How Neuromarketing, Artificial Intelligence and Machine Learning can improve Technology Companies and their Marketing Strategy

A food market research case using implicit and explicit techniques

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Abstract

This dissertation was written as part of the MSc in E-Business and Digital Marketing at the International Hellenic University.

The introduction of this thesis consists of five parts. In the first part, we will state the general topic and outline the background of it. The second part indicates the research questions. The third part will include the contribution of this thesis. The next part will state the objectives of the research. Finally, in the last part, we will outline the structure of this thesis.

The core of this thesis is based on face tracking using an automated emotion recognition model in mobile phones. Therefore, this chapter will introduce Neuromarketing and more specifically face recognition and its application in Neuromarketing. Moreover, an extended review of Machine learning and Artificial Intelligence (AI) models will be also included. Face recognition and Emotion detection mobile applications will be included in the literature review part. Finally, emotion recognition in food marketing will conclude this part.

The purpose of this chapter is to introduce the methodology we followed giving clear details of the method. Specifically, in this part, we will analyze the whole procedure in three steps that are face detection, extraction of the features, and classification. In parallel, part of the methodology is verification which will be achieved with a questionnaire specially designed to be answered by the people who will participate in the research. In this part, we will also provide the description of the food campaigns used in this research.

In this part, we will present in figures (tables, photographs) and written text what we found out concerning our research questions including details and how they were analyzed step by step. We will also comment on the significance of key results and critically evaluate the study by interpreting and explaining the results.

In the final chapter, we will summarize the results and the details of this thesis. We will clearly restate the thesis statement and answer the main research question explaining how it can contribute to the field of Neuromarketing and Artificial Intelligence. The final part is the recommendations for future work on the topic as well as the knowledge we gained through this process.

In this research project, I could not have achieved my current level of success without a strong support group. First of all, I would like to thank my Supervisor, Prof. Tzafilkou Aikaterini, who has provided me with patience, advice and guidance throughout the research process. She was very cooperative and willing to help me anytime. Furthermore, I am grateful to my family and Andreas Xiros, who supported me with understanding and encouragement to finish this dissertation. Without their love and their help I could not manage it, that's why the minimum I can do is to dedicate this dissertation to them.

Keywords: Neuromarketing, Artificial Intelligence, Machine Learning, Digital Transformation, Marketing Strategy

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1 Introduction

1.1 Background and motivation

Emotions are an integral part of people's lives and specifically social interaction. Most of the activities that humans regularly undertake include emotional experiences that can have impacts on people's actions. Moreover, we must take into consideration the fact that emotions are considered to be the most significant nonverbal language to communicate which is also confirmed by Ekman who suggested that emotions are expressed in a universally equal manner [1]. According to him, there are six common emotions shared by all humans: happiness, sadness, anger, scared, surprise, and disgust [2]. This is why understanding emotions and the reasons behind can be proved a powerful tool for anyone who wants to search and come closer to human brain without asking them how they feel.

Research on emotions has become a multidisciplinary research field of growing interest in various fields such as psychology, sociology, marketing, information technology, and e-learning. For this reason, several tools have been developed and used for this purpose. Static methods such as questionnaires or interviews have been overpassed or used in parallel with innovative ones that have been created through the rapid development of computer technology. Specifically, there is a wide number of emotion recognition systems that can recognize how humans feel from speech, images, or videos.

However, face recognition is one of the most studied research topics and this is based on the fact that facial expressions are considered to be essential to the expression of emotions. "Face" is a versatile subject, and it demands understanding from various perspectives. Artificial Intelligence and Deep Learning technologies have led to dynamic changes over the last years and this is also reflected in the rapid development of smartphones and mobile applications and services. However, due to the limited resources available, it is still hard to process real-time video in smartphones [3]but it is still challenging to provide emotion recognition through these devices.

Neuroscience has also a close relationship with computer science generally and specifically Artificial Intelligence and Deep Learning since changes have led to dramatic advances in neural networks. This is actually the part where the origins of AI methods are closely related to Neuroscience [4].There are also many neuroscientists who tried to better understand human brains and build intelligent machines. In 1943, the first artificial neuron model: MP model, was proposed by the neuroscientist McCulloch and the logic scholar Walter Pitts who provided a significant contribution to the development of neural networks[5]. Since then both fields of neuroscience and Artificial Intelligence have grown enormously and provided great tools to understand the human brain, which makes it possible to achieve emotion detection through face recognition using better algorithms and models.

As already mentioned, measuring emotions could be crucial in various fields. However, industry and the public have grown interest in the measurement of emotions in customer and sensory science in light of the fact that the estimation of loving/worthiness/inclination couldn't dependably foresee food decisions. Specifically, food choice could be influenced by emotions and this is also confirmed by findings showing that a high degree of positive emotion may change people's behavior. Changes in facial expressions can lead to new objective measures of the affective responses to foods, since the internal feelings are frequently accompanied by them[6].

The present study is based on the development of facial expression models that correspond to the six basic types of emotions (happiness, sadness, anger, scared, surprise, and disgust). The present research is applied to the area of food marketing with the use of questionnaires and face observation during participants are watching a food video campaign.

1.2 Research Questions

Face recognition has been widely used in many research studies. In our case, we will use it to measure emotions through a real-time mobile face recognition application. It is very important to detect real time emotions, and in every case, we should be aware of the origin of them to examine the campaigns. Moreover, in the process of emotion recognition, we should not just recognize but also categorize the emotions to have a whole aspect of the results. Facial features will help us indicate what kind of emotions participants have.

This research will be applied to the area of food marketing. Therefore, the research questions of this thesis are:

Q1. What are the main emotions indicated by the food campaigns?

Q2. Which emotions (positive or negative) have a significant impact on the participants' intention to buy the promoted food product?

Q3. Which emotions can be recognized through face tracking methodologies (app) during watching the digital food campaign?

Q4. Are the facial expression recognition results compatible with questionnaire self-reported results?

1.3 Contribution

The contribution of this thesis is based on emotion detection through face recognition using a mobile application and questionnaires, specially designed to be answered by the people who will participate in the research.

We will conduct an experiment on real-time face recognition. We will use a mobile emotion recognition application on a specific sample to detect how the sample reacts to a video campaign. These videos will demonstrate organic vs regular chocolate. In this way, we will understand consumer emotions and the reasons behind them by observing their facial expressions. Moreover, finding suitable mobile applications for face recognition using mobile devices by comparing and analyzing how the existing ones work, is also introduced in this thesis. At the end, we will have a whole overview of how Neuromarketing, AI and Machine learning can be used to improve technology companies and their marketing strategy.

1.4 Objectives of this thesis

Our main objective is to "Examine the effect of emotions (positive and negative) to the audience intention to buy the digitally promoted food product".

The effectiveness of the campaign is based on the emotions that creates to the participants. Though, in order to take the emotions under consideration, it is essential to

“Evaluate the facial expression recognition application results, compared with self-reported data”.

1.5 Structure of this thesis

This thesis consists of five chapters. In the first part, we state the introduction where an overview of the general topic and research objectives is presented.

In the second chapter, we will introduce the literature review which is based on face tracking using an automated emotion recognition model in mobile phones. We will present Neuromarketing and more specifically face tracking and its application in Neuromarketing. Face recognition and emotion detection applications will be also compared and analyzed in order to understand better and have a view of the experiment that will follow.

The third chapter will include the methodology we followed to conduct the experiment. In this section, we will describe the research design, the data collection, and analysis methods as well as the tools and materials to be used. Therefore, the participants and the procedure will be also included as well as the survey instrument and the user's task.

In the fourth chapter, we will analyze in figures (tables, photographs) and in written text what we found out in relation to our research questions including details and how they were analyzed step by step. We will also comment on the significance of key results and critically evaluate the study by interpreting and explaining the results.

Finally, in the last chapter, we will clearly restate the thesis statement and answer to the main research question. Therefore, the recommendations for future work on the topic as well as the knowledge we gained through this process will be also part of the final chapter.

2 Literature review

2.1 Introduction

Scientific development in recent years has led mankind to confront two different but though closely related challenges: technology and human potential. Today, technology plays a crucial role in the era of big data, where a large volume of data is generated every second, and without the improvements that have already been done, it would be impossible to get any insight. Humans have already improved that predicting the future based on computer-based analytical processes, is possible. These digital evolvements are constantly changing, thus the need arises for incorporating traditional views in modern concepts.[7] Neuromarketing, Artificial Intelligence (AI), and Machine Learning (ML) are fields that are part of these improvements and they may seem independent but in fact they can highly be associated in most of the cases.

Today, there is no application area in which Artificial Intelligence oriented solutions are not used. Artificial Intelligence (AI) deals with human intelligence and how this can be represented in computers. Because of its great analysis strength, Artificial Intelligence techniques are often employed in various research problems that can not be handled with traditional computational approaches. Despite its relative infancy in the market, recent advancements in AI technology have already driven many industries into success. One of those is marketing. AI in marketing may be complex but is quickly evolving especially in this area, having already proven to be incredibly useful for it. Marketing currently represents the 4th largest use case of AI concerning resources spent, and the 6th largest industry adopter of AI technology, with around 2.55% of the total industry having been invested in it. [8]

Within the umbrella of AI are included subcategories, such as machine learning and deep learning, that produce real-world applications of AI, such as voice and image recognition. Machine learning is the aspect of AI that uses computer programs to automatically learn and improve from the experience without being explicitly programmed. Enabling analysis of massive quantities of data, while generally delivering faster and more accurate results, shows that Machine Learning is a promising field that has already disrupted our daily lives. Some of the most trending real-world applications of Machine Learning are the following.

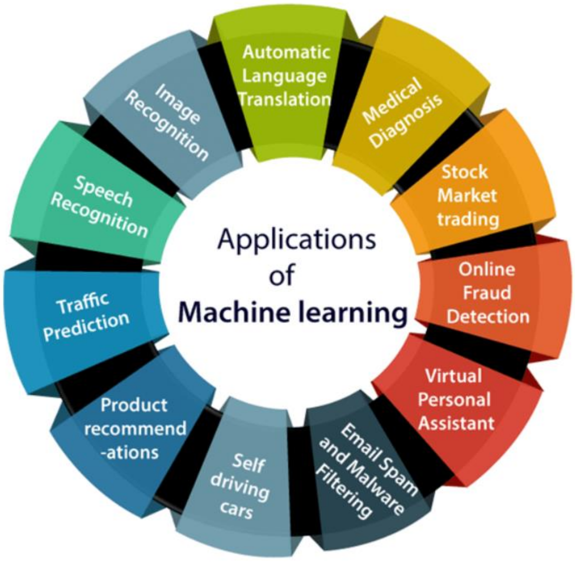


Figure 2.1: Applictions of Machine Learning [9]

Marketing, as a field, has already taken advantage of these applications. As consumer expectations grow for more personalized experiences, Machine Learning is becoming an invaluable tool to help meet those demands. As an incredible breakthrough in the field of Artificial Intelligence, Machine Learning can play a crucial role where it is applied and has changed the way businesses collect and analyze data and even the things that data can do.

Neuromarketing is a fairly new discipline. However, the promise that neurobiology can reduce the uncertainty and conjecture that traditionally hampers efforts to understand consumer behavior has led this field to fast development. “Neuromarketing” is a combination of Neurology and Marketing, as the term reveals, and it refers to the measurement of physiological and neural signals to gain insight about customers’ behavior. So, this field is inevitably connected with the field of marketing and specifically marketing research. In this context, AI has taken bioscience to the next level by empowering researchers to conduct experiments more efficiently and helping them find patterns they never knew that existed. The integration of AI in Neuromarketing studies is very few, but in perspective, are very promising and taking into consideration the fact that Marketing is also an area where innovation and creativity plays a fundamental role, we can conclude that AI can show its artistic and imaginative sides through

Neuromarketing [10]. Better understanding biological brains could play a vital role in building intelligent machines and this can be reflected from the fact that Machine Learning techniques have transformed the analysis of neuroimaging datasets, such as in the multivariate analysis of fMRI and magnetoencephalographic (MEG) data[4]

Artificial Intelligence, Machine learning, and Neuromarketing can be perceived as disruptive technologies since they can significantly alter the way that consumers, industries, or businesses operate. Marketing, as already mentioned, is one field that recognizes the potential of these technologies and incorporates them into their business processes. Marketing evidently evolved from traditional, via digital into intelligent, and marketers are already leveraging the advantages of these fields to gain valuable insights into customers, competitors, and markets. Marketing decision making not only refers to tactical marketing mix instruments (the well-known 4Ps), but also to strategic issues, such as product development and innovation. Knowing that marketing is a complex field of decision making, we can understand that some problems are relatively well-structured but there are also many weakly-structured or even ill-structured ones.

The food industry is one of the leading industries around the world and food market research is a field that works mainly to improve brand offerings and launch new products in multiple markets. A wide network of field researchers and food analysts works together to blend data and knowledge in order to get insights about consumer’s behavior.

Since motions are central components of people's lives, both interpersonally and intrapersonally, it can be understood that food market research is a multidisciplinary field that can be analyzed from different approaches. Consumer emotions play a key role in an individual's overall experience with a product. However, little is known about how people regulate their emotions in their daily lives. Studies have used different methods to understand the consumer's emotions. These methods can be explicit or implicit. Explicit methods are based on self-reports and implicit are based on subconscious spontaneous response. In the second category, AI, Machine Learning, and Neuromarketing have gained a critical competitive advantage through the tools they can provide to research. Food elicited emotions are difficult to be measured, and many non-verbal tools using skin conductance or heart rate can determine a direct reaction to the emotional response of consumers. Moreover, given the effectiveness of emotional marketing, companies that invest in emotion recognition technology, called Emotion AI, providing more insights about consumer’s behavior.

The human brain cannot be replaced. However, it is a fact that machines are very good at analyzing large amounts of data by picking up subtleties in micro-expressions on humans' faces and capturing subconscious reactions that might happen even too fast for a person to recognize. Using technology in combination with the human brain can provide tremendous developments in many fields and make our lives easier. However, it is important to remember that the human brain cannot be underestimated. It is the one which created machines and, in any case, "It's human plus machine" and not the opposite.

2.2 Face recognition

One of the most studied research topics in recent years is face recognition. Various techniques have been designed to detect and recognize faces since it has been indicated that face plays an important role not just in confirming the identity of a face but also to show one's emotions. The advances in related fields, particularly in Machine Learning, image processing, and human recognition have helped the development of facial expression recognition [11] making face recognition software one of the most powerful tools ever been made.

A face recognition system is a computer application capable of identifying a person from a digital image or a video frame image [12], since it can operate in either or both of two modes: (1) face verification (or authentication), and (2) face identification (or recognition). The first mode includes a coordinated match, which is one-to-one and compares a query face image against a format face picture whose identity is being claimed. In the second mode, there are one-to-many matches in which all the template images in the database are compared against a query face image [13].

