Neuromarketing and Global Branding Reaction Analysis Based on Real-Time Monitoring of Multiple Consumer's Biosignals and Emotions

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Abstract

Consumers' selections and decision-making processes are some of the most exciting and challenging topics in neuromarketing, sales, and branding. Multicultural influences and societal conditions are also crucial aspects to consider from a global perspective. Applying neuroscience tools and techniques in international marketing and consumer behavior is an emergent and multidisciplinary field that aims to understand consumers' thoughts, reactions, and selection processes in branding and sales. This study focuses on real-time monitoring of different physiological signals using eye-tracking, facial expressions recognition, and Galvanic Skin Response (GSR) acquisition methods to analyze consumers' responses, detect emotional arousal, measure attention or relaxation levels, analyze perception, consciousness, memory, learning, motivation, preference, and decision-making. The primary purpose of this research was to monitor human subjects' reactions to these signals during an experiment designed in three phases consisting of different types of branding advertisements. The non-advertisement exposition was also monitored during the gathering of survey responses at the end of each phase. A feature extraction module was implemented with a data analytics module to calculate statistical metrics and decision-making supporting tools based on Principal Component Analysis (PCA) and Feature Importance (FI) determination based on the Random Forest technique. The results indicate that when compared to image ads, video ads are more effective in attracting consumers' attention and creating more emotional arousal.

Keywords: Neuromarketing, Branding Reaction, Consumer Biosignal, neurosciences, Galvanic Skin Response, eye-tracking

I. Introduction

Neuromarketing, the scientific study of the nervous system applied to marketing, is a quickly evolving sector that has its most significant footprint in the United States while growing globally at a fast pace. Marketers now recognize that brain and biometric research can lead to a deeper understanding of consumer preferences.

Neuroscience studies have continued to expand quickly because of easily accessible shared findings, which have fostered integration into other fields of work (Bočková, Hanák, & Michal, 2021). Neuromarketing has become synonymous with consumer neuroscience, a term coined by the commercial sector (Brenninkmeijer, Schneider, & Woolgar, 2020). It loosely refers to measuring physiological and neural signals to gather relevant insight into consumers' preferences, motivations, and decisions, which may assist in the development of advertising, new products, price structure, and many other marketing aspects (Harrell, 2019). Such measuring also employs brain scanning and imaging, and additional brain measurement techniques and technologies to gather brain reactions to marketing stimuli and to circumvent the "problem" of relying on consumers' self-reports" (Brenninkmeijer, Schneider, & Woolgar, 2020). These monitoring processes and analysis enable the studies of how the brain and body react to marketing signals through various measurement technologies and might be construed as a customer relationship tool (CRM) as it shares insights on the pre-and post-consumer purchasing journey.

From innovators designing unique products and services to companies expanding their offerings, customer inquiry has and will continuously be a high priority for market researchers, marketing professionals, entrepreneurs, and large corporations worldwide. Marketing research methods have included focus groups, surveys, social media listening, interviews, experiments, field trials, and observation, to name a few (BrandWatch, 2019). However, through the use of neuroscience lab techniques, scientists, academics, and market researchers realized that answers given by consumers are often biased or skewed. These answers can be conscious or unconscious due to the influence of stereotypes, cognitive biases, emotions, social and moral norms, or simply because they cannot express their feelings, thoughts, and what motivates their purchase decision (Bitbrain). As Michael Platt, the director of the Wharton Neuroscience Initiative, says, "What comes out of our mouths is not always a perfect rendition of what is going on in our brains" (Harrell, 2019). In other words, the risk of error in understanding consumer preferences is very high using traditional marketing research methods (Gurgu & Gurgu, 2020).

Emotions play a vital role in our lives, affecting our thinking and behavior alongside reasoning, developing associate degrees of opinions and perspectives. Researchers (Lin & Utz, 2015; Tess, 2013) have argued that social networking activities may cause emotional and mawkish reactions. Lin and Utz (2015) have used emotional self-reports to analyze positive (e.g., joy and surprise) and negative (i.e., fear, disgust, jealousy) reactions by reading through Facebook chats.

Advertising in social media is intended to influence and incite consumers' perspectives and attitudes to foster individuals' welfare and the community. Music plays an essential role in advertising as it strongly influences the cognitive processes of attention and the emotional functions of evaluation and, subsequently, the product's attributes (Cuesta, Martínez-Martínez, and Niño, 2018). However, marketing researchers' central inquiry is not how to influence consumers' choices and decisions but how to foretell their behavior.

In general, consumer reactions are rarely rational, often exhibiting inconsistencies between their statements, what they say, their behaviors, and what they do. Such behavioral dichotomies lead market researchers to the field of neuromarketing and its related applications, intending to understand best the cognitive and emotional effects that can be identified along with a glimpse into the consumer's thoughts. A vast array of recent research (García-Madariaga et al., 2019; Alvino et al., 2020; Ausin-Azofra et al., 2021; Garczarek-Bąk, Szymkowiak, and Disterheft, 2021) in the field of neuromarketing has argued that emotions and inner feelings are more effective in the process of purchasing decisions. Neuromarketing research and techniques, therefore, are becoming essential in measuring the emotional state and the impact some stimuli, such as a brand, a product, and its features, may have on the consumer's preferences and behavior. The digital business process transformations occurring across industries around the globe are drawing even more attention to this field, as consumers spend more time online engaged in e-commerce, online games, and virtual worlds.

Applying neuroscience tools and techniques in international marketing and consumer behavior is an emergent and multidisciplinary field that aims to understand consumers' thoughts, reactions, and selection process in branding and sales. As a process for choosing one out of several alternatives, consumer selection and decision-making are among the most exciting and challenging topics in neuromarketing, sales, and branding. Multicultural influences and societal conditions are also crucial aspects to consider from a global perspective. Among the innovative technologies available in neuroscience today and brand data sourced from the consumer's brain and biometric tools, neuromarketing has become a fast-growing industry. The global neuromarketing market in 2020 was valued at $1.158 billion and is projected to be $1.896 billion by 2026 (Akbarialiabad, Taghrir, Bastani, & Paydar, 2021). Ramsøy (2019) argues that the total market interest in consumer neuroscience, neuromarketing, and non-conscious assessment methods have reached a tipping point, embraced by 80% of the industry using one or more of the [non-conscious] essential methods available.

