642.

Marinova, D., Singh, S.K. and Singh, J. (2018). Frontline problem-solving effectiveness: a dynamic analysis of verbal and nonverbal cues. *Journal of Marketing Research*, 55(2), 178-192.

Maynard, D.G. & Greenwood, M.A. (2014) Who cares about sarcastic tweets? Investigating the impact of sarcasm on sentiment analysis. In: *LREC 2014 Proceedings. Language Resources and Evaluation Conference (LREC)*, 26-31 May 2014, Reykjavik, Iceland. ELRA. ISBN 978-2-9517408-8-4

McKenna, B., M. Myers & M. Newman. (2017). Social media in qualitative research: Challenges and recommendations. *Information and Organization*, 27(2), 87-99. https://doi.org/10.1016/j.infoandorg.2017.03.001

Miller, H., Thebault-Spieker, J., Chang, S., Johnson, I., Terveen, L. & Hecht, B. (2016). “Blissfully happy” or “ready to fight”: Varying Interpretations of Emoji. *International AAAI Conference on Web and Social Media*. https://grouplens.org/site-content/uploads/ICWSM16_Emoji-Final_Version.pdf

Murthy, D. (2008). Digital Ethnography: An Examination of the Use of New Technologies for Social Research. *Sociology*, 42(5), 837-855. doi: 10.1177/0038038508094565

Nisar, T.M., Prabhakar, G., Ilavarasan, P.V. & Baabdullah, A.M. (2020), Up the ante: electronic word of mouth and its effects on firm reputation and performance. *Journal of Retailing and Consumer Services*, 53, 101726. https://doi.org/10.1016/j.jretconser.2018.12.010

Nunan, D., & Domenico, M. D. (2013). Market research and the ethics of big data. International *Journal of Market Research*, 55(4), 505-520

Packard, G. & Berger, J. (2017). How language shapes word of mouth’s impact. *Journal of Marketing Research*, 54(4), 572-588.

Patterson, A. (2012). Social-networkers of the world, unite and take over: A meta-introspective perspective on the Facebook brand. *Journal of Business Research*, 65(4), 453-578. doi:10.1016/j.jbusres.2011.02.032

Rocklage, M.D., Rucker, D.D. & Nordgren, L.F. (2021). Mass-scale emotionality reveals human behaviour and marketplace success. *Nature Human Behaviour*. https://doi.org/10.1038/s41562-021-01098-5

Rose, S, Spinks. N. & Canhoto, A.I. (2014) *Management Research – Applying the Principles*. London, Routledge

Ryan, M. E. (2009). Making visible the coding process: Using qualitative data software in a post-structural study. *Issues in Educational Research*, 19(2), 142-161.

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review*, 110, 145–172.

Sands, S., Ferraro, C., Campbell, C. and Tsao, H.-Y. (2020), Managing the human–chatbot divide: how service scripts influence service experience. *Journal of Service Management*, 32(2), 246-264. https://doi.org/10.1108/JOSM-06-2019-0203

Schultze, U. (2010). Embodiment and presence in virtual worlds: A review. *Journal of Information Technology*, 25(4), 434–449.

Shirdastian, H., Laroche, M. & Richard, M.O. (2019). Using big data analytics to study brand authenticity sentiments: the case of Starbucks on Twitter. *International Journal of Information Management*, 48, 291-307, 10.1016/J.IJINFOMGT.2017.09.007

Tang. D., Wei., F., Yang, N., Zhou, M., Liu, T. & Qin, B. (2014). Learning Sentiment-Specific Word Embedding for Twitter Sentiment Classification. *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*. Baltimore, Maryland, USA, June 23-25 2014. 1555–1565.

Thelwall, M., & Stuart, D. (2006). Web crawling ethics revisited: Cost, privacy, and denial of service. *Journal of the American Society for Information Science and Technology*, 57(13), 1771–1779.

Thura, T., Na, J.-C., & Khoo, C. S. G. (2010). Aspect-based sentiment analysis of movie reviews on discussion boards. *Journal of Information Science*, 36(6), 823–848. https://doi.org/10.1177/0165551510388123

Tirunillai, S. & Tellis, G.J. (2014), Mining marketing meaning from online chatter: strategic brand analysis of big data using latent Dirichlet allocation. *Journal of Marketing Research*, 51(4), 463-479.

Ullah, R., Amblee, N., Kim, W. & Lee, H. (2016). From valence to emotions: Exploring the Distribution of Emotions in Online Product Reviews. *Decision Support Systems*, 81, 41-53.

Villarroel Ordenes, F., Grewal, D., Ludwig, S., Ruyter, K.D., Mahr, D. & Wetzels, M. (2017), Cutting through content clutter: how speech and image acts drive consumer sharing of social media brand messages. *Journal of Consumer Research,* 45(2), 988-1012.

Villarroel Ordenes, F. & Zhang, S. (2019). From words to pixels: text and image mining methods for service research. *Journal of Service Management*, 30(5), 593-620. DOI:10.1108/josm-08-2019-0254

Wollebæk, D., Karlsen, R., Steen-Johnsen, K., & Enjolras, B. (2019). Anger, Fear, and Echo Chambers: The Emotional Basis for Online Behavior. *Social Media + Society*. https://doi.org/10.1177/2056305119829859

Zhang, M. & Luo, L. (2018). Can user generated content predict restaurant survival: deep learning of yelp photos and reviews. *Advances in Neural Information Processing Systems* 28 (NIPS 2015), Montreal, December 7-12, available at: https://ssrn.com/abstract=3108288 (accessed July 5, 2019).

Zwebner, Y., Lee, L. & Goldenberg, J. (2013). The temperature premium: Warm temperatures increase product valuation. *Journal of Consumer Psychology*, 24 (2), 251–259.