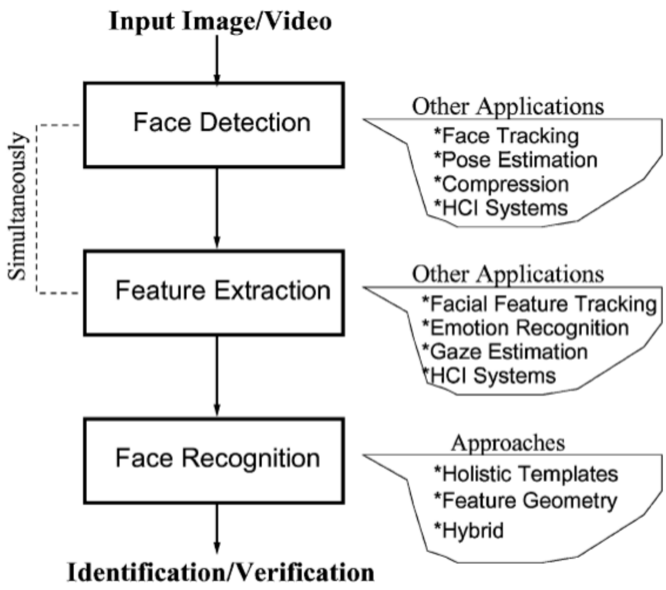


Figure 2.2: Configuration of a generic face recognition system. [14]

The earliest work on face recognition can be traced back at least to the 1950s in psychology [Bruner and Tagiuri 1954] and the 1960s in the engineering literature [Bledsoe 1964]. However, research on automatic machine recognition of faces really started in the 1970s [Kelly 1970] and after the seminal work of Kanade [1973] providing important consequences for engineers who designed algorithms and systems for machine recognition of human faces. [14] that lead to the first successful demonstration of machine recognition of faces was made by Turk and Pentland[2] in 1991 using eigenfaces that are made by extracting characteristic features from the faces.[15]

Today, every system can use its model for recognition. The following are some successful ones. Active Shape Models (ASMs) is one of the most well-known statistical models. They can be used for good geometric features such as measurements among coordinates of landmarks on the face.

Gabor wavelets representation and local binary patterns (LBP) are very popular for appearance features that have to do with changes of the facial appearance, e.g. wrinkles and furrows. Finally, the Active Appearance Model (AAM) is also a good and trustful method. [16]

Face recognition has a large number of applications. Nowadays, it is a task that humans perform routinely and effortlessly in their daily lives from their mobile devices to the security systems of ATMs in the banks. Concerning mobile phones, it is a fact that as new technologies are developed in this field, secure and flexible methods create a distinctive print to gain access and also help the user need not remember passwords[17]. For the same reason, ATMs started to use face recognition in order to unlock a smart card and authorize a transaction.

However, face recognition presents a challenging problem in the field of image analysis. Reliable face recognition is still a great challenge to computer and pattern recognition researchers. Though a face recognition system should be able to automatically detect a face in an image, there are still technical problems that need to be assessed, especially for unconstrained tasks where viewpoint, illumination, expression, occlusion, accessories, and so on vary considerably[18]. Specifically, pose and illumination has proved to be a much more difficult issue that affects the appearance of faces and needs to be solved [13]. This problem lies in the fact that in current systems a test image can be recognized under specific conditions, similar to those of the training images [19].

Moreover, there is one more challenge regarding privacy and this is because this technique such as face recognition could, at least in principle, be used to recognize people "passively," without their knowledge or cooperation, since there are still no legal guidelines for where and how face recognition technology can be used in public spaces [20] . We know that a person could be identified by other means such as voice or fingerprints but the human face reveals a great deal of information, since apart from identity it can tell anything about the emotions of a person.

For this and the reasons mentioned above, face recognition was and remains one of the most important biometric techniques since it also provides the advantages of being natural and passive over other techniques. It may present some challenges in the field of image analysis and computer vision, such as verification and identification, but we cannot deny that the attention over the last few years that has been received is great due to its applications in various domains.

2.3 Face tracking

Face tracking is a crucial vision-based tool to be used in human-computer interaction. In order to analyze people's faces, tracking is a crucial step that needs to be concluded. Although it is treated as a preprocessing step, face tracking is actually a part of face recognition. Researchers use multiple approaches, thus there is no perfect method that has great accuracy and can give absolute results. However, there are tracking algorithms that follow the same logic to produce results.

In these solutions, the movement of the face is converted into a set of orders to interact with the computer. In order to follow the face position, the first step is to distinguish the face in a picture so as to extract the features and analyze them. As already mentioned, there are various algorithms that are used for this procedure. These algorithms are generally categorized as feature-based and image-based methods[21].

In the first type, which contains feature-based methods, facial features such as nose, eyes, and lips are identified by performing geometrical analysis on their locations, proportions, and sizes. On the contrary, image-based methods are popular in Computer Vision due to their robustness and depend on checking the picture through a window to find the face candidates [22].

Face tracking technology can be used both online or offline. The approaches that involve online methods do not need training to perform face tracking. They use previous frames in the tracking procedure. On the contrary, offline methods need specific training. For this reason, they often include an object detector and then fit a statistical model on the detected object. Some examples of the most popular offline methods use Active Shape Models (ASMs) and Active Appearance Models (AAMs)[23].

2.4 Face recognition and its application in Neuromarketing

Neuromarketing (NM) is a multidisciplinary field that integrates neurology, marketing, and cognitive psychology. Specifically, Neuromarketing is described as a research field, a field of neuroscience, a field of study, a part of marketing, an interconnection of perception systems, a scientific approach, a subarea of neuroeconomics, and a distinct discipline[24]

The term “Neuromarketing” is a relatively recently developed concept. It was first used back in 2002 by Ale Smidts, a German professor who presented Neuromarketing as “the study of the cerebral mechanism to understand the consumer’s behavior to improve the marketing strategies”. Nevertheless, according to The Economist, this discipline’s founder is Jerry Zaltman, who conducted the first FMRI study as a marketing tool a few years earlier, in 1999 [25].

The diversity in neuroscience research lines is also reflected in the variety of the neuromarketing techniques that take advantage of this diversity and are not restricted only to the brain or to the central nervous system but include all of the areas and physiological and cognitive processes [24].

Neuroimaging tools measure changes in brain activation and activity location (e.g. motor area, language area, and hippocampus) in response to internal or external cues. However, based on the variation of their abilities to quickly measure activity in a specific brain area (temporal resolution) and differentiate between different regions in the brain, neuromarketing techniques are used for different purposes from the researcher[26]. Zurawicki, Kenning and Plassmann, and Calvert divide the types of tools used in Neuromarketing research into the ones that record metabolic activity, the ones that record electrical activity in the brain, and the ones that do not record electrical activity in the brain [27].

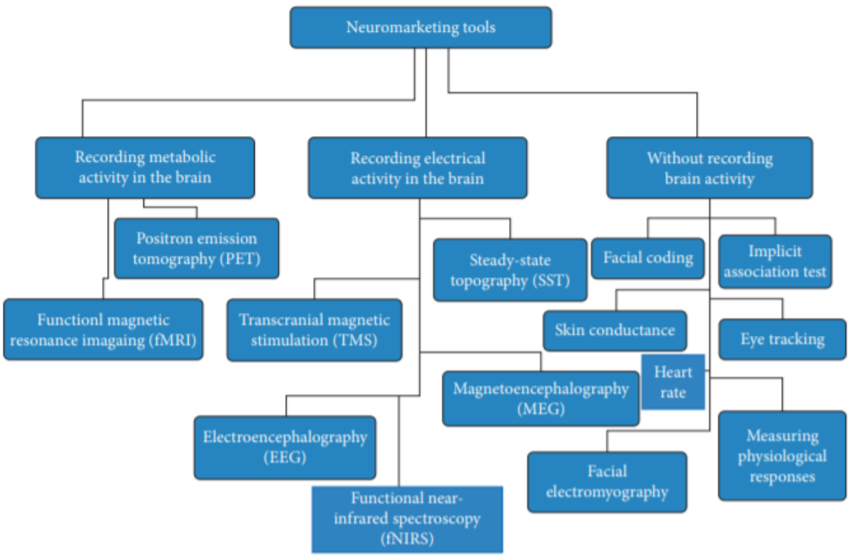


Figure 2.3: Classification of Neuromarketing tools [27]

Face recognition or is a useful procedure for the analysis of behavior and cognition. As we have already mentioned, facial recognition is a technology that can identify people, by scanning their facial structure and expressions with the use of special software and video cameras. The software simply compares the captured face from the camera, with other pictures of faces, that are stored in a database as a reference, and determines the emotions of the captured person.

In neuromarketing facial electromyography (fEMG), is a technique that has been studied to evaluate its utility as a tool for measuring emotional reaction, since expressions of emotion are associated with specific patterns of facial muscle activity and it is known that the human face provides non-verbal cues to aid in the observation and of emotion in others. Marketing scientists have started using facial recognition as a tool to further improve their goals, which is to design their products to attract more consumers. That can be achieved, by understanding how people feel about a product, by reading even the slightest movement variation of the facial muscles[28].

Facial electromyography (fEMG) is a technique employed by researchers to measure the underlying electrical activity that's generated when muscles contract. In this procedure electrodes that are attached to the skin surface can detect impulses generated by the activity of facial muscles around the eyebrows, cheekbones, and the mouth[29]. Facial EMG is primarily concentrated on the investigation of several muscles in the face, including the corrugator supercilii, the zygomaticus major, and the orbicularis oculi. Researchers interested in investigating positive emotional experience are advised to record an activity from both the zygomaticus major and the orbicularis oculi in contrast to the corrugator supercilii muscle, which is associated with the experience of negative affect, or the unpleasant dimension of valence[30] .

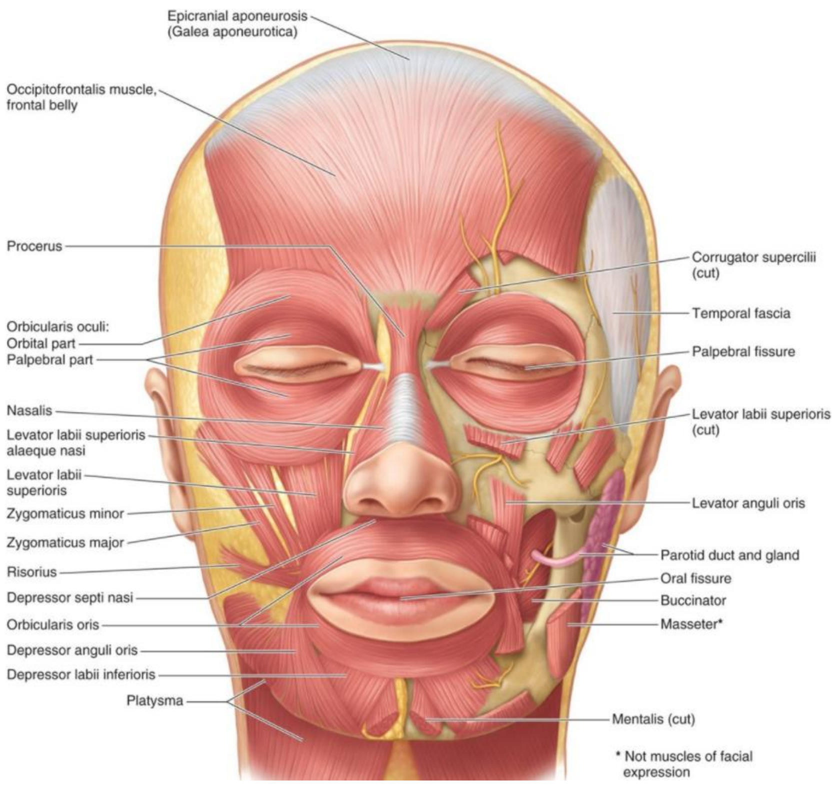


Figure 2.4: Head anatomy [31]

Facial EMG can also be considered within the Facial Action Coding System (FACS) framework, which has been developed by Ekman and Friesen for describing facial expressions by Action Units (AUs) [32]. The FACS manual describes the criteria for observing each Action Unit but It also outlines how AUs appear in combinations [33]. However, FACS is not actually the system that analyze the meaning of the expressions, since interpretations of emotions emerge only during the data processing stage [29].

Although there are many advantages concerning Facial electromyography (fEMG), it would be an omission if we did not refer to some limitations around the use of this technique. First of all, the involvement of the same muscle in different emotions may cause negative results because it might detect an emotion that produces both angry and sad facial expressions. One more related issue is that many muscles in the face are very close to each other. Finally, Facial electromyography (fEMG) allows for recording only a few muscle sites at one time and this is because covering a subject's entire face with recording electrodes would cause an uncomfortable experience for the subject that may produce wrong results [30] .

2.5 Machine learning and AI models

Artificial Intelligence, Machine Learning, and Deep Learning—is crucial to be understood on their own but is also important to be perceived how they are related to each other. The first one is divided into three main branches:

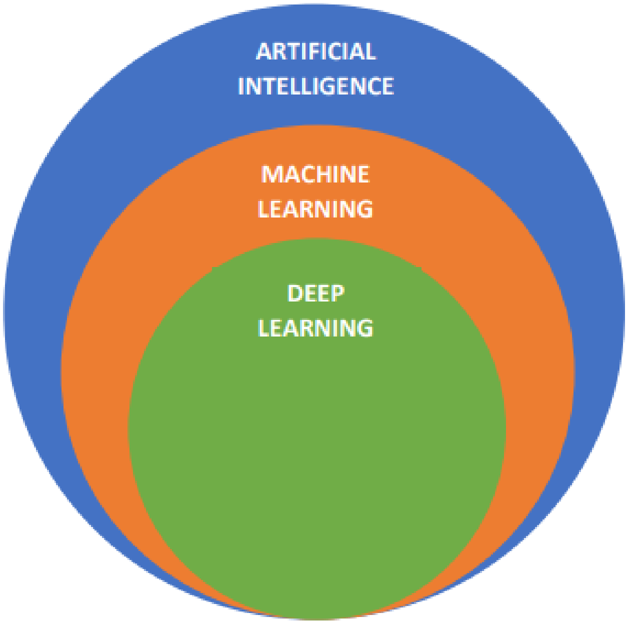


Figure 2.5: Deep learning, Machine learning and Artificial Intelligence [34]

Artificial Intelligence is the first of the three terms as historically originated. However, in the late 1970s a new interest in machine learning emerged and though some researchers were skeptical about it, during the 1980s researchers became more serious about the real-world potentials of learning algorithms[35]. The field of ML has grown rapidly since then providing many solutions with its applications, since it allows software applications to become more accurate at predicting outcomes without the necessity to program them. Deep learning, from the other side, allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction[36]. Today, due to the increase in the need for behavioral biometric systems and human-machine interaction, it is a fact that ML-based applications have received enormous attention. The ability to automatically learn and improve from experience without being explicitly programmed can provide and has already done, enormous developments in various research fields. Emotion detection is one of them and today a lot of intelligent systems have already been introduced and used not only as software in desktop PC's but also in mobile phones due to the availability of built-in sensors in them. Face detection and analysis is the first and important part of emotion detection. In order to automate this process, many machine learning algorithms are used to classify the user's emotional state.