The focus of this research is an attempt to understand better consumers' global product brands' choices based on their reactions to real-time monitoring of multiple biosignals and emotions. Selections are made whenever consumers are confronted with more than one option for which an action is needed to obtain or avoid these alternatives. The reflective process that precedes the choice is a decision. Many non-invasive techniques were adopted for reading the brain activity of the consumers who volunteered for this study, thus capturing and analyzing their brain signals and emotions.

Research Question

The overarching question for this research is:

RQ: How can multiple real-time physiological monitoring tools support the evaluation of image and video ads' effectiveness?

Based on the main research question, two null hypotheses and respective alternate hypotheses were stated:

Hypothesis 1:

H_0: The effectiveness of attracting consumers' attention to a brand's video ad is the same as that of image ads when measured through physiological monitoring.

H_1: The effectiveness to attract consumers' attention to a brand's video ad is more significant than image ads when measured through physiological monitoring.

Hypothesis 2:

H_0: Customer's emotional arousal is not influenced during video ads compared to image ads of similar brands.

H_1: Customer's emotional arousal during video ads is more significant than image ads of similar brands.

Objectives

The main objective of this work is to effectively measure consumers' reactions when exposed to image and video ads based on real-time monitoring of multiple physiological data, such as Galvanic Skin Response (GSR), eye-tracking, and facial expressions recognition.

Secondary objectives include:

- Perform an exploratory data analysis on consumers' reactions when exposed to image and video ads.
- Evaluate which ads created greater emotional arousal.
- Evaluate potential correlations between physiological measures.
- Reduce dimensionality to allow data visualization and attributes clustering.

- Determine the most relevant features for the consumer behavior analysis and evaluate if age is a potential attribute for the effective classification of different types of ads.

II. Literature Review

In attempting to understand best and predict consumers' preferences and decision-making processes, one of the main challenges is understanding emotional reactions when exposed to advertisements and their effects on them. Multiple acquisition methodologies supply a better level of detail in the decision-making process. Still, a vast array of secondary research available in the literature addresses many different methods for understanding and predicting consumers' purchase decisions. Thus, stimulus capturing equipment, stimuli response tracking, and metrics definitions play a vital role in neuromarketing research experiments.

Ramsøy et al. (2017) initially analyzed data from two different datasets using eye-tracking (ET) to measure the effects of brands on preferences for clothes. After that, the participants were asked to evaluate six red brand wines in another experiment, and their pupil dilatation was measured and captured. The idea was to develop metrics for assessing pupil dilations and posture and the Willingness to Pay (WTP) during brand exposure. García-Madariaga et al. (2017), in addition to ET, used electroencephalography (EEG) to measure attention during consumers' visualizing of nine products. They used analysis of variance (ANOVA) to test for statistical significance of the ET metrics, such as the number of fixations on each area of interest (AOI) and attention measures from the EEG. Similarly, Krajina and Mladenovic (2018) also used ET and qualitative research methods on a selected sample of university students viewing an educational website to investigate consumer behavior. They tracked the AOI, the number of fixations, dwell time, and fixation duration as consumer behavior metrics.

Cuesta et al. (2018), investigating the influence of music in advertisements, also used ET and facial expressions, and galvanic skin response (GSR). They used the T-test to investigate the fixation time, facial emotions, and GSR measures. The participants were exposed to the same TV ad for a perfume where half of them were assigned to view it with the music version.

Alvino et al. (2019) also relied on EEG to measure brain biosignals during a consumer perception of wines. These researchers applied ANOVA and Friedman tests to analyze changes in the beta bands under other conditions, such as types of wine and frequency bands. The participants were asked to taste and judge four different wine brands while collecting their signals.

Juárez-Varón et al. (2020) proposed a method for predicting which areas attract the attention of potential customers for two educational toys' packaging. They used ET to analyze the attention of the experiment participants. After collecting the data, preprocessing, and selection stages, they applied the Classification and Regression Trees (CART) model classifier. In the same year, Mañas-Viniegra et al. (2020) investigated university students' attention and emotional intensity when visualizing images of corporate logos and their respective chairman. They adopted ET and GSR responses to capture attention and emotional arousal levels while viewing the stimulus. They applied a Mann–Whitney test between similar AOIs and compared the GSR peaks between two groups of participants.

Most recently, Garczarek-Bąk et al. (2021) proposed a comparison between neuromarketing-related measurements, such as EEG, electrodermal activity (EDA), and ET data, to see which could serve as the best predictor of a product choice. They measured various stimuli, including average pupil size, number of fixations, frontal alpha, beta and gamma asymmetry, and peaks per second biosignals while the participants were watching television advertisements. Garczarek-Bąk's research team then applied a Logistic Regression model to determine which biosignals measures explained the most significant part of the variance of a purchase decision. Ausin-Azofra et al. (2021) used ET, GSR, and Facial Coding (FC) for consumer behavior in a 360-video advertisement. After collecting and preprocessing the data, they used Kolmogorov-Smirnov statistics and t-tests to explore the subjects' response differences. Tun-Min et al. (2021) adopted a different approach by investigating how the brain makes purchase decisions when encountering different visual presentation strategies. For this purpose, they used fMRI to study brain activation preceding purchase decisions under three visual presentation strategies: (1) static picture, (2) image zooming, and (3) rotation video. The stimuli employed included 100 one-piece dress pictures. The participants ranked each product on a Likert scale from Unattractive, Neutral, and Attractive. They preprocessed the fMRI images and applied the Support Vector Machines (SVM) algorithm to predict buying decisions.

Table 1 summarizes the relevant studies attempting to understand best and predict consumers' preferences and decision-making processes based on their emotional reactions when exposed to advertisements and their effects on them. None of these studies considered an experimental design that took a *progressive* and *evolving* approach to view different stimuli, such as the one we adopted in this study. Only the brand's logo was initially used as a stimulus in this study. We then added a static poster ad of a product associated with the brand. Finally, a video ad including an experience with the brand and the product was added.

Table 1 – List relevant studies attempting to understand the influence of various stimuli on consumers' emotional reactions to ads and their effects.