Convolutional neural network (ConvNets or CNNs) is one of the most important innovations in the field of computer vision and it is also one of the main categories to do image recognition. Taking an image as input, it assigns importance to various fields of it and then comes to differentiation of one image from the other[37]. For faster and more accurate face detection, a deep-learning-based approach that uses three cascaded convolutional neural networks (CNNs) called Multi-Task Cascaded Convolutional Neural Network (MTCNN) can be used. In MTCNN, face detection and face alignment are done simultaneously, allowing it to detect non-aligned faces better. However, apart from its advantages, MTCNN is slow on CPU [37]. Apart from K-Nearest Neighbor, Linear Discriminant Analysis and Neural Networks (ANN) that are algorithms used for classification of prediction of emotion, it would be an omission if we did not refer to one of the most powerful classification algorithms, which are SVM. When they have to be used for emotion detection, multi-class SVM is used instead of a binary to detect emotions such as anger, contempt, disgust, fear, happiness, sadness, and surprise. Any variances, in this case, are being removed by K-fold cross-validation where the dataset is divided k times into k slices, and prediction results are averaged over all iterations. [38] Flexibility and robustness can also be offered by the statistical shape model (Active Shape Model, ASM), which advantages laying on it come from the fact that the solution is constrained by a flexible statical model[14] .

Being a state-of-the-art for many years,since 2001 when Paul Viola and Michael Jones proposed it, Haar feature cascade classifiers is also an effective machine learning-based approach, where a cascade function is trained on lots of images with and without faces. In contrast with this approach, OpenCV's Deep Neural Network face detector is based on the Single Shot Detector (SSD) framework with a ResNet-10 Architecture as the backbone and it is trained on lots of facial images from the web. Real-time detection and detecting faces on different scales are the strengths of Haar feature cascade classifiers, contrary to its weakness which is the fact that Haar feature cascade classifiers fail to work on non-aligned images and those with occlusions [37].

Requiring a small amount of training data to estimate parameters, Naïve Bayesian classifiers are effective in numerous real and complex situations and despite their basic design and oversimplified assumptions, Bayesian classifiers have been used to detect emotions using facial expressions in many researches [39]. Compared to this approach, CAMshift[8][9] and Lucas-Kanade optical flow can be directly applied to the current frame, without pre-training. The first one is an adaption of the Mean Shift algorithm for object tracking, which is a robust, non-parametric technique that climbs the gradient of a probability distribution to find the mode (peak) of the distribution. However, they differ on a point which is the continuous adaptive probability distributions that CAMShift uses, in contrast with Mean Shift which is based on static distributions [40]. Optical flow-based tracking proposed by Lucas and Kanade uses another method to track faces by extracting visual features from the region to be tracked estimating the optical flow between every two subsequent frames [40].

Various researches of emotion detection in mobile phones and ordinary PCs, use Viola-Jones technique, which uses Ada-boost algorithm. Although, it combines a lot of weak classifiers the results show a formation of a strong classifier by iterations, where a weak classifier reduces the weighted error rate per iteration. This method can run in real-time, including 3 core mechanisms, the integral image, classifier learning with AdaBoost, and attentional cascade structure [11]. Referring to emotion detection using mobile phones, in a recent research, it is interesting that the Neural Network based GMM classifier to investigate Gaussian mixtures has brought the highest accuracy score providing above 99% of accuracy. This also confirms the fact that the most recent emotion detection attempts (2019-2020) seem to prefer NN, SVM, and MC models, without though seeing any significant progress towards achieving high accuracy scores [41].

In video recordings of facial expressions, Cohn Kanade's database can be listed as one of the most popular databases. In the recordings, the top of the facial expressions is extensively analyzed by the activation of the Action Units (AUs), resulting in very accurate analysis and very few errors till date[42].

The presence of all this data analyzed by these models is having a profound impact on almost every aspect of our lives. Machine Learning and Artificial Intelligence are two of the most powerful tools we have today in order to make predictions, solve problems or just make our lives easier by being used across a wide variety of industries and applications. And the surprises do not stop here. Both fields continue to become more intelligent and prevalent and as the years go by we may be challenged not only by the efficiencies that have brought into our lives but also by the limitations we may confront as human beings.

2.6 Face recognition mobile applications

Face recognition technology is becoming even closer to people’s daily lives. As already mentioned, face recognition systems identify people by their face images providing a high level of security or just experience. In the first case, users do not need to use cards, keys, passwords or keypads in order to access their personal data, since the application works as a door to any information. This innovative technology of identification and interaction continues to evolve since it can also be applied in different sectors, from financial to medicine and genetic.

Regarding the security sector, the first to use facial recognition technology were governments. Over the last few years, companies also started to train deep learning algorithms to recognize fraud detection. Today, we all know that almost all smartphones are now using face recognition to be unlocked. This technology is a powerful way to protect personal data ensuring that they remain safe until the user decides to provide access to them. Companies like BioID help people to authorize transactions securely and conveniently. BioID's is a multifactor user authenticator that provides patented liveness detection that ensures that biometric samples come from a live person and not from a photo or video [43]. Similarly, True Key is a password manager that works in a similar way placing more emphasis on multi-factor authentication[44]. FaceFirst, is also a platform that enables a full range of surveillance, customer engagement, mobile, access control, and desktop forensic face recognition capabilities [45]. Helping user lock applications safer and quicker, IOBIT applock delivers security but it works only in Android 4.4+. Created only for Android Applock app lets users lock almost any type of file[46]. Finally, FaceVault application uses facial recognition-based software to keep out snoops but only works with iOS devices [47].

Medical professionals can now identify illnesses by looking at a patient's features. Face2gene is an application that uses the aggregation of "gestalt," comprising data summarizing features of patients' facial images, to suggest candidate syndromes [48]. However, this system cannot be used alone but as an assistant tool in the developmental medicine and genetic clinic.

Face recognition can also be applied in the Financial sector. A lot of innovative technologies appeared in order to increase the security of transactions for both the customer and the business. FacePHI is entirely designed and developed its own robust algorithm, already validated by the banking sector, it was created in order to enhance the client experience by providing a method of identification and interaction with the bank's mobile application[49].

Business is one more sector that can take advantage of Face Recognition. RAILER is a company that already provides Face Recognition Mobile Attendance Management solutions For Companies and Schools. It provides real-time tracking using specific sensors and QR codes giving a solution to managers [50].

Facial recognition technology may have been traditionally associated with the sectors mentioned above but there are also successful applications developed around people's everyday life providing different experiences. The use of Mojipop application can help users to create their own funny cartoon stickers and use them in their daily conversations[51]. Taking advantage of augmented reality, artificial intelligence, and computer vision, Blippar is one more company that helps users unlock augmented reality experiences from everyday objects and places. This application gives the ability to anyone who owns it, to learn more about what they want just by scanning it [52]. One more AI-powered mobile application that is worth to be mentioned is Facepp. The FaceApp started the trend of people posting photos of their old selves on social media and is still a well- known application that allows users to apply several transformative filters[53]

2.7 Emotion detection mobile applications

Machine emotional intelligence is evolving rapidly and has already consequences in various fields such as healthcare, business, and education. This means that is already part of our everyday lives. Mobile phones, particularly smartphones, are also part of this technological evolution. Today, a smartphone is not only a commercial product but a portable computer with which the user can connect and communicate instantly, work from anywhere, file taxes, track spending, buy products or just use his device for entertainment. Transformed into essential connections to the Internet world, it is obvious that smartphones are strengthening the ties between people and technology. However, it is crucial to refer to the fact that the smartphone evolution is not only due to the development of their characteristics but also to the mobile apps that are taking advantage of them. Augmented Reality (AR) and Artificial Intelligence (AI) have been used extensively for this purpose, providing apps that enhance the user's experience. Emotion detection mobile applications have gained a lot of attention and therefore they have been increasing due to their smart features and user acceptability.

Affdexme is created by Affectiva, a company that is focused on advancing its technology in key verticals: automotive, media, audience and customer analytics, social robotics, and human behavioral research. Various market research firms such as Mars and Kellogg's trust Affectiva technology to measure consumer emotional responses to digital content, such as ads and TV programming. Affectiva uses Emotion AI technology to help clients develop better advertising through pre-testing and today with the use of Affectiva's Affdex Software Developer Kit (SDK) can now be demonstrated through AffdexMe. Real-time analysis of facial expressions can help users see their own face on the screen with specific metrics through their smartphone. The application can be used both from Android and iOS devices. The only condition is of course the existence of a front built-in camera.[54] .

Affectiva uses deep learning technology to model more complex problems and get higher accuracy. The specific tasks address includes face detection and tracking, speaker diarization, voice-activity detection, and emotion classification from face and voice. On-device performance requires exploring trade-offs between model complexity (memory, FLOPs) and model accuracy but the basic deep learning architectures Affectiva uses are:

- Convolutional Neural Networks (CNN)
- Multi-task (multi-attribute) networks for both regression and classification
- Region proposal networks
- Recurrent Neural Networks (RNN)
- Long Short-Term Memory (LSTM)
- Deep Recurrent Non-Negative Matrix Refactorization (DR-NMF)
- CNN + RNN nets[55]

Emotimeter is one more application that can detect emotions from facial expressions using cutting edge machine learning technologies. This app was developed by reAImagine and was created to be used not only in real-time from the images obtained by the camera but also from recorded videos or photos from the user's smartphone gallery. Emotion recognition for Ms and Feely can be used and produce almost the same results. Both applications detect human faces in photos and identify emotions communicated by the facial expressions in an image. However, they have small differences such as the fact that Feely can analyze faces in real-time from the camera and images, a very important characteristic and Emotion recognition for Ms cannot provide it.

Taking into consideration the evolution of emotion detection mobile applications, it can be understood that Emotion AI continues to search for new ways to get insights about how people feel. It is obvious that smartphones are part of people's life but when it comes to market researches, fueled by advanced deep learning techniques and massive amounts of data, we can conclude that smartphones cannot be used alone without a monitor by a Software API. Emotion AI technology can really help businesses capture attention by getting into the human's brain because it is not always about how people say they feel, it is about how they react and do feel.

2.8 Emotion recognition in food marketing (food market research)

It is widely accepted that changes in eating in animals and man can be affected by emotional arousal and that these changes vary according to the specific characteristics of the individual and the emotional states in question [56]. Based on the conditions, physiological correlates, frequency of occurrence, and duration emotions could differentiate, and may also vary in their associability with eating. Generally, when emotion occurs more frequently in eating contexts than other emotions and leads to physiological and behavioral changes, this emotion could lead to high degree associations with eating [57].

Many studies attempted to investigate the relations between emotions and eating since emotions as well as food are central components of people's lives. These researches have helped many food companies to understand the important role that psychological and social factors can play in food-related consumption. However, research also shows that since the exposure to food advertisements can influence viewers' food choices toward unhealthy foods, many food advertisements are significantly associated with unhealthy food consumption decisions leading to emotional eating and sometimes overconsumption [58]. Indeed, knowing that food consumption has never been only about satisfying physical hunger but lies on a wide range of variables, such as hunger, appetite, cost, accessibility of food (cooking and time), culture, perceived emotions, we can easily conclude that the motivation to eat can easily be affected[59] .

Consumers respond to foods in two ways: Firstly, through a physiological response, which includes changes in facial expression and autonomic nervous system activity. Secondly, through changes in brain activity and an emotional response.

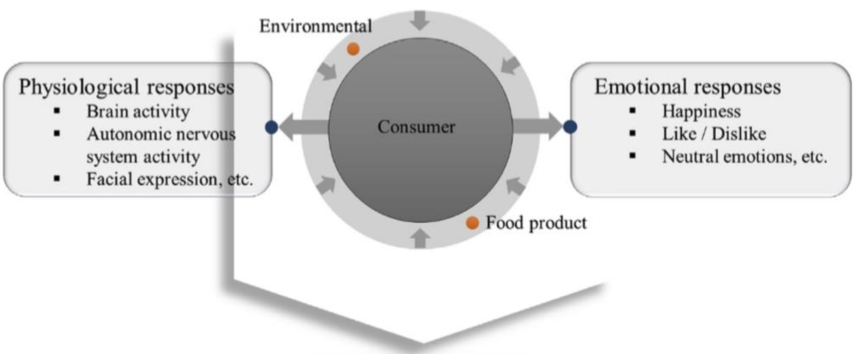


Figure 2.6: Food acceptability [60]

Various methods have been developed for measuring food elicited emotions. These methods include discriminating emotions for particular foods based on sensory and conceptual attributes [59].

They use different approaches to estimate the emotional connection between consumers and food based on specific emotions are studied in consumer psychology which are humans possess six basic emotions (happiness, surprise, fear, sadness, anger, and disgust). Questionnaires are regularly used for food-related emotion research. They are the most commonly used techniques to measure emotional responses and usually include many emotion words (14-39) and their contribution to the interpretation of results is less than straightforward [61].

However, questionnaires have deficiencies due to the fact that emotions are difficult to verbalize and the “emotional” lexicon differentiates across cultures and languages, especially when it comes to foods [62].

Eye-tracking is also a technology that gives accurate data about the individual's eye movement and fixation on a specific target, and is conceived as a valid method to record the non-cognitive reaction[63].Techniques, such as eye-tracking, that do not use talk or writing can reduce the conscious impact on the final response and avoid the deliberate reaction.

Physiological measures and measures reflecting brain activity can be also used to evaluate an individual's unconscious response to food stimuli. In the first category, we can refer to Heart rate (HR), electrodermal activity (EDA), skin temperature (ST), and blood pressure (BP)[62]. However, self-reported methods still are more likely to be used to measure food-evoked emotions in a product development context because they do not provide the same detail [64]. Brain states can also serve as a measure of emotion. Specifically, brain wave changes can create many emotions and affect decision-making. Electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and positron emission tomography (PET) [62], are also recognized as non-verbal methods since they can indirectly register emotions while participants are consuming, smelling, or looking at food.

However, it would be an omission if we did not refer to the fact that body movements or time-related factors such that failing to properly control can possibly affect physiological variables and lead to incorrect conclusions[65]. Mauss and Robinson confirm this stating that “although there has been some progress in understanding the neural correlates of fear, disgust and potentially sadness, the discrete-emotions perspective has yet to produce strong replicable findings” [66].

It is a fact that emotional connection is a strong motivator of behavior. Emotions are rapidly becoming more relevant and important to understand consumer product conceptualization, since emotions influence people's eating behavior, including food choice, motivation to eat, and amount of food intake. Food companies aim to understand deeper consumer's preferences and behavior to develop and promote food products that resonate with the target audience. Their food products must be transformed by these messages in the forms of packaging, branding, and commercials. Although there are several ways to measure emotion elicited by food, explicit methods are the most common, since apart from the fact that they are a fast and easy approach, explicit methods are also user-friendly as they do not require much involvement of the participant[67]. Implicit methods, which include physiological measures and measures that reflect brain activity may decrease cognitive biases but they are still not common since they are time-consuming and may produce wrong results due to the proper control they need.

2.9 Mobile emotion recognition in food marketing (food market research)

Many researchers have attempted to explain consumer's behavior. Taking into account the fact that food choice is influenced by many interrelated factors, including flavor, consistency, and appearance, as well as sentiments and values [68] , it can be concluded that research in food marketing is a multidisciplinary field that can be analyzed from different approaches. In this process understanding consumer emotions and the reasons behind is very important since emotions can be the source of consumer's choices. Being aware of the association of emotions with the food itself, as well as components of the food experience, such as the context in which it is consumed or the memories associated with a particular food, we can confirm that food can elicit a wide range of emotions [69]. Food is a fundamental human need that is not only driven by physiological and emotional states but also influences them and indeed researchers suggest that eating or choosing certain food items over others can reduce negative psychological states [70].

Companies have now understood the power of interpreting consumer's behavior and the role that emotional data plays in food consumption and lead to ultimately market success. However, they are also aware of multiple emotional dimensions food choice involves. For this reason, they have developed many methods to get into the consumer's brain. In the methods of measuring emotions, they are included traditional conscious verbal approach (questionnaires) and those involving cognitive, physiological, and/or behavioral expressions. [71]. There are major advantages to both approaches. For instance, the main advantage of the verbal methods is that rating scales can be assembled to represent any set of emotions and can be used to measure mixed emotions. In the non-verbal, on the other hand, as they are language-independent which means that they can be used in different cultures[72].

Many researchers depend on their studies on the fact that emotions are associated with specific reactions. So, in order to understand human behavior they use non-verbal methods. The study "Consumer facial expression concerning smoked ham with the use of face reading technology tried to determine emotions expressed by a consumer during or immediately after sampling using FaceReader. Developed by Vicar Vision and Noldus Information Technology, FaceReader recognizes facial expressions by distinguishing six basic emotions (happy, angry, sad, surprised, scared, disgusted, and neutral) with an accuracy of 89%. It is based on Ekman and Friesen's theory of the Facial Action Coding System (FACS) that states that basic emotions correspond with facial models and many researchers have already used it for different reasons [73]. Using the technology of facial expression recognition, the present study tried to statistically interpret the results obtained after the consumption of smoked ham as a consequence of the duration of the flavor sensation in the mouth. Each consumer received one slice of ham of 3 mm (size 1.5 cm × 3.0 cm) at room temperature (21 ± 2 °C) in plastic containers coded with 3-digit random numbers. In the present study, the emotions of participants were recorded by a video camera within 30 s after the consumption of a particular piece of ham [71]. The results, in this case, were completely based on the emotional reactions of consumers using a face visualization method.

Verbal self-report instruments can typically assess the subjective feeling component of emotions. The most well- known self-report instruments require respondents to report their emotions with the use of a specially designed questionnaire. For instance, in the research "Development of a Measure of the Motives Underlying the Selection of Food: the Food Choice Questionnaire", the Food Choice Questionnaire (FCQ) was developed through factor analysis of responses from a sample of 358 adults ranging in age from 18 to 87 years in order to assess a broad range of factors perceived as relevant to food selection. The results finally showed interesting differences in motives for food choice associated with sex, age, and income were found[74]. Food Choice Questionnaire (FCQ) is also used in other studies concerning the food market such as in "Motives underlying healthy eating: using the food choice questionnaire to explain variation in dietary intake". Designed in this case to assess the reported importance of nine factors that may influence food choice (health, convenience, price, sensory appeal, natural content, mood, familiarity, ethical concern, and weight control) suggested that most of the factors in food choice are significantly associated with food intake[75].

Many studies also use a combination of methods. The study "Evoked Emotions Predict Food Choice" used both non-verbal and verbal models to predict food choice. The first one is EsSense Profile, which is a verbal emotion measurement instrument, and the second PrEmo, which presents emotions non-verbally as animated cartoon characters. During the use of PrEmo, the respondents are first shown a (picture of a) product and subsequently instructed to use the animations to report their emotion(s) evoked by the product. This self-report instrument that measures 14 emotions, which are portrayed by an animation by means of dynamic facial, bodily, and vocal expressions[72]. In this research, cross-validation helped researchers to show that they were able to predict individualized choices with high accuracy. Moreover, comparing the two methods the results showed that measurement of non-verbal food-evoked emotions more accurately predict product choice than verbal food-evoked emotions indicating that liking is no strong predictor for food choice in real-life environments [76].

A combination of methods was also used in "Effects of emotional responses to certain foods on the prediction of consumer acceptance" research. A personal interview in combination with Noldus FaceReader technology was chosen as the most appropriate methods for data collection and accurate detection of significant differences in facial expressions elicited by different food samples, which were five samples of different breads, wholemeal wheat flour, and multigrain and two samples of different chocolates (dark and milk). During the research 109 students (27% males and 73% females) from the Kaunas University of Technology (Lithuania) between 21 and 24 years of age, were asked to taste the whole presented sample at once, take fifteen seconds to reflect on the taste impressions and then give a signal with a hand and visualize the taste experience of the sample with a facial expression best representing their liking of the sample. The findings in this research showed clear relationships between certain sensory and emotional perceptions during product evaluation [6].

An interesting research also used more than one method to gain results. Affective responses triggered by food odors were measured with continuous, implicit (facial expressions and ANS responses) and discrete, explicit (pleasantness and nonverbally reported PrEmo emotions) measures. Specifically, the physiological data were collected at 200 Hz via a Biolab data acquisition system (MindWare Technologies) for HR, skin conductance level (SCL), and skin temperature (ST), and the facial expressions of participants were filmed with a Logitech C600 webcam where the facial expression data were automatically analyzed by FaceReader 5. Moreover, the participants had to rate animated figures expressing an emotion, on a 5-point scale, to indicate to what extent their feeling elicited by the stimulus was expressed by the animations [77]. This procedure helped researchers to have a more descriptive overview of this subject.

As already mentioned, food-evoked emotions are crucial factors in predicting consumer's food preferences. Due to this fact, multiple emotion measurement tools have been developed to assess a wide variety of emotional reactions to the food product experience. However, there are several things to take into account when designing a research. Each method has advantages and limitations that researchers take into consideration before conducting their studies and get more accurate results.

2.10 Face emotion recognition in food marketing (food market research)

Consumer research has grown rapidly in the last few years. Accurate measures for understanding consumer's choices have been developed in order to evaluate their behavior. Emotions are a good way to get into the human's brain and come closer to their intentions by giving dynamic information about their behavior. Emotion measurement methods can be classified into two categories: explicit (or declarative) and implicit. Both methods have pros and cons.

Explicit methods are based on self-reports, relying on conscious post-rationalization and measuring emotions in a static manner. They can be seen as personalized variable since emotional language can be defined and interpreted in different manners from one participant to the next[78]. Implicit physiological methods have been developed to understand deeper consumer behavior and from different aspects, because they are based on subconscious spontaneous response. However, it is hard to suppress or falsify yet gathering clear readings can be challenging [78].

Facial expressions have been studied by many scientists, such as Charles Darwin (1872) as indicators of emotional states and tools for communicating emotions [79], since for a long time faces are believed to be the primary nonverbal channel for the communication of emotion. A study by Mehrabian and Ferris (1967) can confirm this statement since it revealed that 55% of the impact of the message is contributed by nonverbal communication, 38% by tone of voice, and 7% by words. [80]

Many automated facial expression analyzers and applications are based on a very influential work from Ekman and Friesen, called Facial Action Coding System (FACS), which is used to classify emotional responses by linking basic emotions with facial expressions[81].

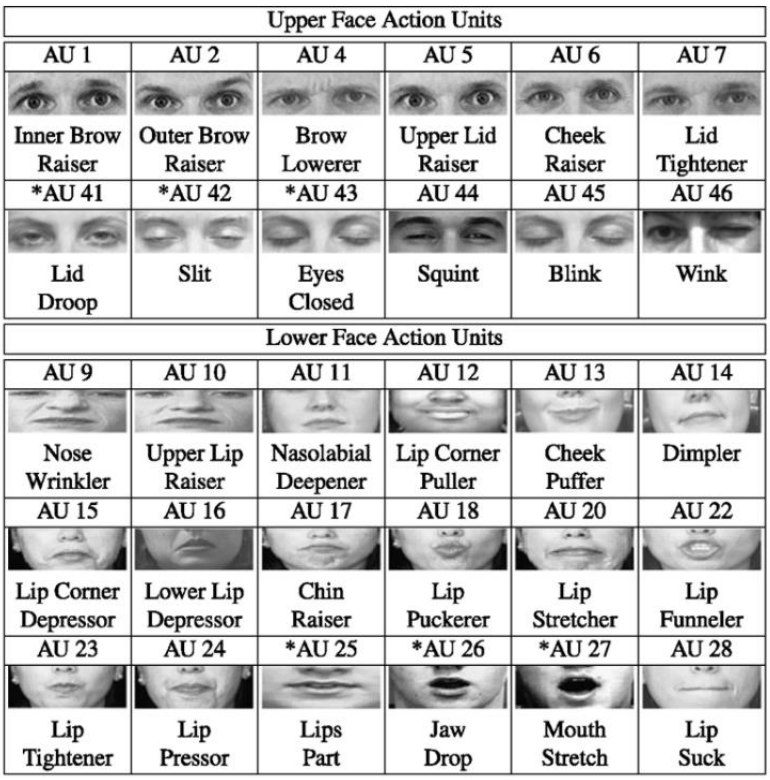


Figure 2.7: Facial Action Coding System (FACS) [82]

However, in the case of consumer emotion research, Facial Action Coding System (FACS) sometimes is proved to be limited due to the following facts. First of all, it incorporates more negative than positive emotions, which results in measuring an unstable set of emotions from a valence point of view. Moreover, this coding system is not well attached to food research, since it does not include emotions that are often expressed in consumer emotion research[83] .

Facial expression measurement remains a useful tool in food marketing since consumer's emotions play a key role in an individual's experience with a product from the part of selection to the part of interaction with it. Muscular facial movement analysis is the key point in every procedure used to understand human behavior. Based on the equipment and the requirements of every research, they can use manual facial coding, automatic facial coding, or both.

Several facial coding methodologies measure human emotions through facial expressions manually, but the most well-known remains Facial Action Coding System (FACS), allowing measurement and scoring of facial expressions in an objective, reliable and quantitative way.

Today, new technologies have been developed providing more efficient translation of facial coding data analysis methods using automatic facial coding. Systems can automatically recognize individual action units or action unit combinations, using facial expression recognition technologies based on the Facial Action Coding System (FACS) or not. In contrast with Statistical pattern recognition, automated facial coding can reveal emergent behavioral patterns that in manual facial coding would have required hundreds of coding hours by human experts and would also be unattainable by the non-expert [84]. However, it is essential to refer to the fact that there are also some limitations within the scope of facial coding. First of all, training for manual coding can be very time-intensive, especially when compared to traditional methods of data gathering (questionnaires). Moreover, failed data capture and/or misrepresentation in the analysis of the facial expression due to face block in the procedure is one more limitation that need to be referred to [78].

3 Methodology

3.1 Measured emotions

Researchers in the last century have discovered several core or basic emotions. In our research, we focused on four out of the "big six" emotions identified by Paul Ekman during the 1970s, which are happiness, sadness, fear, anger, surprise, disgust [85]. Many researches have confirmed that these emotions are universal for all human beings [86] and many studies have used this list to identify emotions. Although this basic list has now been expanded by Ekman including amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame [81], we will examine the first list which includes six emotions.

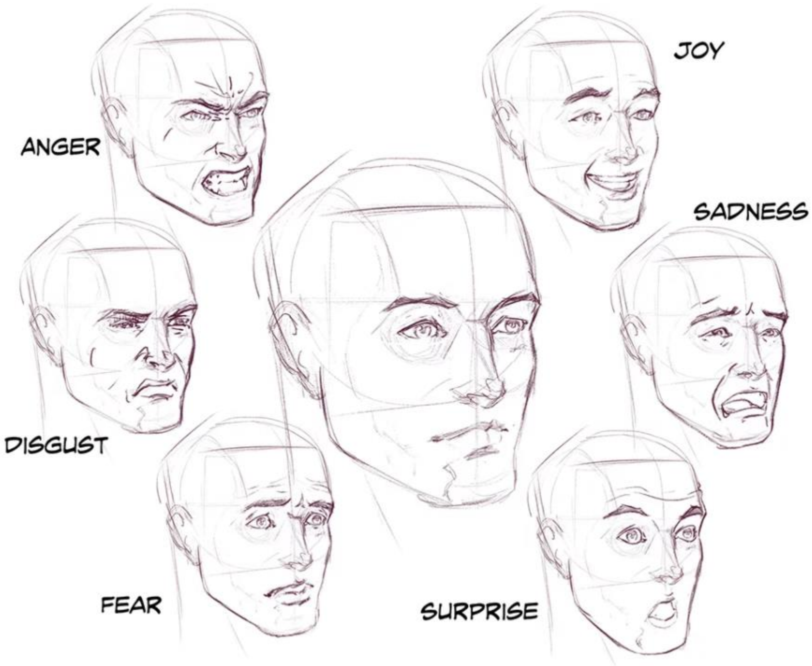


Figure 3.1: Facial expressions [87]

- *Fear* is a powerful emotion and it is defined by avoidance behavior. For this reason, fear can play an important role in survival.
- *Anger* helps release energy and that is indeed anger's main purpose. It can be one of the most dangerous emotions and it is accompanied by changes in heart change and muscle tone.
- *Happiness* is often defined as a pleasant emotional state. Similarly, to all emotions, happiness can be a brain process that simultaneously makes appraisals and perceives the body.[88]
- *Sadness* is defined as a negative emotion and most of the time is accompanied by feelings of disappointment and hopelessness.
- *Surprise* is an emotion accompanied by a startle response following something unexpected. Surprise can be positive, negative, or neutral based on the situation that caused it.
- *Disgust* is one more powerful emotion and arises as a feeling of aversion towards something offensive.[89]

In our research, we will examine perceived happiness, perceived sadness, perceived anger and perceives surprise.

3.2 Food campaigns description

Our research is focused on chocolate campaigns. The chocolate industry is a large one and continues to evolve. Chocolate marketing activity usually includes strong campaign targeting customers in a straightforward way. In our case, we chose to focus on campaigns that present both regular and organic chocolate and use different ways to show their products.

3.2.1 Galaxy "You can do it all"

Galaxy had long been one of the UK's favorite chocolate brands. The positioning of Galaxy as a more refined, sophisticated pleasure is well established and promoted from its campaigns that include women as main characters. Audrey Hepburn was also a Galaxy girl staring in an advertisement featured a computer-generated image of her.

In this campaign, Galaxy tries to tempt customers with a fresh female voice in the new campaign "You can do it all". The 1 minute- ad which was launched in August 2019, encourages women to make time for themselves. Showing a young woman jogging, juggling her career, being a mother and activist, always trying to do it all, the Galaxy brand promotes pleasure as an essential in our everyday life, since the advert ends with the tagline "Galaxy – Choose Pleasure" flashing across the screen.

As she urges herself to "lean in and get a glass-ceiling smashing job," the voiceover says "There's a voice in your head that says 'You can do it all'. You can have a high-flying glass ceiling smashing job, and a happy glowing super mom"

Finally, the main character suddenly stops and shouts "Shut up!" from the top of her lungs.

The ad closes with a scene, where the young woman approaches a man in the crowd who’s holding a Galaxy bar. She grabs it from his hands, and walks away with it. This “fresh, contemporary and modern” repositioning of Galaxy shows company’s hopes to appeal to a younger generation. The ‘You Can Do It All’ campaign targets young women who strive to do it all and try to find some time in their everyday life for pleasure.

3.2.2 M&S Food: Easter Adventures in Chocolate

Marks & Spencer is the biggest non-supermarket retail group in UK. Apart from clothes, the company also sells a range of food and home goods under the banner of “luxury for less”. In this campaign, Marks & Spencer used a different way to approach customers in a special period. In the Easter of 2015, the company launched a series of new Adventures in Food TV ads to promote its “exclusive Easter collection” with chocolate eggs and chocolate bunnies. “Easter Adventures in Chocolate” shows how delicious chocolate is in an inspiring way.