Reference	Acquisition	Stimuli	Metrics	Evaluation, or method
Ramsøy et al., 2017	ET	images of clothes and	Pupil dilatation, distance to the screen	Not clear

		wines		
Madariaga et al., 2017	EEG, ET	Products	Attention, number of fixations, AOI heatmap	ANOVA
Krajina and Mladenovic, 2018	ET	Website	Areas of Interest (AOI) heatmap, number of fixations, dwell time, and fixation duration	Not clear
Cuesta et al., 2018	ET, GSR, FC	Video ad	Fixation time, facial emotions, and GSR peaks	T-Test
Alvino et al., 2019	EEG	Wine tasting	Beta bands	FFT, ANOVA, and Friedman
Juárez-Varón et al., 2020	ET	Toy packaging	Number of fixations, fixation duration, AOI heatmap	CART
Mañas-Viniegra et al., 2020	ET, GSR	Image of brands	Time From Fixation, number of fixations, GSR peaks, Mean fixation duration	Mann–Whitney test
Ausin-Azofra et al., 2021	EEG, GSR, ET	Product brands	Number of fixations, Mean fixation duration	Kolmogorov-Smirnov and T-tests
Tun-Min et al., 2021	fMRI	clothes images	Brain images	SVM
Garczare, Bąk, 2021	EEG, GSR, ET	Television advertisements	Average pupil size, number of fixations, Frontal alpha, beta and gamma asymmetry, peaks per second	LR
Garczare, Bąk,2021	EEG, GSR, ET	Television advertisements	Average pupil size, number of fixations, Frontal alpha, beta and gamma asymmetry, peaks per second	LR
This work	ET, GSR, FC	Logo, product, and Video Ad (Professional bicycles)	Seven emotions, attention and engagement (facial coding), GSR peaks, Mean fixation duration	Mann-Whitney-Wilcoxon test; Principal Component Analysis (PCA), Feature Importance (FI)

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III. Research Methodology and Data Collection

To consider a reliable analysis of the participants' reactions and consequent selection of favorite brands when exposed to different stimuli, it is necessary to understand the data acquisition platform and the experiment modeling in detail. The digitally automated platform allows the simultaneous monitoring of multiple physiological signals such as GSR, HR, ET system, and emotion classification based on facial expressions analysis.

During the data collection phase, multiple physiological signals were recorded to provide an experimental analysis of the efficacy of different types of branding advertisements from international companies, within the same industry, based on the participants' reactions when exposed to varying stimuli. It included a standalone logo ad of the company, a product ad associated with the logo, and a video ad associating the logo and the product embedded in an experiential setting. It focused on real-time monitoring of different physiological signals and the automatic classification of facial expressions to analyze consumers' responses, detect emotional arousal, measure attention or relaxation levels, and analyze perception, consciousness, memory, learning, motivation, preference, and decision-making.

The experiment was designed in three phases consisting of distinct human subjects (consumer) branding advertisements exposure. The non-advertisement exposure was also monitored during the collection of survey responses at the end of each phase.

3.1 Research Instruments and Methods

The experiment collected consumers' preferences among four professional international bicycle brands. Figure 1 describes the four steps comprising the research design. First, the Acquisition Module consists of the hardware and software used to collect data from the Eye-Tracking (ET), Galvanic Skin Response (GSR), and Facial Expressions (FE) detection. Secondly, the Stimuli Module, corresponding to the experiment execution, with the participant's exposure to the brand's ads and preference survey responses. After that, the Feature Extraction Module calculated the corresponding statistical metrics and graphical analysis per stimuli and participant. Finally, the Data Analytics Module, proposed as a first-level computational tool to perform data analysis and interpretations, focuses on three main techniques: Linear Correlation, Principal Component Analysis (PCA), and Feature Importance (FI) estimator based on Random Forest. Each data analysis technique is described later in this section.

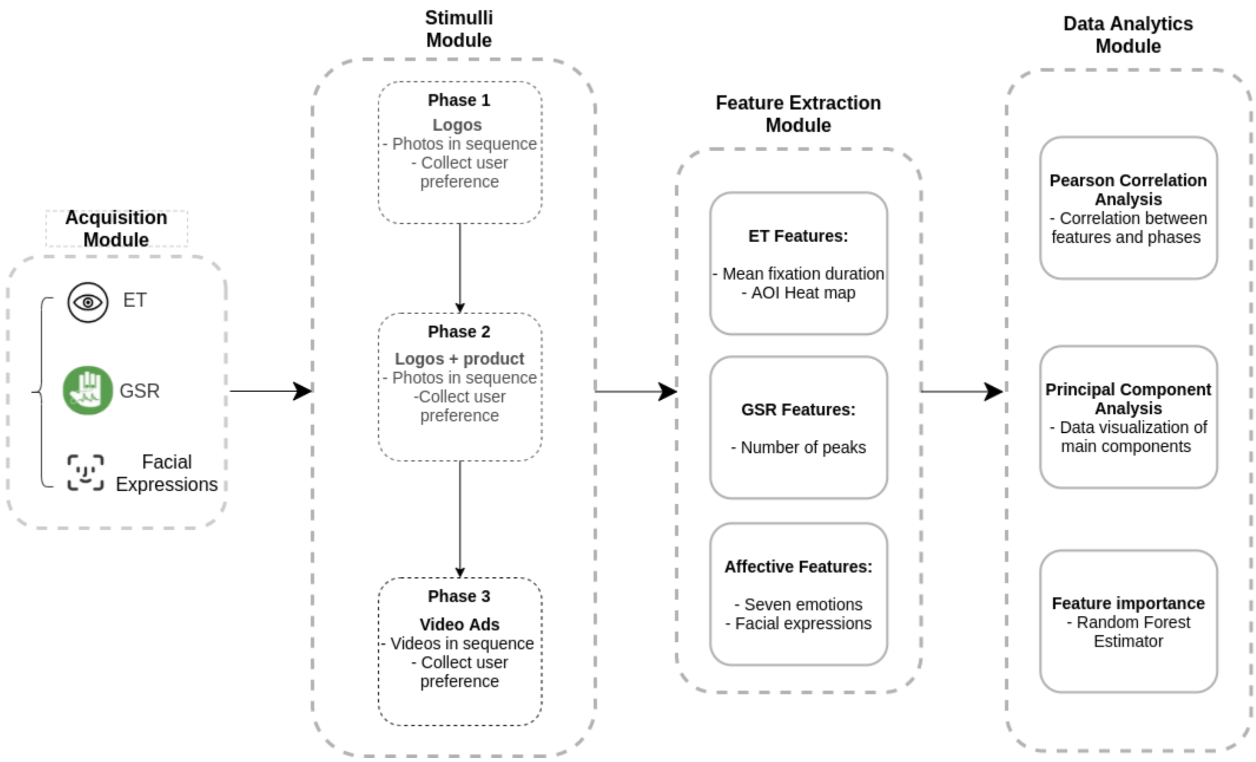


Figure 1 - General description of the integrated solution, divided into four modules.