Focusing on the main parts of the procedure of how a chocolate egg is made, Marks & Spencer manages to combine successfully pleasure with sophisticated design urging customers to feel the taste of Easter and run to the first store to get their own egg.

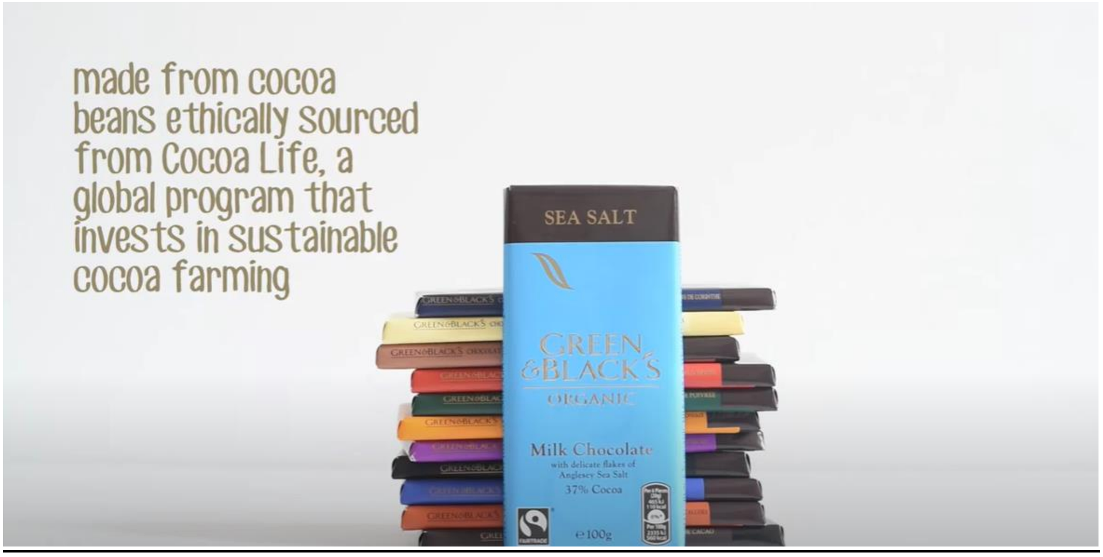
The campaign has not specific target audience. This positioning shows company's attempt to get into customer's heart and mind through the confusion of emotions for Easter with these emotions for chocolate.

3.2.3 Green & Blacks Fair Trade Organic Chocolate Bars

Organic food sales are growing, yet they are not strong on promotions since the food market is still controlled by conventional food. For this reason, after a long research, we did not manage to find plenty of campaigns. Green & Blacks is the only big company that chose to invest in a promotion video.

Green & Blacks is One of the best Fairtrade chocolate brands and has made its name as an organic chocolate maker since being founded in London by Craig Sams and Jo Fairley in 1991. Three years later, its Maya Gold bar was the first chocolate in the UK to be awarded the Fairtrade mark. Today the giant is owned by US food giant Mondelēz International, parent of Cadbury.

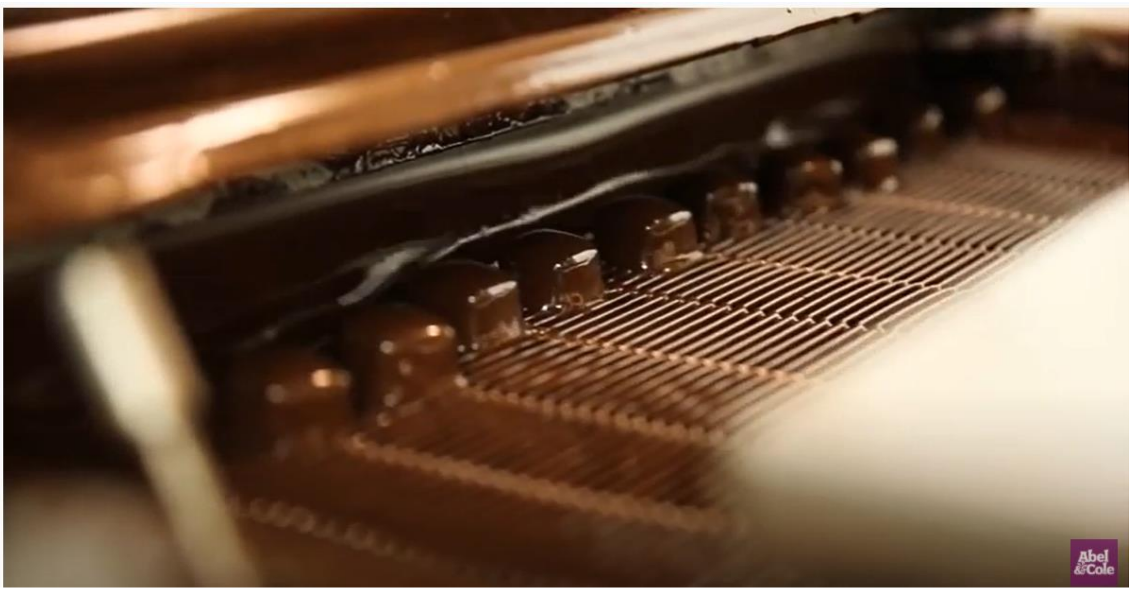
This campaign promotes Green & Black's collection, which includes a wide variety of organic chocolates. It is clear that the campaign targets people that prefer organic products. The company chose to create a simple campaign structure, something that can be understood both from graphics and music. Presenting the basic and most important facts about the chocolate bars, the company uses minimalistic letters to show what a customer should know about these chocolates. Starting from general and most useful information such as the fact that the bars are "100% organic" and "100% fair trade", under the happy tunes of music the company continues to give more details about the products.

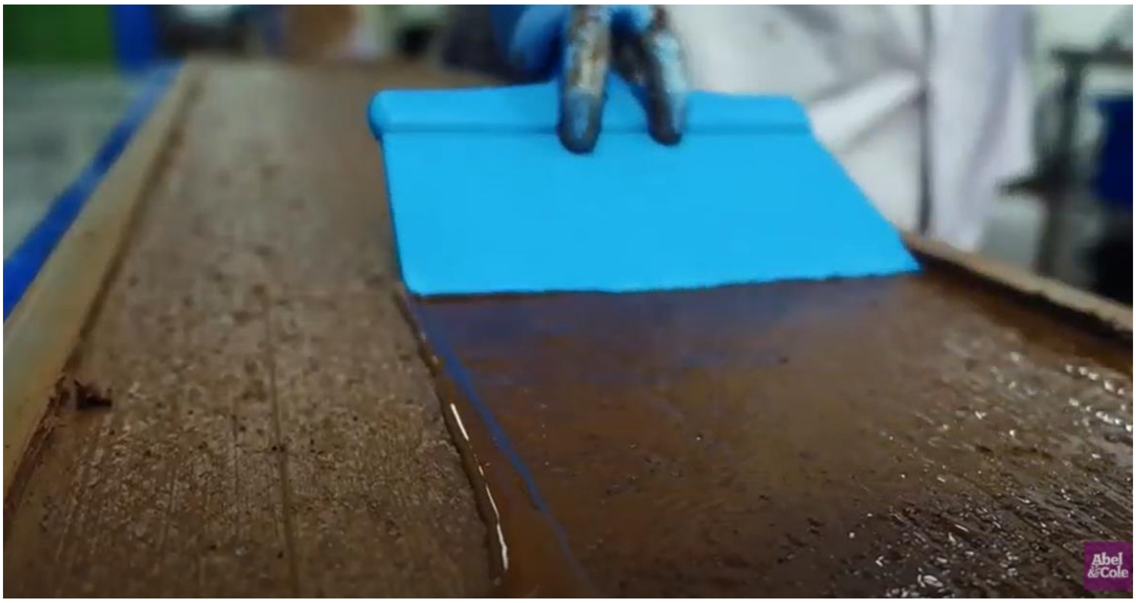


3.2.4 Booja-Booja Dairy Free Chocolate Truffles by Abel & Cole

Abel & Cole is an organic veg (and lots more) box scheme. The company was created in 1988 by Keith Abel and since then Abel & Cole is delivering the world of organic to doorsteps up and down the country of UK.

In contrast with the previous companies, Abel & Cole chose to promote its dairy free chocolate truffles with a different though inspiring way. Following a standard framework that is used from almost all organic companies, they promoted this product through a presentation of how the truffles are created. Targeting vegans as well as people who choose gluten free products, the video starts with a tempting way showing the steps of truffle production.





As the campaign continues to move forward showing delicious chocolate scenes from the insight of the factory, a man who manages the production, starts to speak about the truffles giving details about the origins of the chocolate and the relationships that the company has built with their suppliers. The quality as he says comes from how the simple products are, since they are made from no more than 6 ingredients.

His voice is steadily heard throughout the campaign, even when his face is replaced by chocolate scenes. The video closes with a scene where the manager says “as you guys probably taste how good they are, you will love them” leaving the audience with the taste of chocolate in their mind.

3.3 Questionnaire

The questionnaire item structure was based on previous o research of emotion recognition related questionnaires. However, there are also questions that were specifically designed for this research. The initial scale comprised of 24 items distributed on 4 dimensions, which were food elicited emotions. A five- point Likert-type scale with 5 degrees of intensity (1 "total disagreement" to 5 "total agreement") was used to measure the items.

Survey questionnaire

Concerning Perceived Happiness, items PH1 and PH2 were adapted after Aynsley SA, Nathawat K, Crawford RM from [90]. The items PH4, PH5, PH6, PH7 after Mikki HP from [91], item PH3 after Poels K. from [92] and items PH8, PH9 are original. For the Perceived Sadness factor, PS1 and PS2 items were adapted from Kwong ASF from [93], PS3 from [92] by Poels K. and PS4 is original. Perceived Anger consisted of 4 items. The first two (PA1, PA2) were reformed from Poels K. from [92] and PA3, PA4 are original. Perceived Surprise comprised of 5 items. PSU1 was the only one adapted from Mikki HP from [91]. The items PSU2, PSU3, PSU4 and PSU5 are original. Finally, Intention to buy consisted of 3 items. ITB1 and ITB2 were reformed from Mutambala C, Aliyar S. from [94] and ITB3 from Chen CC, Chen CW, and Tung YC from [95]. Apart from these factors, a general question was posed in the end of the questionnaire.

Perceived Happiness

PH1I really liked watching these campaigns [90]

PH2 I would like to see at least one of these campaigns again [90]

PH3 I lost track of time[92]

PH4 I felt detached from the outside world while watching the campaigns[91]

PH5 I can not tell that I got tired while watching the campaigns [91]

PH6 I am likely to recommend these campaigns to others/ I am likely to talk about these campaigns to others [91]

PH7 I think the campaigns are visually appealing[91]

PH8 I feel that I want to eat chocolate

Perceived Sadness

PS1 I found it hard to concentrate [93]

PS2 I did not enjoy this procedure[93]

PS3 I felt bored during watching these campaigns[92]

PS4 I was not attached to any of these campaigns

Perceived Anger

PA1I found it a waste of time [92]

PA2 I felt that I could have done more useful things [92]

PA3 I felt that I wanted to stop watching

PA4 I felt nervous while watching the campaigns

Perceived Surprise

PSU1I felt captivated by the stories of the campaigns[91]

PSU2 I had unexpected feelings while watching the campaigns.

PSU3 My motivation to take part in this procedure increased unexpectedly while watching the campaigns.

PSU4 I was interested to notice every part of the campaign

PSU5 I was curious to see what's next.

General Question

GQ Which campaign gave you the most intense feelings?

Intention to buy

ITB1 I am positive towards purchasing one of these chocolates[94]

ITB2 It is likely that I will purchase one of these chocolates in the near future (i.e. the next three months) [94]

ITB3 I would advise others to buy one of these chocolates[95]

3.4 Procedure

For the first part of this research, the methodology that has been adopted for carrying out this study was based on quantitative techniques. To achieve the study objectives, a self-administered survey questionnaire was developed based on the findings of the literature review. This specific customized questionnaire has been created to collect the data. The type of sampling method that has been selected is the non-probability sampling method. The statistical population of the research included 34 people who were no strangers to the researcher but were included in the cycle of relatives and friends. 17 of 34 people who participated in the research had to see the first two campaigns (New Galaxy and Booja Booja) and after that complete the questionnaire. This procedure was the same for the other 17 people.

The second part of this research was based on both quantitative and qualitative techniques. The statistical population of this part of research which included 10 people had to watch two campaigns in pairs (New Galaxy with Booja Booja and M&S with Green & Black's) using Face Reader from their mobile devices and after that complete the questionnaire.

4 Results

4.1 Analysis of the Software

FaceReader is a commercially available software program that can automatically analyze facial expressions regarding seven emotional states: happiness, sadness, anger, surprise, scared, disgust, and neutral, which refers to the absence of any significant emotion. However, participants' self-reports and an appropriately executed experiment are also required to minimize possible contradictory results. So in our case, we also used self-reported questionnaires which were analyzed with IBM SPSS which is a widely used software for interactive statistical analysis.

4.2 Statistics

4.2.1 Cronbach's alpha

Cronbach's alpha is a measure of internal consistency, that is, how closely related a set of items are as a group. It is considered to be a measure of scale reliability. Cronbach's alpha is not a statistical test, it is a coefficient of reliability (or consistency). We used Cronbach's Alpha for each variable. In the output, we can easily see that we have a good reliability coefficient in all of our variables. For reliability analysis, as can be seen in Table 1,2,3,4 all the Cronbach's Alpha results were above 0.7, which is considered "acceptable", since the minimum acceptable value for Cronbach's alpha ca 0.70 and the maximum expected value is 0.90; Specifically, The alpha coefficient for the perceived happiness is .869, the perceived sadness .772, the perceived anger .767, the perceived surprise .803 and the intention to buy .896, suggesting that the variables have relatively high internal consistency. Below it can be seen the analytical table of the variables:

Table 1 Cronbach's Internal Consistency

Construct item	Number of items	Cronbach's alpha (>=0,70)
Perceived happiness	8	0,869
Perceived sadness	4	0,772
Perceived anger	4	0,767
Perceived surprise	5	0,803
Intention to buy/taste	3	0,896

4.2.2 Test of normality (Shapiro Wilk)

A two-tailed paired t-test was used to statistically compare means and determine significant differences ($p<0,5$) in acceptability between samples.

The test of normality showed that most of the samples comply with the normal distribution with a p-value in Perceived Happiness (PH) .193, Perceived Sadness (PS) .027, and Perceived

Surprise (PSU),066. However, 2 samples do not comply with normal distribution with a p-value in Perceived Anger (PA) .001 and Perceived Intention to Buy (PITB) .004.

Concerning the data that do not follow a normal (or approximately normal) distribution, it is preferred to use non-parametric statistical methods and for those that follow a normal distribution, it is better to use parametric statistical methods. In the first case, we will use Spearman's rank correlation and in the second case Pearson's rank correlation.

Table 2 Shapiro-Wilk's normal distribution test

	Statistic	df	Sig.
Average Happiness	,980	88	,193
Average Sadness	,980	88	,027
Average Anger	,944	88	,001
Average Surprise	,973	88	,066
Average Intention to buy	,956	88	,004

4.2.3 Descriptive Statistics

Tables 3,4,5,6,7,8,9 and 10 present the results of the descriptive statistics of the examined variables in all campaigns. As depicted, almost all items have been ranked above medium (higher than 3,00/5,00). Specifically, (FR) New Galaxy and (FR) M&S scores in happiness follows similarly high levels, implying the emotions of the participants that answered the questionnaire after watching the campaign and using the Face Reader.

In this way, our 1rst hypothesis (i.e What are the main emotions indicated by the food campaigns) was tested and it was found that the main emotions indicated by the food campaigns are happiness and surprise with the following scores:

New Galaxy Surprise 3,0588

Booja Booja Happiness 3,0809

M&S Happiness 3,6397

Green & Black's Happiness 2,9559

Face Reader New Galaxy Happiness 4,0705

Face Reader Booja Booja Happiness 3,100

Face Reader M&S Happiness 4,0000

Face Reader Green & Black's Surprise 3,2000

Table 3 Descriptive Statistics of Emotions in New Galaxy

	Min.	Max.	Mean	Std. Dev	Std.Error
Average Happiness	1	5	2,9926	,78992	,19158
Average Sadness	1	5	2,8529	,75031	,18198
Average Anger	1	5	2,8676	,79607	,19308
Average Surprise	1	5	3,0588	,63939	,15508
Average ITB	1	5	2,7451	1,00367	,24343

Table 4 Descriptive Statistics of Emotions in Booja Booja

	Min.	Max.	Mean	Std. Dev	Std.Error
Average Happiness	1	5	3,0809	,62803	,15232
Average Sadness	1	5	2,6471	,77590	,18818
Average Anger	1	5	2,3382	,72855	,17670
Average Surprise	1	5	3,0000	,77470	,18787
Average ITB	1	5	3,4510	1,13003	,27407

Table 5 Descriptive Statistics of Emotions in M&S

	Min.	Max.	Mean	Std. Dev	Std.Error
Average Happiness	1	5	3,6397	,50172	,12169
Average Sadness	1	5	2,2059	,56758	,13766
Average Anger	1	5	1,9265	,57122	,13854
Average Surprise	1	5	3,0706	,74813	,18145
Average ITB	1	5	3,5294	,70768	,17164

Table 6 Descriptive Statistics of Emotions in Green & Black's

	Min.	Max.	Mean	Std. Dev	Std.Error
Average Happiness	1	5	2,9559	,82199	,19936
Average Sadness	1	5	2,7647	,92479	,22429
Average Anger	1	5	2,5441	,74601	,18093
Average Surprise	1	5	2,6235	,79650	,19318
Average ITB	1	5	3,0784	,88608	,21491

Table 7 Descriptive Statistics of Emotions in Face Reader New Galaxy

	Min.	Max.	Mean	Std. Dev	Std.Error
Average Happiness	1	5	4,0705	,51235	,37914
Average Sadness	1	5	1,9000	,54772	,41473
Average Anger	1	5	1,8500	,23570	,22913
Average Surprise	1	5	3,8800	,16956	,24495
Average ITB	1	5	4,0000	,18547	,10541

Table 8 Descriptive Statistics of Emotions in Face Reader Booja Booja

	Min.	Max.	Mean	Std. Dev	Std.Error
Average Happiness	1	5	3,1000	1,05845	,85513
Average Sadness	1	5	2,7000	,88388	,59330
Average Anger	1	5	2,2500	,83666	,47335
Average Surprise	1	5	3,0800	,38243	,39528
Average ITB	1	5	4,2000	,26533	,37417

Table 9 Descriptive Statistics of Emotions in Face Reader M&S

	Min.	Max.	Mean	Std. Dev	Std.Error
Average Happiness	1	5	4,0000	,68465	,69821
Average Sadness	1	5	1,6000	,60208	,63875
Average Anger	1	5	1,6500	,79582	,30619
Average Surprise	1	5	3,7600	,31225	,26926
Average ITB	1	5	4,0667	,28566	,35590

Table 10 Descriptive Statistics of Emotions in Face Reader Green & Black's

	Min.	Max.	Mean	Std. Dev	Std.Error
Average Happiness	1	5	2,8500	1,21642	1,25499
Average Sadness	1	5	2,9500	1,35324	,98995
Average Anger	1	5	2,6500	,72265	,54400
Average Surprise	1	5	3,2000	,56125	,60519
Average ITB	1	5	3,4000	,44272	,32318

4.2.4 Gender-group comparisons

A Mann-Whitney test was used to compare gender-related groups. The results showed no gender differences except one, in Booja Booja campaign which showed that gender plays a significant role in Perceived sadness (Asymp. Sig ,043 <0,05). For the variables that we did not found statistically important differences, we present the results in Appendix A, Tables A1-1, A1-2, A1-3, A1-4, A1-5, A1-6, A1-8.

Table 11 Mann-Whitney Comparison (Grouping Variable: Gender) in Booja Booja

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
Average Happiness	26,500	81,500	-,834	,404
Average Sadness	14,500	42,500	-2,021	,043
Average Anger	31,500	59,500	-,348	,728
Average Surprise	23,000	78,000	-1,190	,234
Average ITB	31,000	86,000	-,392	,695

4.2.5 Bivariate correlations

To evaluate the differences across Education and Intention to Buy, Employment and Intention to Buy, Age and Intention to Buy it was used Kruskal Wallis Test. The test revealed (in)significant differences in the Employment and Age and significant differences in M&S campaign in the Perceived Happiness and Perceived Surprise compared with Education, which is presented in Table 12. However, concerning education, we did not have enough participants (in Face Reader) of all educational levels in M&S and Green & Black's campaigns and as a result, we could not run any statistical test. For the variables that we did not found statistically important differences, we present the results in Appendix A, Tables A1-9 – A1-17.

Table 12 Kruskal Wallis Comparison (Grouping Variable education) in M&S

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	6,579	2	,037
Average Sadness	2,852	2	,240
Average Anger	,541	2	,763
Average Surprise	6,822	2	,033
Average Intention to buy	,507	2	,776

4.2.6 Spearman and Pearson Correlation

To test our 2nd hypothesis (i.e Which emotions (positive or negative) have a significant impact on the participant's intention to buy the promoted food product?), Spearman and Pearson correlation between the variables was used. The correlation analysis in Tables 13, 14, 15, 16, 17, 18, and 19 revealed several significant correlations between the measured variables. These results can be also observed in Table 20 where all the results are presented in one table. For the variable that we did not found statistically important differences, we present the results in Appendix A, Table A1-30.

In the first and second campaigns New Galaxy and Booja Booja we can make a positive conclusion on the intention to buy of the campaigns, because of the high or above medium sores (i.e. higher than 3,00/5,00) in measured Intention to Buy. This can be indicated by the significant positive correlation between Perceived Happiness (i.e. ,848**) and Intention to buy and Perceived Surprise (i.e. ,681**) and Intention to buy in the second campaign. It is also important to point that the aforementioned were the positive correlations with the highest scores and in the first campaign, we had significant ones in all emotions and in the second one we saw positive correlations in perceived happiness too.

Table 13 Pearson's and Spearman's Correlation Matrix in New Galaxy

	PH	PS	PA	PSU
ITBT				
Correlation Coefficient	,848**	-,489*	-,588*	,674**
Sig. (2-tailed)	,000	,047	,013	,003
N	17	17	17	17

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)

Table 14 Pearson's rho and Spearman's rho Correlation Matrix in Booja Booja

	PH	PS	PA	PSU
ITBT				
Correlation Coefficient	,510*	-,383	-,333	,681**
Sig. (2-tailed)	,036	,129	,191	,003
N	17	17	17	17

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)

In the third campaign M&S, we notice significant negative correlations in Perceived Sadness (i.e. -,561*) and Perceived Anger (-,623**), with the second one to be the most important, which means that as these emotions get more intense the intention to buy/taste gets smaller.

In the fourth campaign, Green & Black's we can also make a positive conclusion on the intention to buy, since Perceived Surprise and Perceived Happiness scores are higher than 3,00/5,00 in measured Intention to Buy. The first one is the highest one with ,865** and the second emotion is ,670**. However, we can see that Perceived Anger is third in line also plays a significant role with -,627** Correlation Coefficient.

Table 15 Pearson's rho and Spearman's rho Correlation Matrix in M&S

	PH	PS	PA	PSU
ITBT				
Correlation Coefficient	,314	-,561*	-,623**	,397
Sig. (2-tailed)	,220	,019	,008	,114
N	17	17	17	17

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)

Table 16 Pearson's rho and Spearman's rho Correlation Matrix in Green & Black's

	PH	PS	PA	PSU
ITBT				
Correlation Coefficient	,670**	-,427	-,627**	,865**
Sig. (2-tailed)	,003	,087	,007	,000
N	17	17	17	17

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)

Continuing with the questionnaires that were completed by the people who used Face Reader we can notice the following results. In the New Galaxy campaign we do not have high or above medium sores (i.e. higher than 3,00/5,00) in measured Intention to Buy. In Booja Booja there is a significant negative correlation between Perceived Anger (-,949*) and Intention to buy, which means that in this case, emotions do have a significant negative correlation with the participant's intention to buy the promoted food product. A significant negative correlation has also the next campaign M&S between Perceived Sadness (-,915*) and Intention to buy. Finally, in Green & Black's it is clear that only Perceived Surprise has a significant correlation with the participant's intention to buy the promoted food product, since the Correlation Coefficient is ,909*.

Table 17 Pearson's rho and Spearman's rho Correlation Matrix in Face Reader Booja Booja

	PH	PS	PA	PSU
ITBT				
Correlation Coefficient	,678	-,856	-,949*	,665
Sig. (2-tailed)	,209	,064	,014	,221
N	5	5	5	5

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)

Table 18 Pearson's rho and Spearman's rho Correlation Matrix in Face Reader M&S

	PH	PS	PA	PSU
ITBT				
Correlation Coefficient	,841	-,915*	-,800	,793
Sig. (2-tailed)	,074	,029	,104	,109
N	5	5	5	5

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)

Table 19 Pearson's rho and Spearman's rho Correlation Matrix in Face Reader Green & Black's

	PH	PS	PA	PSU
ITBT				
Correlation Coefficient	,678	-,432	-,527	,909*
Sig. (2-tailed)	,209	,468	,361	,033
N	5	5	5	5

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)

The aforementioned results are presented in the following table.

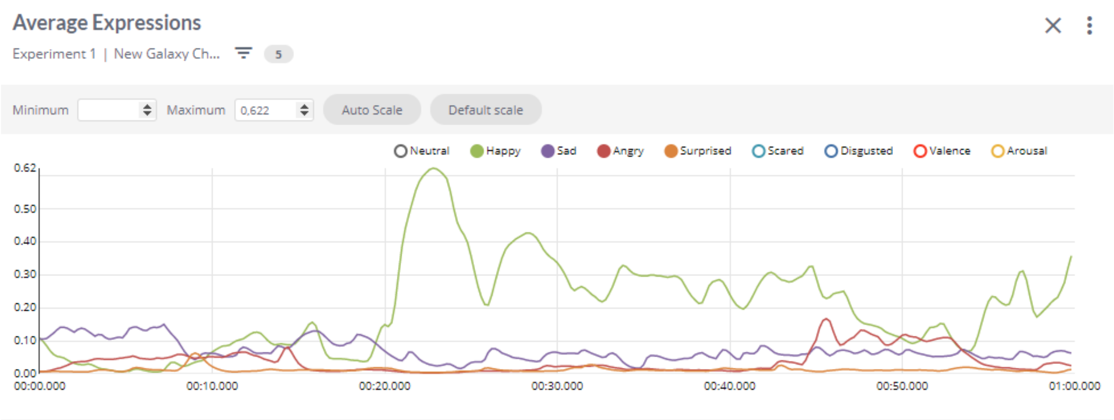
Table 20 Pearson's and Spearman's Correlation Matrix of all campaigns

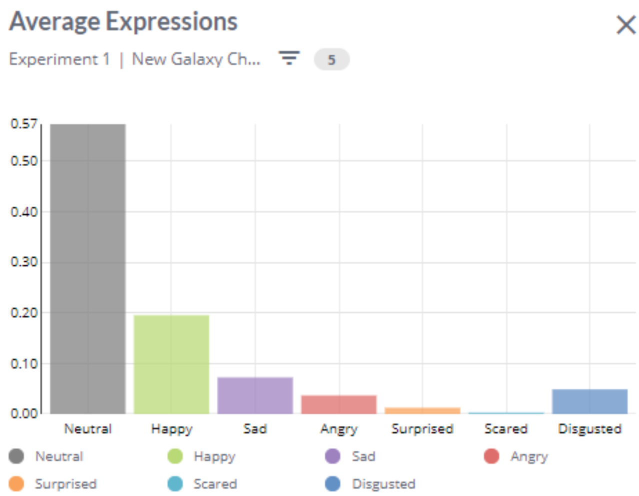
		PH	PS	PA	PSU
ITBT					
New Galaxy	Correlation Coefficient	,848**	-,489*	-,588*	,674**
	Sig. (2-tailed)	,000	,047	,013	,003
	N	17	17	17	17
Booja Booja	Correlation Coefficient	,510*	-,383	-,333	,681**
	Sig. (2-tailed)	,036	,129	,191	,003
	N	17	17	17	17
M&S	Correlation Coefficient	,314	-,561*	-,623**	,397
	Sig. (2-tailed)	,220	,019	,008	,114
	N	17	17	17	17
G&B	Correlation Coefficient	,670**	-,427	-,627**	,865**
	Sig. (2-tailed)	,003	,087	,007	,000
	N	17	17	17	17
Face Reader					
New Galaxy	Correlation Coefficient	,259	,699	-,344	,000
	Sig. (2-tailed)	,674	,189	,571	1,000
	N	5	5	5	5
Booja Booja	Correlation Coefficient	,678	-,856	-,949*	,665
	Sig. (2-tailed)	,209	,064	,014	,221
	N	5	5	5	5
M&S	Correlation Coefficient	,841	-,915*	-,800	,793
	Sig. (2-tailed)	,074	,029	,104	,109
	N	5	5	5	5
G&B	Correlation Coefficient	,678	-,432	-,527	,909*
	Sig. (2-tailed)	,209	,468	,361	,033
	N	5	5	5	5

4.2.7 Face reader results

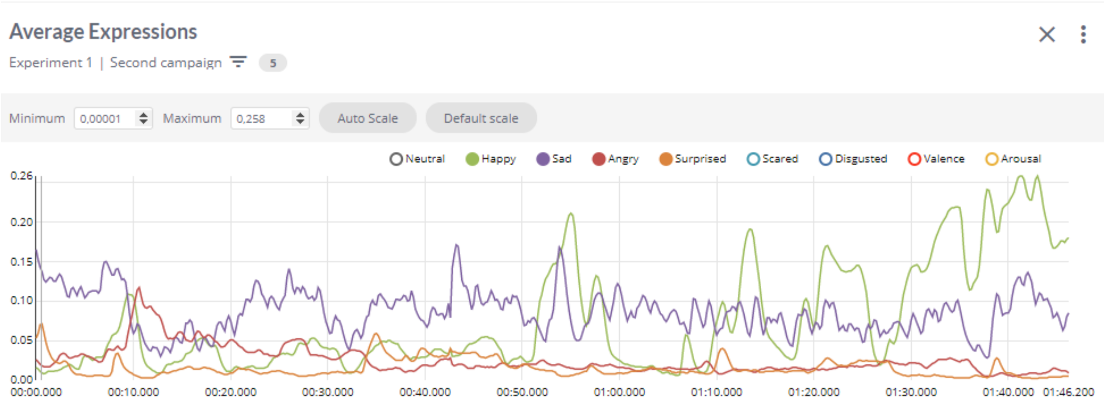
To test our 3rd hypothesis (i.e Which emotions can be recognized through face tracking methodologies (app) during watching the digital food campaign?) we collected the results from Noldus Face Reader. According to participants' reactions, we recognized the following emotions.