3.1 - Participants' profile

The sample consisted of nine participants within the age interval of 13 to 47 years old (mean 25.88 and Std. Dev 13.31). All the participants read and agreed with the electronic declaration of informed consent at the beginning of the experiment, declared no history of psychiatric disorders, and self-declared to be under no significant stress nor relevant humor changes when data collection was performed.

3.2 Experiment Apparatus and Materials

The monitoring experiment was performed with the following equipment and software:

- Eye-tracker - Tobii Pro Nano - gaze capture frequency 60 Hz;
- GSR/Heart Rate - Shimmer3 GSR+;
- Facial expressions were captured using a high-definition (HD) integrated webcam and Affectiva's AFFDEX technology, which provides facial expressions measures, core emotions, and behavioral indices such as head orientation, attention, blinks, and blink rate;
- iMotions Software Platform version 8.1 for data collection, synchronization, and analysis.

- Python v3.8.1 with additional toolboxes: pandas v1.3.4, scikit-learn v0.24.2, scipy v1.7.2;
- Data Acquisition Station - i7 8-core CPU, 16 GB RAM;
- Video board AMD Radeon/32GB;
- Windows 10 Operating System.

3.3 - Experiment Design

The experiment was designed considering three phases of stimuli exposure, each preceded by an explanation to the participants about the coming phase. At the end of each set of stimuli, the participants' reactions and feedback on their selected brand were collected through a digital survey. Visual observations were conducted informally to register general and relevant responses from the participants.

Before starting the experiment, the participants received a verbal explanation about the scope of the investigation related to branding preferences and the physiological monitoring tools. At the same time, the sensors were installed and tested. In addition, it was clarified that a digital camera would record their facial expressions. No audio was recorded. Data protection requirements for anonymity and confidentiality were assured to each participant. Finally, before starting the effective data collection, an individual eye-tracking system calibration was performed, working as a pre-adjustment phase to the sensors and the setup.

The general experiment modeling is depicted in Figure 2, divided into three phases according to the type of stimuli. Four randomly sequenced logo image ads were presented in the first phase, with six seconds per stimulus. The participants' preferences were collected at the end of the phase. In phase 2, the stimuli series consists of four image ads comprising the logo and two pictures of the products (bicycles) following the same brand sequence of phase 1. At the end of phase 2, the participants' preferences were collected. Finally, in phase 3, four video ads (one for each brand) were presented, followed by a third survey to gather feedback on the favorite brand.

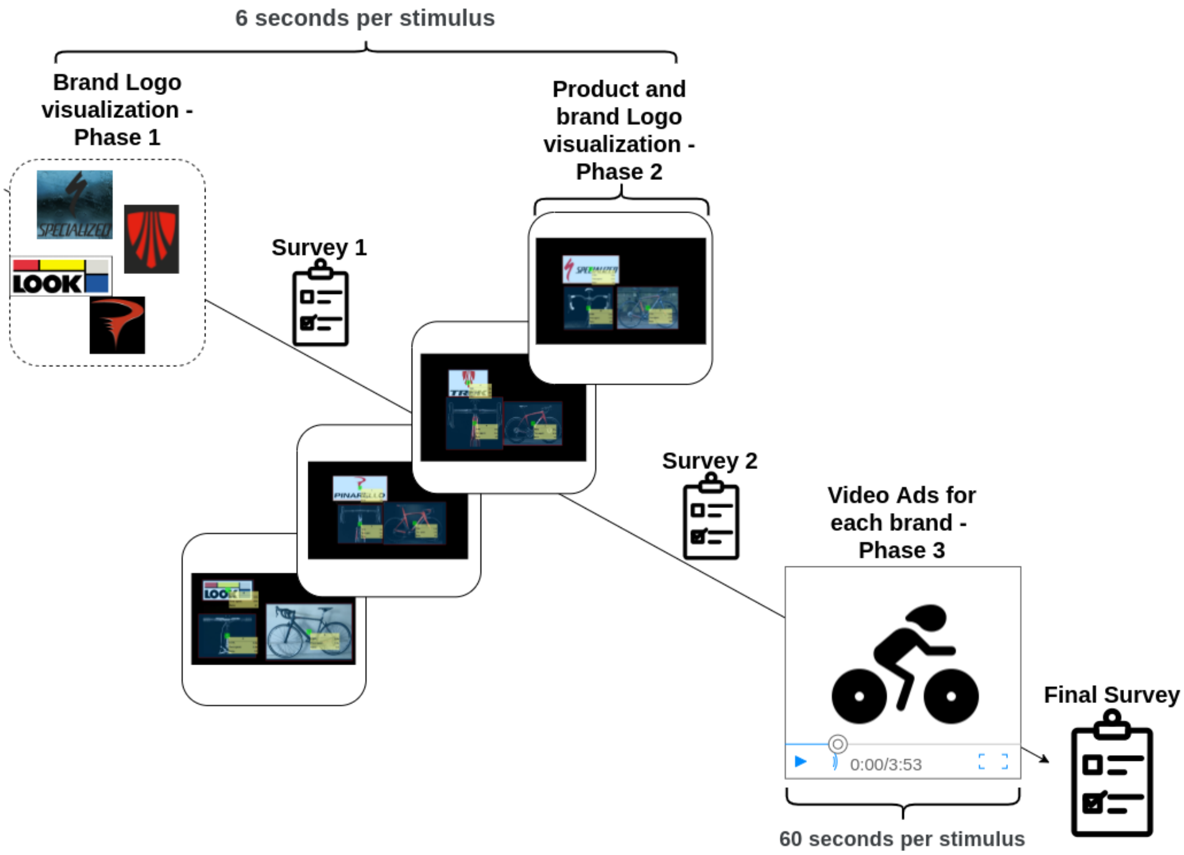


Figure 2 - Sequence of stimuli in detail, divided into three phases.

The four video ads presented during Phase 3 were selected directly from each brand's official social media channels with a similar duration of 60 seconds on average. It is relevant to highlight that despite each brand presenting similar products to the market, they all had different approaches to their promotional videos. One was inspirational, while the others ranged from friends gathering together to only showing the product and extreme sports scenes.