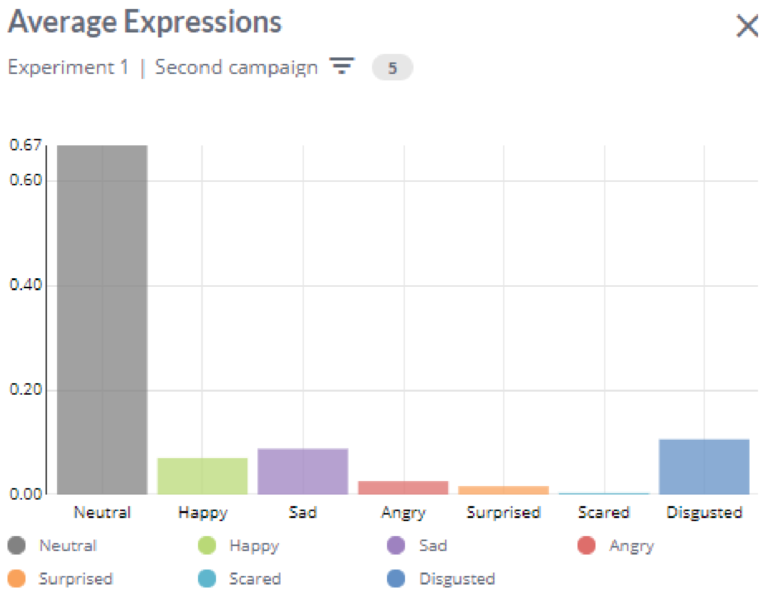
In the first campaign New Galaxy, it is clear that Neutral emotions dominate. This means that the participants seldom showed notable facial expressions while viewing the video. However, the line chart produced by FaceReader showed that different emotions co-occurred, and specifically Happiness which is the next notable emotion seemed to be clear. Specifically, Happiness touches very high levels in specific moments, especially in the middle of the video.



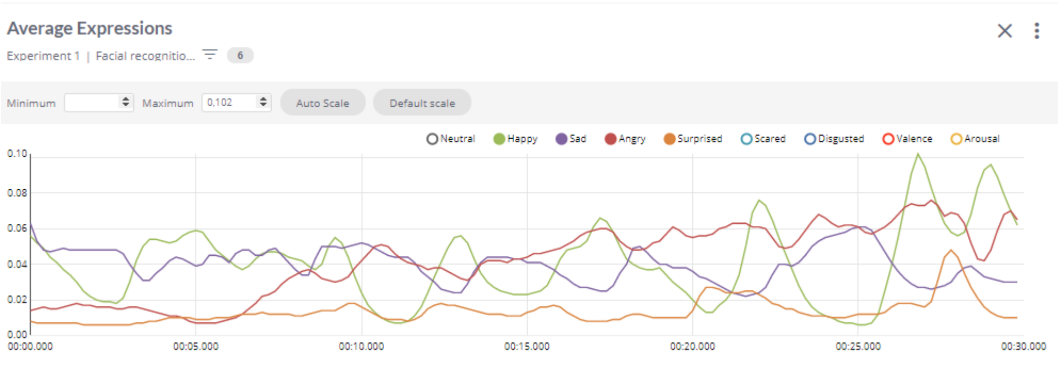


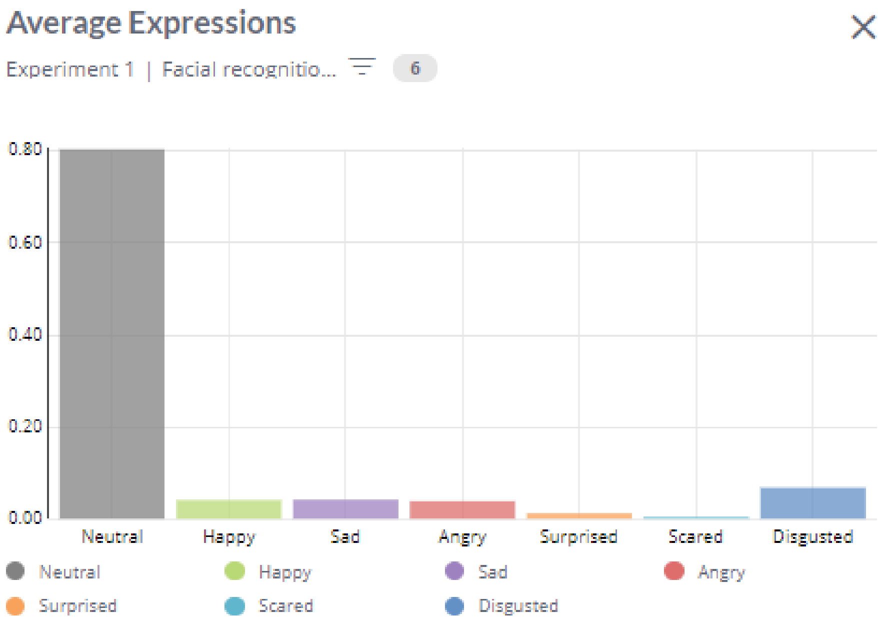
In the second campaign Booja Booja, we can see from the bar chart that the most prominent emotion is again the Neutral State. Nevertheless, in contrast with the previous campaign, here we can note from the line chart that the values from other emotions changed frequently with Happiness and Sadness to be at high levels. It is important to highlight that Happiness was at specific times at very high levels. However, it seems that in the bar chart it is the fourth emotion experienced by participants because it remained at low levels too throughout the procedure.



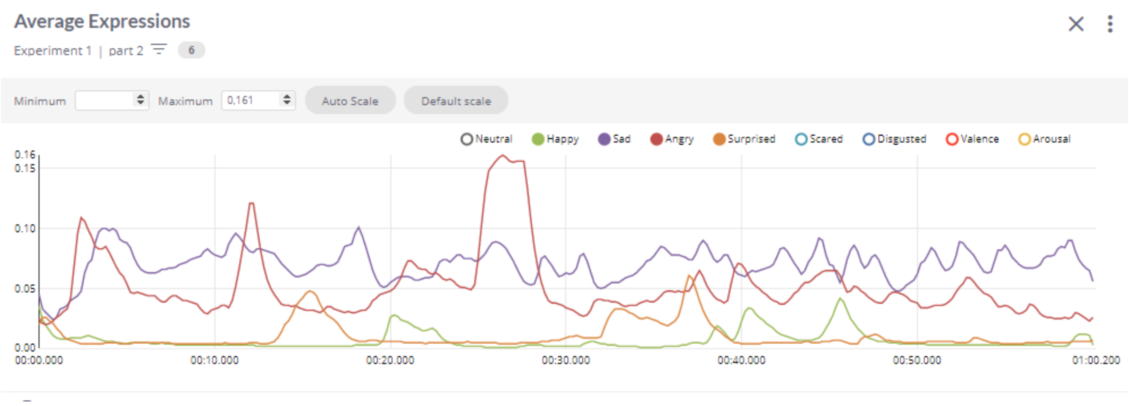


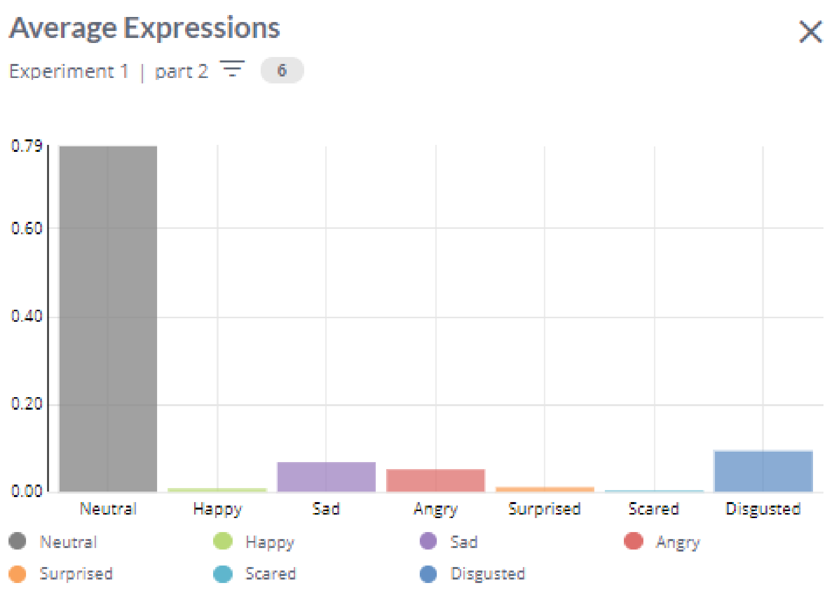
In the third campaign, M&S, the results showed that there were 4 notable emotions apart from Neutral, which was the most dominant emotion for the third time. The results demonstrated that the participants experienced emotions of Happiness, Sadness, Anger, and Surprise between different levels in specific times as the line chart indicated.





In the fourth and final campaign, Green & Black's, we can see that the participants experienced the most negative emotions. Discussion, Sadness, and Anger were at high levels after the Neutral state. In the line chart, it is obvious that the aforementioned emotions were recorded and experienced by the participants almost the same but with different frequency.





Finally, to test our 4rth hypothesis (i.e. Are the facial expression recognition results compatible with questionnaire self-reported results?) we compared the results from the two methods we used. Questionnaire self-reported results indicated that happiness and surprise were the emotions with the highest scores. Specifically, in New Galaxy campaign Happiness mean was up to 4,0705, in Booja Booja Happiness mean was 3,100, in M&S Happiness mean was 4,0000 and in Green & Black's participants experienced Surprise whose mean was up to 3,2000.

The Face reader results indicated that apart from the Neutral state, which was the first emotion in line with the highest levels in all campaigns, the emotions shown in charts were not the same. Only in the first campaign, New Galaxy, participants experienced the same feeling which was Happiness. And although the levels of experienced emotions were almost the same, in the other two campaigns, Booja Booja and M&S, the results showed that the most dominant emotions were negative ones. In the third one, Green & Black's, we had the most extreme deviation, since Surprise which was in high level from participants that answered the questionnaire after watching the campaign, seemed that in Face Reader was at the lowest levels.

However, the line chart played a significant role in our results, since it indicated points where Happiness and Surprise were at very high levels. Specifically, in the Booja Booja and M&S campaign we can see that although the facial expression recognition results were not compatible with questionnaire self-reported results, the main emotions indicated by campaigns in questionnaires do have points in specific seconds that are very high. And these results are similar to the face results of more than 2 participants.

4.3 Discussion and results of every campaign

New Galaxy

In the first campaign, New Galaxy, it is clear that there is a significant correlation between all the variables (all emotions) and the intention to buy. This is indicated by the high or above medium scores (i.e. higher than 3,00/5,00) in measured Intention to Buy. The most significant correlation, which is also positive, can be noticed in Perceived Happiness. However, this correlation can not be confirmed by the questionnaires filled with Face Reader, since we do not have any significant results. Nevertheless, Happiness is the second notable emotion after Neutral which is also clear in Face Reader results. Especially in the middle of the video

Happiness touches very high levels. These results are corroborated with the research about "Consumer facial expression about smoked ham with the use of face reading technology. The methodological aspects and informative value of research results", which indicates that liked samples elicited more intense facial expressions of happiness than disliked samples[71]. After all, it is clear that all emotions (positive and negative) have a significant correlation with the participant's intention to buy the promoted food product, with Happiness being the most dominant one which means that the New Galaxy campaign has a positive influence on its target group.

Booja Booja

In the second campaign, Booja Booja, we can make a positive conclusion on the intention to buy of the campaigns, because of the high or above medium scores (i.e. higher than 3,00/5,00) in measured Intention to Buy. Specifically, two out of three significant correlations were positive with Perceived Surprise (i.e. ,681**) being the most dominant. Face Reader bar chart indicated that the values from other emotions changed frequently with Happiness and Sadness to be in high levels. Nevertheless, this can not determine the results because Happiness, which is a positive emotion, was at specific times at very high levels. Taking into consideration these facts, we conclude that Booja Booja campaign promotes this product in a good way.

M&S

In M&S campaign, although Happiness was the main emotion indicated, the results from the Face Reader showed that the participants experienced emotions of Happiness, Sadness, Anger, and Surprise between different levels in specific times as the line chart recorded. Unfortunately, the campaign also had significant negative correlations, because of the high or above medium scores (i.e. higher than 3,00/5,00) between measured Intention to Buy and negative emotions. In this research, where we combined both implicit and explicit methods, we should take under consideration the fact that most implicit measures, such as facial expression and physiological responses, provide a continuous measurement in contrast with explicit ones where provide discrete information at a certain point in time about emotional responses elicited by the food product are provided. [96] and conclude that Face

Reader helped us understand that in this case, our research showed that customer's response might not be good enough to buy the product and further research is important to be done.

Green & Black's

In the fourth campaign, Green & Black's we can also make a positive conclusion on the intention to buy, since Perceived Surprise and Perceived Happiness scores are higher than 3,00/5,00 in measured Intention to Buy. This can be also confirmed by the fact that Surprise and Happiness were also the main emotions indicated by the campaign in questionnaires. However, in Face Reader results, we had the most extreme deviation in Green & Black's campaign, since Surprise which was in high level from participants that answered the questionnaire after watching the campaign, seemed that in Face Reader was at the lowest levels. This might be linked to the fact that some participants can lack the introspective capacity to correctly identify, recognize and then verbalize the perceived emotion, something that is a major limitation and problem of explicit methods (Lagast et al., 2017) or may similar with the results from "Measuring emotions associated with food in consumer testing" research where it has been shown that emotions and liking ratings do not always agree (Kostyra et al., 2016). Having this outcome, it seems that further research for this campaign is important to have valid and complete results.

4.4 Practical Implications

This part of the analysis concerns the conclusions that can be drawn from each campaign, based on the results of both implicit and explicit measures using questionnaires and Noldus Face Reader. For this reason, we identified and highlighted the key findings of each campaign in the field of food market research that will help marketers develop, a more grounded understanding of how video content should be and used effectively and efficiently to increase sales.

New Galaxy

The New Galaxy campaign promotes a chocolate bar. The results showed that this campaign evoked multiple emotions. However, the most significant correlation between all of them and Intention to buy the promoted product was positive and noticed in Perceived Happiness, an emotion that reaches very high levels in specific moments, especially in the middle of the video.

Taking into consideration the campaign, it is easy to understand why it draws the attention of the participants. Trying to tell a story of the everyday life of a woman in 1 minute, the campaign uses a fresh female voice and intense music to create an atmosphere behind the theme and motivate the audience. Breaking old gender stereotypes, the campaign reflects the energy, movement, and passion through different vivid colors that switch one another and grab the attention of the audience, and convinces them to keep watching the video. It is also interesting to highlight that the color of the woman's T-shirt is red, a color tightly associated with different kinds of activity.