3.4 Features

From the several metrics generated by the monitoring system, the detailed list of features tracked in this experiment can be found in Table 2.

Table 2 - Table of features tracked by the monitoring systems used in this study.

Data Collection	Feature	Description
Facial Expression AFFDEX	Count_Emotion(i)	Automatic classification of the seven basic emotions based on facial expressions. i=[1,7], where

		1: Anger 2: Contempt 3: Disgust 4: Fear 5: Joy 6: Sadness 7: Surprise
Facial Expression AFFDEX	Count_Attention	The "Attention" detection is an additional parameter provided by the facial expressions detection system
Facial Expression AFFDEX	Count_Engagement	The "Engagement" detection is an additional parameter provided by the facial expressions detection system
Galvanic Skin Response (GSR) - Shimmer G3	Has_peaks	A boolean indicator for the occurrence of GSR peaks
Galvanic Skin Response (GSR) - Shimmer G3	Number_of_peaks	Number of GSR peaks during a stimulus exposition
Eye-tracking	Mean_fixation_duration (ET-MFD)	Mean fixation time during a stimulus exposition
Eye-tracking	Heat maps (ET-HM)	Visual representation of AOI eye fixations

3.5 Data Analytics Module

Three methods (presented in Figure 1) were considered and are described as follows to perform an exploratory analysis of the data with its various physiological and metrics.

3.5.1 Correlation Analysis

The correlation between the variables was a helpful interpretation tool during the exploratory data analysis. It allowed for the determination of the relationship between two quantitative variables and the degree to which these variables were related (i.e., if changes in one variable corresponded to changes in another). For example, it enabled us to assess if there were any correlations between the number of GSR peaks with the detection of specific emotions, such as joy or surprise.

The Pearson correlation coefficient was used to evaluate features during each phase of the experiment, the intraphase and interphase correlation, and the correlation between different phases. The Pearson correlation coefficient r is an index used to evaluate the existence of a linear relationship between the features being monitored. If the two variables are normally distributed, the standard measure of determining the correlation coefficient, often ascribed to Pearson, is (Haslwanter, 2016)

$$r = \frac{s_{xy}}{s_x . s_y} \tag{1}$$

where, s_x,s_y are the sample standard deviations of variables (features) x and y, and s_{xy} is the sample covariance, defined as

$$s_{xy} = \frac{\sum_{i=1}^{n}(X_i - \underline{X})(Y_i - \underline{Y})}{n - 1} \tag{2}$$

The correlation index *r* ranges from -1 to +1, considering:

- -1 strongest negative correlation;
- 0 no correlation;
- +1 strongest positive correlation.

3.5.2 Principal Component Analysis

When considering using data analytics strategies on neuromarketing data, one of the critical tasks was to perform an automatic participants' classification or clustering. Principal Component Analysis (PCA) as a dimension-reduction tool, was appropriate for such a task in this experiment since it allowed for a reduction of the large set of existing variables to a smaller set of new attributes (or components) that still contains most of the information of the original data.

This unsupervised method generated the components from the linear combination of the original attributes. It was used for dimensionality reduction and data visualization through a subset of generated components (Murphy, 2012). The following steps were executed for PCA:

- We standardized the data.

$$X_{New} = \frac{X - mean(X)}{Std(X)} \tag{3}$$

- Found the covariance matrix from the given data.

$$C[i,j] = cov\left(x_i,x_j\right) \tag{4}$$

- Carryed out eigenvalue decomposition of the covariance matrix.

$$C = V\Sigma V^{-1} \tag{5}$$

- Sorted the eigenvalues and eigenvectors.

$$\Sigma_{sort} = sort(\Sigma)\ V_{sort} = sort(V, \Sigma_{sort}) \qquad (6)$$

The N first components rated by PCA are the best vectors preserving the cumulated explained variance and the maximum information of the dataset. In this work, we applied PCA to visualize each brand's two main generated components along with the phases. The Scikit-learn (Pedregosa et al., 2011) python library was used to perform the analyses.

3.5.2 Feature Importance using Random Forest Classifier

Considering that it would be useful to determine which features are more significant for different neuromarketing experiments or approaches, this experiment used a technique known as Feature Importance (FI) determination. It assigned scores to each feature (see Table 2) to reduce unnecessary input features during the analysis, future classification, or clustering tasks. It is based on the Random Forest algorithm, a set of Decision Trees with their subsets of nodes and leaves. These trees are constructed by partitioning the data samples into successive subsets. When selecting the best combination of features and values as the splitting point, the FI, also known as Gini importance, or Mean Decrease Impurity (MDI), of a variable Xm for predicting Y is calculated and used as criteria for separation quality (Lyu, 2017) according to the following equation.

$$MDI(X_m) = \frac{1}{N_T}\sum_T \sum_{t \in T: v(s_t) = X_m} p(t)\Delta i(s_t, t) \qquad (7)$$

where p(t) is the proportion N_T/N of samples reaching t and $v(s_t)$ is the variable used in split s_t. The weighted impurity decreases $p(t)\Delta i(s_t, t)$ for all nodes t where Xm is used, averaged over all N_T trees in the forest.

The forest's average number of overall trees measures the feature's importance. In this study, we applied the Random Forest Estimator Classifier to calculate the significance of each feature in our data. The Scikit-learn (Pedregosa et al., 2011) python library was used to perform the analysis.

3.5.3 Statistical Test - Mann-Whitney-Wilcoxon

The Mann-Whitney-Wilcoxon test was used to compare whether there was a difference in the dependent variable for the two independent groups being analyzed. This non-parametric test is applicable when the sample size is small ($n < 30$) and the data are not assumed to be normally distributed. It enabled the comparison of whether the distribution of the dependent variable was the same for the two groups and, therefore, from the same population. This test was used in place of an unpaired t-test to test the null hypotheses with two samples coming from the same population and test whether observations in one sample tend to be larger than observations in another.

In this study, we considered the significance level, α (alpha), of 0.05, indicating a 5% risk of concluding that a difference exists when there is no actual difference. Hence, it is acceptable to reject the null hypothesis for a p-value of less than or equal to alpha.

IV. Data Analysis, Results, and Discussion

The data analysis and evaluation of the research results considered several independent and dependent aspects and variables. Firstly, the survey responses were presented and discussed, highlighting the possible experimental correlations between the participants' responses and the monitored metrics. This process was followed by analyzing the occurrence of emotional arousal measured by the GSR sensor in each specific phase, followed by the ET monitoring results presented in two parts. The first part shows the mean fixation duration of each brand during phases 1 and 2. In contrast, the second is focused on phase 3, establishing the potential visual correlation between the video scenes and the number of GSR peaks. Finally, each experiment phase analyzes and evaluates the automatic classification of the seven emotions and the measures of engagement and attention levels based on facial expressions.

4.1 Brand Preferences Surveys

Three surveys collected the participants' preferred brands at the end of each experiment design phase. As shown in Figure 11, significant changes occurred from one phase to the subsequent ones.

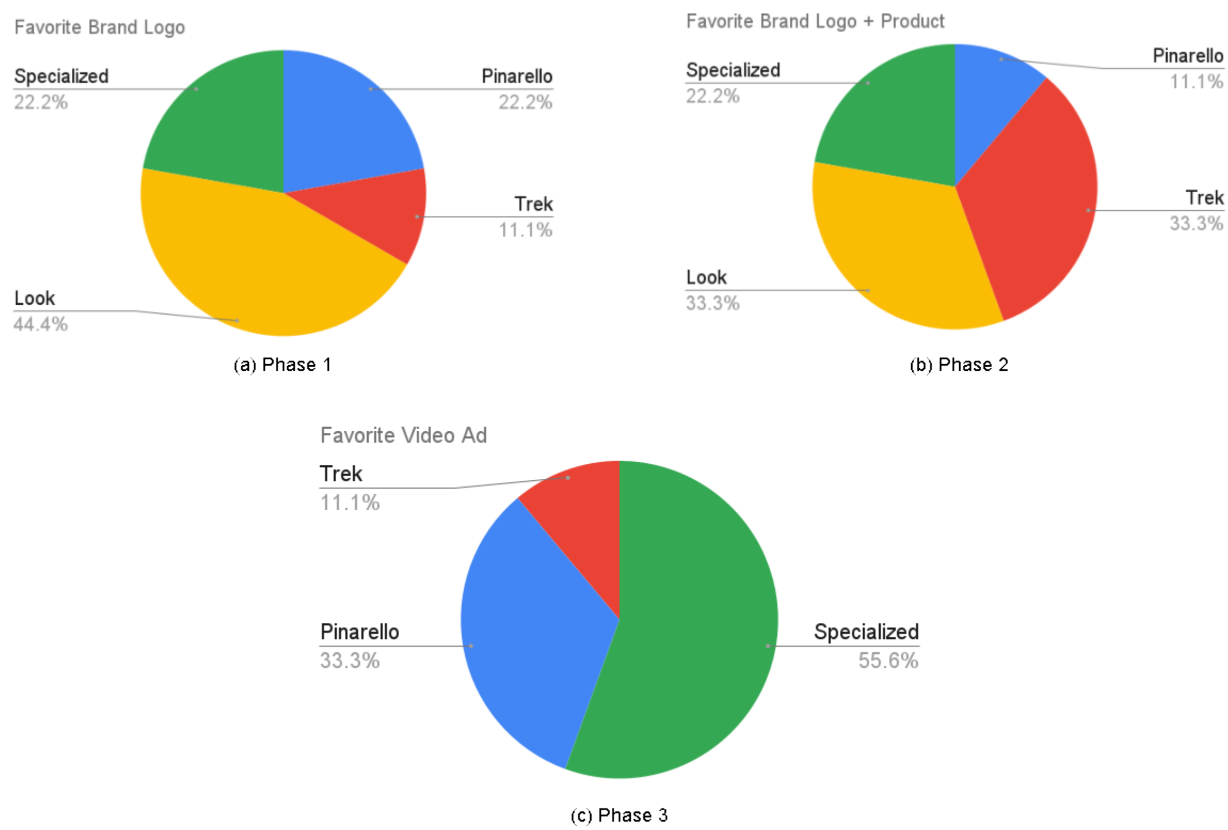


Figure 11 - Answers to the participants' brand preferences survey questions:

There was no consistent brand preference shown throughout the three phases. Initially, in phase 1, the logo brand ad for Look achieved a higher score, showing a clear preference for the logo style, as it was distinctively different from the other brands, with an evident geometric design. The preference for Trek increased significantly in phase 2, with the logo associated with the product, indicating that the product (only included in this phase) generated increased interest. Finally, in phase 3, the Specialized brand's video ad (the brand had scored second to last in the previous phase) jumped from 22% to 55% in preference. Such a significant jump may be directly correlated to the style of video advertisement, highlighting the product's strengths related to the practice of extreme sports.

4.2 Emotional Arousal

As previously indicated, emotional arousal was measured by the GSR monitoring tool. It is essential to highlight that the skin response, also known as skin conductance, is a response from the Autonomic Nervous System (ANS), the part of the nervous system accountable for the control of bodily functions not consciously directed, such as breathing, the heartbeat, and digestive processes, and indicates emotional arousal without the possibility of classifying its nature or source. Hence, a GSR peak may indicate different responses from the sympathetic system, the part of the nervous system responsible for the increase of heart and breathing rate, blood pressure, pupil size, and feelings of Surprise, excitement, Fear, stress, etcetera. Nevertheless, the occurrences of GSR peaks in this experiment indicate participants' engagement differently, which is considered the first analysis.

The feature consists of the total number of GSR peaks per stimulus for each brand, as depicted in Figure 3. Phase 3 (video stimuli) was expected to have a significantly higher number of peaks because of the longer duration and possibly because of audiovisual sensations. Comparing Phases 1 and 2, only the first brand, Look, increased the number of peaks when moving from "Logo" to "Logo+Product" stimulus. In addition, Look and Specialized were the brands with the highest increase in the number of GSR peaks during Phase 3, which may indicate the participants' preferences for their videos and should be compared with the participants' preferences stated in the final survey.