Using a sense of humor, another campaign by Heineken was also created based on stereotypes and everyday life and received a lot of attention.

Specifically, humor in combination with the presentation of a moment of a couple's house-warming party, where the hostess surprises her friends with the walk-in closet filled with clothes and shoes and the man shows his friends a fridge filled with Heineken beer, promotes the main message very clearly "Beer makes men as happy as women do when it comes to clothes and fashion". Aiming to appeal to male customers, Heineken targets men and promotes masculinity versus femininity.[97]

Booja Booja

The Booja Booja video promotes organic truffles in an entirely different way. The results in this campaign also showed that participants had multiple emotions, but not as much as the New Galaxy ad. We also noticed both positive and negative correlations but two out of three were the positive ones with Perceived Surprise (i.e. ,681**) to be the most dominant, meaning that Booja Booja campaign promotes the chocolate truffles in a good way.

The results can be reflected from the video which starts with a tempting way, showing the steps of truffle production. A light happy music in combination with the male voice of the production manager who gives details about the origins of the truffles cover the whole video.

The senses of taste and smell were also depicted throughout the campaign. The color combinations in this case are not intense. They are closer to warm to create harmony under the tunes of music and switch of scenes that mainly show how the product is created inside of the factory. A complete video walkthrough of the entire process of truffle creation seems also to play a significant role in the results since the main purpose in these cases is to tempt the audience by showing the quality of the product.

Content storytelling is a factor that has contributed to the success of other marketing projects such as the Tsinghua University Library's video marketing project "Falling in Love with the Library", where the story featured in the video series is based on the real campus life, reflecting what students experience in their everyday activities. [98]

Green & Blacks

Green & Blacks promote organic chocolate. The results in this campaign did not help us completely understand the consumer behavior, since we had a significant deviation between them. This means that further research for this campaign is important to have valid results.

The minimal campaign structure may be the answer to our results since the company chose to promote the chocolate in a very simple way. Happy tunes of music and vivid colors are a good attempt to draw the attention of the participants, but finally, it seems that video content is not enough to motivate the audience to buy the product as Face Reader results indicated.

M&S

Marks & Spencer promote Easter Chocolate products. The results in this campaign also had significant negative correlations because of the high or above medium scores (i.e. higher than 3,00/5,00) between measured Intention to Buy and negative emotions. Moreover, the fact that Face Reader showed that the participants experienced emotions of Happiness, Sadness, Anger, and Surprise between different levels in specific times, lead us to the conclusion that further research is important to be conducted to have clear results.

These results might also reflect the fact that the Marks & Spencer campaign was part of the campaign series created to promote Easter products. All the campaigns followed the same motive using a combination of tempting scenes of chocolate with happy tunes of music under the theme of sophisticated design. Using warm colors and slow motion in many parts, this video seems that tries to promote pleasure and not the products themselves.

Findings in our food market research using both implicit and explicit techniques, raised the aforementioned practical implications. Given the significant correlations and the results that Face Reader indicated, it is obvious that storytelling of how a product is created can lead to higher engagement. The audience looks for specific information and results demonstrated that when it comes to organic products it is very important to promote quality, which can be shown from the production process. Storytelling in this case seems also to be significant since it guides viewers through relatable narrative-based content and creates an emotional connection. When it comes to regular chocolate, the results showed that humor in combination with scenes of everyday life can increase engagement and intention to buy. People like to see themselves and feel comfortable in front of them. Today, Businesses need to show they do not only understand their audience but care about their audience's needs and interests. Furthermore, when it comes to targeting a specific gender, it is interesting to point out that our research demonstrated the persistence of stereotypes. Finally, according to the results, colors seem to influence attitudes towards regular chocolate, which is the primary goal of the campaign. Influencing the moods and feelings of the audience, vivid colors help form a certain attitude towards a brand.

These results could be used as a base for researchers, who could make a comparative research using pairs of organic and non-organic chocolates to evaluate if these campaigns do have a positive or negative correlation with the intention to buy of consumers.

4.5 Limitations of this research and future directions

It is also important to point out the limitations and requirements of FaceReader 4 in general. It does not work with Apple mobile phones, so participants did have to own Android mobile phones. Currently, the FaceReader technology does not match the accuracy of other methods in detecting subtle changes in facial expressions. The participants needed to face the camera in a specific place and try not to cover their face with hair because the detection was not clear.

Moreover, we should underline the limitations of the research in general. First of all, the research was controlled and under the guidance of the researcher. This fact might affect the facial expressions and the perceived emotions. Furthermore, Neutral Emotion which was measured by Face Reader was not concluded in the questionnaire as a variable, which means that users did not have this choice in self-report. Finally, this study used convenience sampling, and the cross-sectional data obtained limited the ability to establish the direction of causality in the relationships between variables. Taking into consideration the aforementioned, we can conclude that future studies are needed to fully address these aspects in greater depth.

5 Conclusion

5.1 Conclusion

Noldus FaceReader technology can detect significant differences in facial expressions elicited Food market campaigns. It can deliver additional information to conventional acceptance tests by indicating specific points where emotions are at high levels. However, more research is needed to see how this technology performs in more complex testing procedures. For instance, a ''happy'' facial expression is not distinctive in the face reader and this derives from the high levels of positive emotions listed in the questionnaire. Nevertheless, this approach provides a good basis for food market research campaigns by collecting and measuring consumers' emotional signals but it is good not to stand alone to deliver results. Taking also into consideration the fact that our research met specific limitations that were mentioned in part *4.4 Limitations of this research*, we can conclude that our results were not only statistically important for this research but also crucial because they emphasize the need for multidimensional observation in future studies. This means that only face might not be enough and any process should be assisted not only by the development of increasingly powerful new mobile cameras and the FaceReader software itself but also by additional Neuromarketing tools that record metabolic activity, record electrical activity in the brain or do not record electrical activity in the brain, based on the nature of the research.

5.2 Future work

We presented an approach for real-time facial expression recognition running on smartphones combined with self-reported questionnaires. To evaluate our first two research hypotheses we have conducted different tests using IBM SPSS and came to the conclusion that the most dominant emotions were happiness and surprise and also these emotions are also connected with the Intention to buy the products shown in the campaigns. To test the third and fourth hypotheses we used Noldus Face Reader from mobile phones. We concluded that the proposed Software is good not to stand alone since the results were quite different from the self-reported questionnaires. In the future work, we will try to examine the users' behavior by combining Face detection with a Neuromarketing tool. It would also be useful to conduct a similar exploratory study on a larger sample to address generalizability issues.

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APPENDIX

A1-1 Mann-Whitney Comparison (Grouping Variable: Gender) in New Galaxy

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
Average Happiness	26,000	92,000	,706	,480
Average Sadness	27,000	48,000	-,612	,541
Average Anger	22,000	43,000	-1,112	,266
Average Surprise	20,000	86,000	-1,323	,186
Average ITB	29,500	95,500	,357	,721

A1-2 Mann-Whitney Comparison (Grouping Variable: Gender) in M&S

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
Average Happiness	35,500	80,500	-,048	,961
Average Sadness	23,500	59,500	-1,222	,222
Average Anger	19,500	55,500	-1,613	,107
Average Surprise	22,000	67,000	-1,367	,172
Average ITB	21,000	66,000	-1,481	,139

A1-3 Mann-Whitney Comparison (Grouping Variable: Gender) in Green & Black's

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
Average Happiness	21,000	57,000	-1,450	,147
Average Sadness	24,500	69,500	-1,111	,266
Average Anger	35,500	71,500	-,049	,961
Average Surprise	22,500	58,500	-1,312	,190
Average ITB	35,500	80,500	- ,049	,961

A1-4 Mann-Whitney Comparison (Grouping Variable: Gender) in Face Reader New Galaxy

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
Average Happiness	2,000	12,000	,000	1,000
Average Sadness	,000	1,000	-1,581	,114
Average Anger	1,500	11,500	-,363	,717
Average Surprise	,500	10,500	1,088	,277
Average ITB	,000	1,000	-1,581	,114

A1-5 Mann-Whitney Comparison (Grouping Variable: Gender) in Face Reader Booja Booja

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
Average Happiness	,000	1,000	1,414	,157
Average Sadness	,000	10,000	-1,414	,157
Average Anger	,000	10,000	-1,414	,157
Average Surprise	,000	1,000	-1,414	,157
Average ITB	,000	1,000	1,491	,136

A1-6 Mann-Whitney Comparison (Grouping Variable: Gender) in Face Reader M&S

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
Average Happiness	2,000	8,000	-,577	,564
Average Sadness	3,000	6,000	,000	1,000
Average Anger	2,000	8,000	-,577	,564
Average Surprise	3,000	6,000	,000	1,000
Average ITB	3,000	6,000	,000	1,000

A1-7 Mann-Whitney Comparison (Grouping Variable: Gender) in Face Reader Green & Black's

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
Average Happiness	2,000	5,000	-,577	,564
Average Sadness	2,000	8,000	-,577	,564
Average Anger	2,000	8,000	-,577	,564
Average Surprise	2,000	5,000	-,577	,564
Average ITB	2,000	8,000	-,609	,543

A1-9 Kruskal Wallis Comparison (Grouping Variable education) in New Galaxy

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	5,752	2	,056
Average Sadness	1,429	2	,0489
Average Anger	2,581	2	,0275
Average Surprise	4,076	2	,0130
Average Intention to buy	6,304	2	,043

A1-10 Kruskal Wallis Comparison (Grouping Variable education) in Booja Booja

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	4,028	2	,133
Average Sadness	,723	2	,697
Average Anger	2,788	2	,248
Average Surprise	3,368	2	,186
Average Intention to buy	1,732	2	,421

A1-11 Kruskal Wallis Comparison (Grouping Variable education) in Green & Black’s

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,160	2	,923
Average Sadness	1,163	2	,559
Average Anger	1,028	2	,598
Average Surprise	,959	2	,619
Average Intention to buy	,277	2	,87

A1-12 Kruskal Wallis Comparison (Grouping Variable education) in Face Reader New Galaxy

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,526	1	,468
Average Sadness	,000	1	1,000
Average Anger	,132	1	,717
Average Surprise	,000	1	1,000
Average Intention to buy	,000	1	1,000

A1-13 Kruskal Wallis Comparison (Grouping Variable education) in Face Reader Booja Booja

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,500	1	,480
Average Sadness	,500	1	,480
Average Anger	,500	1	,480
Average Surprise	,000	1	1,000
Average Intention to buy	,139	1	,709

A1-14 Kruskal Wallis Comparison (Grouping Variable employment) in New Galaxy

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	3,236	3	,357
Average Sadness	5,848	3	,119
Average Anger	5,945	3	,114
Average Surprise	3,782	3	,286
Average Intention to buy	3,254	3	,354

A1-15 Kruskal Wallis Comparison (Grouping Variable employment) in Booja Booja

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	1,653	3	,647
Average Sadness	2,037	3	,565
Average Anger	3,791	3	,285
Average Surprise	1,650	3	,648
Average Intention to buy	5,797	3	,122

A1-16 Kruskal Wallis Comparison (Grouping Variable employment) in M&S

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,345	3	,951
Average Sadness	3,709	3	,295
Average Anger	5,635	3	2,408
Average Surprise	2,408	3	,492
Average Intention to buy	3,577	3	,311

A1-17 Kruskal Wallis Comparison (Grouping Variable employment) in Green & Black’s

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	3,701	3	,296
Average Sadness	1,963	3	,580
Average Anger	4,196	3	,241
Average Surprise	,551	3	,908
Average Intention to buy	,754	3	,860

A1-18 Mann-Whitney Comparison (Grouping Variable employment) in Face Reader New Galaxy

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	3,789	2	,150
Average Sadness	3,000	2	,223
Average Anger	3,789	2	,150
Average Surprise	2,211	2	,331
Average Intention to buy	2,000	2	,368

A1-19 Mann-Whitney Comparison (Grouping Variable employment) in Face Reader Booja Booja

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,400	2	,819
Average Sadness	3,000	2	,223
Average Anger	3,600	2	,165
Average Surprise	1,400	2	,497
Average Intention to buy	3,500	2	,174

A1-20 Mann-Whitney Comparison (Grouping Variable employment) in Face Reader M&S

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,800	3	,849
Average Sadness	2,105	3	,551
Average Anger	3,800	3	,284
Average Surprise	2,200	3	,532
Average Intention to buy	2,200	3	,532

A1-21 Mann-Whitney Comparison (Grouping Variable employment) in Face Reader Green & Black’s

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	3,200	3	,362
Average Sadness	3,200	3	,362
Average Anger	3,200	3	,362
Average Surprise	3,800	3	,284
Average Intention to buy	3,111	3	,375

A1-22 Kruskal Wallis Comparison (Grouping variable age) in New Galaxy

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	7,228	3	0,65
Average Sadness	2,808	3	,422
Average Anger	3,272	3	,352
Average Surprise	1,230	3	,746
Average Intention to buy	6,253	3	,100

A1-23 Kruskal Wallis Comparison (Grouping variable age) in Booja Booja

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	1,536	3	,674
Average Sadness	2,589	3	,459
Average Anger	2,615	3	,455
Average Surprise	1,648	3	,648
Average Intention to buy	,874	3	,832

A1-24 Kruskal Wallis Comparison (Grouping variable age) in M&S

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,087	1	,768
Average Sadness	,482	1	,488
Average Anger	,000	1	1,000
Average Surprise	,245	1	,621
Average Intention to buy	,564	1	,453

A1-25 Kruskal Wallis Comparison (Grouping variable age) in Green & Black’s

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,615	1	,433
Average Sadness	,154	1	,695
Average Anger	,196	1	,658
Average Surprise	,787	1	,375
Average Intention to buy	,812	1	,367

A1-26 Kruskal Wallis Comparison (Grouping variable age) in Face Reader New Galaxy

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	3,789	2	,150
Average Sadness	3,000	2	,223
Average Anger	3,789	2	,150
Average Surprise	2,211	2	,331
Average Intention to buy	2,000	2	,368

A1-27 Kruskal Wallis Comparison (Grouping variable age) in Face Reader Booja Booja

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	,400	2	,819
Average Sadness	3,000	2	,223
Average Anger	3,600	2	,165
Average Surprise	1,400	2	,497
Average Intention to buy	3,500	2	,174

A1-28 Kruskal Wallis Comparison (Grouping variable age) in Face Reader M&S

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	2,133	2	,344
Average Sadness	,561	2	,755
Average Anger	2,133	2	,344
Average Surprise	3,200	2	,202
Average Intention to buy	,800	2	,670

A1-29 Kruskal Wallis Comparison (Grouping variable age) in Face Reader Green & Black's

	Kruskal-Wallis H	df	Asymp. Sig.
Average Happiness	2,133	2	,344
Average Sadness	2,133	2	,344
Average Anger	3,200	2	,202
Average Surprise	2,133	2	,344
Average Intention to buy	2,815	2	,245

A1-30 Pearson’s rho and Spearman’s rho Correlation Matrix in Face Reader New Galaxy

	PH	PS	PA	PSU
ITBT				
Correlation Coefficient	,259	,699	-,344	,000
Sig. (2-tailed)	,674	,189	,571	1,000
N	5	5	5	5

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)