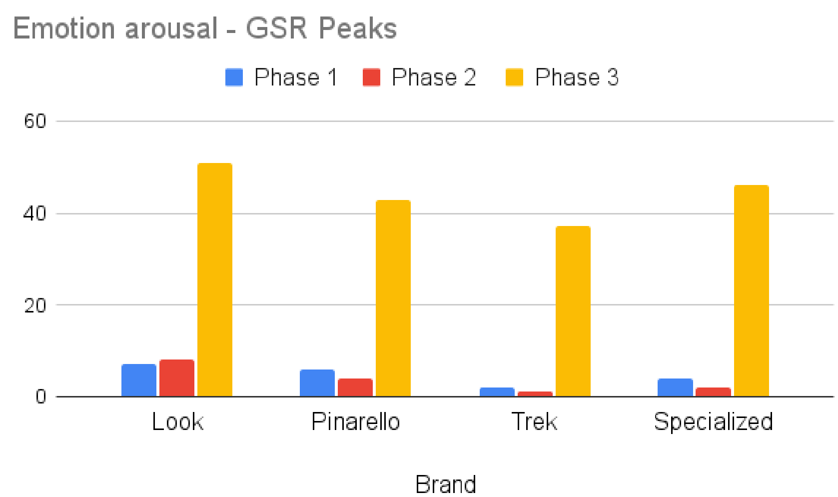


Figure 3 - Emotional arousal considering the total number of GSR peaks per phase according to each brand.

Considering each phase separately, a similar trend can be found for each of the numbers of GSR peaks. For phases 1, 2, and 3, the absolute number of peaks continuously decreased from Look (B1) to Pinarello (B2) and from Pinarello (B2) to Trek (B3). After that, the number of GSR peaks increased during the stimuli presentation for Specialized (B4) compared to B3.

4.3 Eye Gaze Monitoring

Eye gaze monitoring is a valuable tool to track the participants' interests, mainly when evaluated with physiological signals monitoring. In this study, two main approaches were considered. The first one was based on the Eye-Tracking Mean Fixed Duration (ET-MFD) metric, considering relevant AOI in each stimulus. The second approach considers the integrated analysis of the selected video ads with corresponding eye-tracking heat maps (ET-HM) in parallel with GSR monitoring (emotional arousal).

4.3.1 Mean Fixation Duration

During eye gaze monitoring, the mean fixed duration was considered a feature for the analysis. Fixations are time segments when the eyes are relatively stationary, allowing the visual system to capture detailed information about what is being looked at.

In Figure 4, the mean fixed duration for phases 1 and 2, which considered stimuli-based static images.

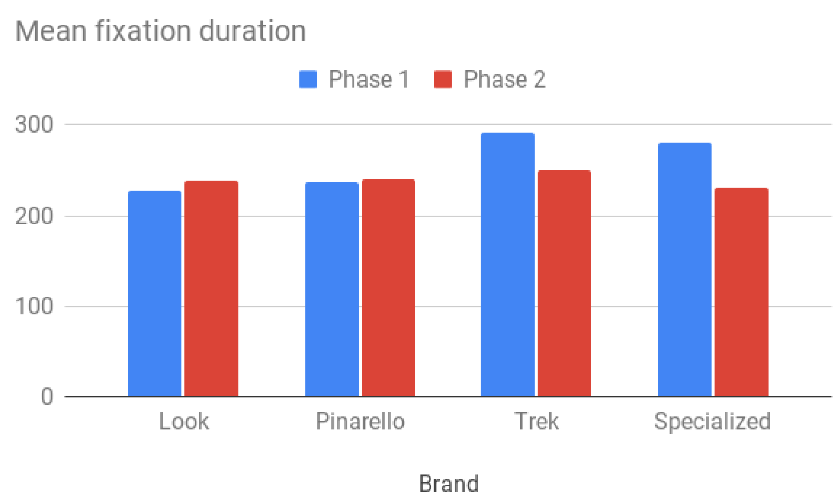


Figure 4 - Mean fixation duration for each brand, stimuli experiment

In comparison, the logo image ad makes it possible to visualize that Trek and Specialized were the brands with the highest mean fixation duration with a higher mean duration in phase 1. Nevertheless, the brands Look and Pinarello presented a higher mean duration in phase 2, indicating that the respondents focused more on the product than the logo.

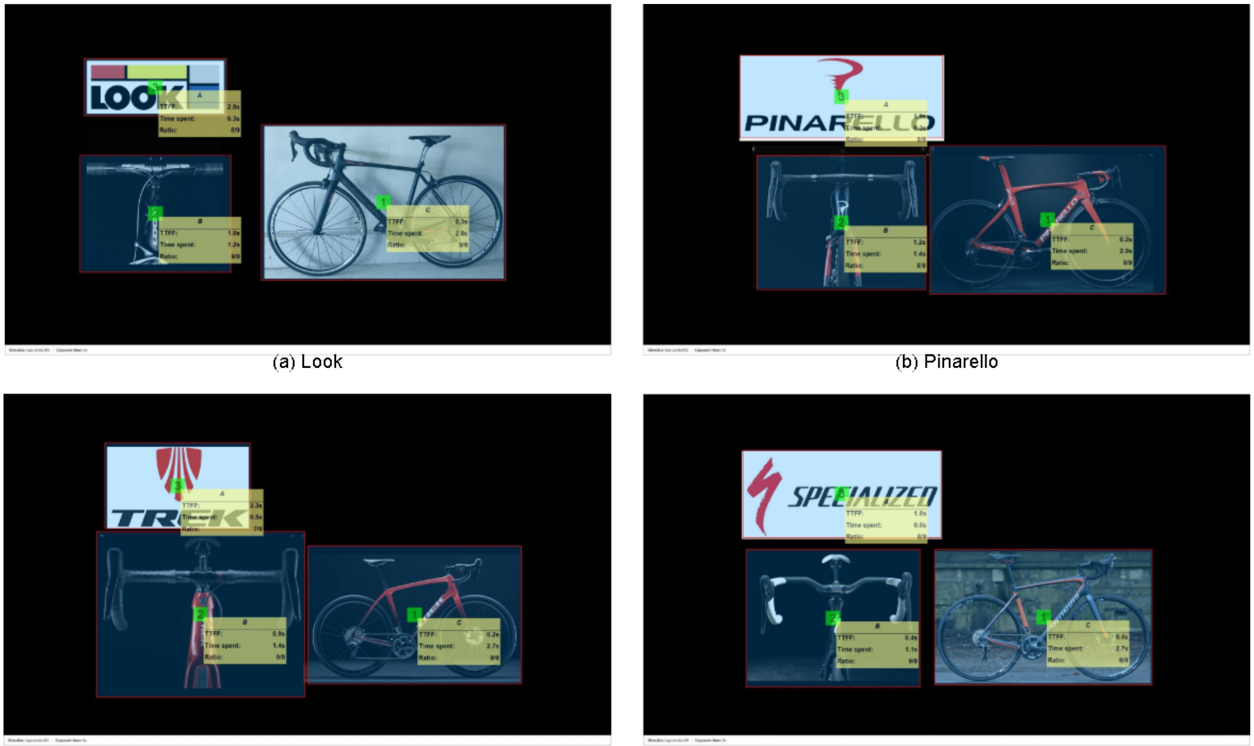
In addition to these general results per brand, the following discussion focuses on the analysis of eye gaze fixation duration in specific AOI collected during phases 1 and 2 and also during the survey responses presented as follows:

i) Phase 1 - Logo images ads
Only one AOI is considered in this phase, with the complete logo of each brand. As illustrated in Figure 5, the results are similar for B2, B3, and B4, while B1 had approximately a duration of 10% less than the other three brands.

Figure 5 - Areas of Interest covering the complete Logos during Phase 1

ii) Phase 2 - Logos and Products

In this phase, three AOIs are offered per stimulus, and Figure 6 provides each stimulus with the AOIs and corresponding durations. The first one is the logo image ad, the second one is the frontal picture of each product ad, and the third AOI is the complete lateral view of the product. When the four stimuli are analyzed, it is possible to detect a similar behavior of the participants when comparing each corresponding AOI. For instance, considering the picture of the lateral view of the product, the ET-MFD for Look is 2.8s, for Pinarello is the highest with 2.9s, while Trek and Specialized are both 2.7s. For the frontal picture of the product, the times are 1.2s, 1.4s, 1.4s, and 1.1s for Look, Pinarello, Trek, and Specialized, respectively. Finally, the AOI with the logos received less attention and less than one second per brand, indicating that the pattern was already recognized from the previous phase.



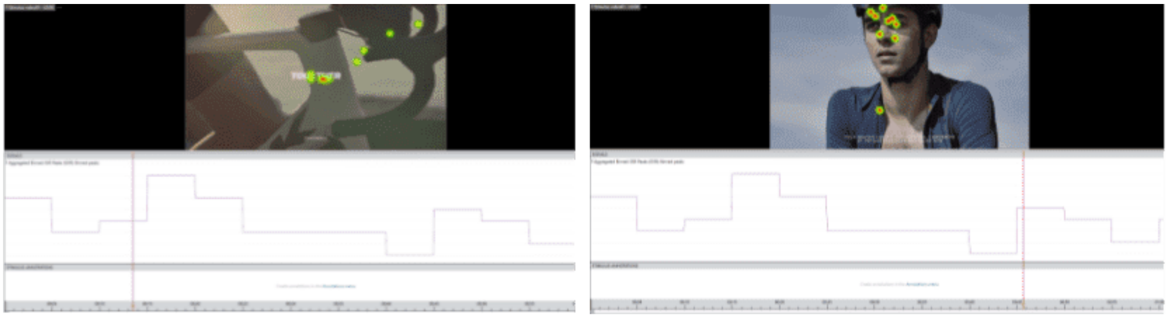
(a) Look (b) Pinarello (c) Trek (d) Specialized

Figure 6 - The three Areas of Interest considered during Phase 2

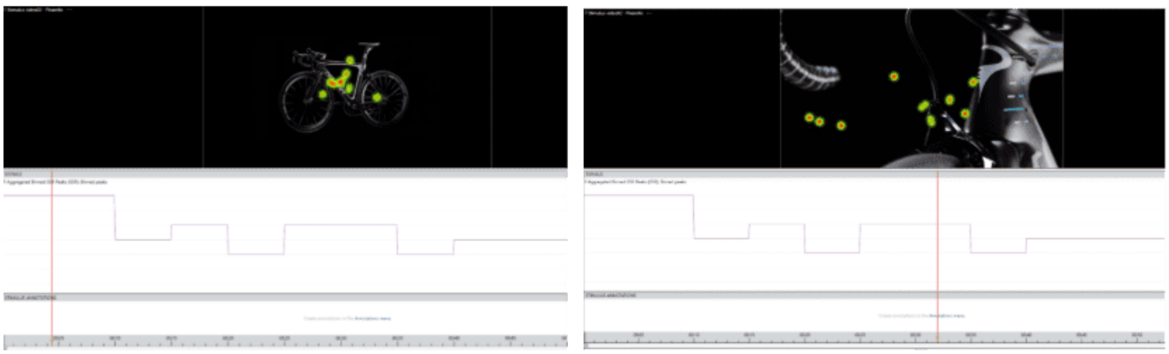
4.3.2 Integrated Monitoring - ET and GSR

This subsection provides integrated results from all the participants, including the eye-tracking and GSR monitoring systems during Phase 3 (video ads), as depicted in Figure 7. For each video, two scenes were selected. The upper part presents the paused video with the corresponding heatmap, which visually represents the distribution of gaze locations. They are shown as a color gradient overlay on the image or stimuli given. The red, yellow, and green colors indicate the number of gaze points directed at different image sections in descending order.

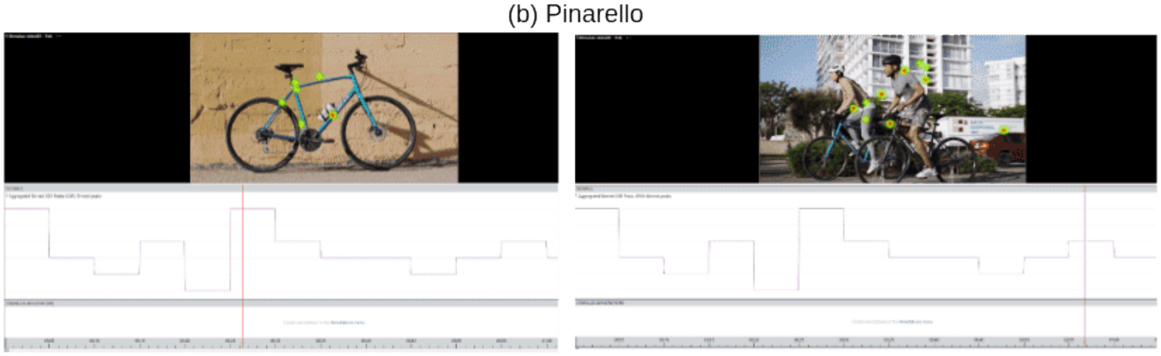
GSR peak scores for all the participants following the video timeline are shown at the bottom of each image. This integrated analysis may identify the most relevant and emotional scenes and support video campaign approvals or changes.



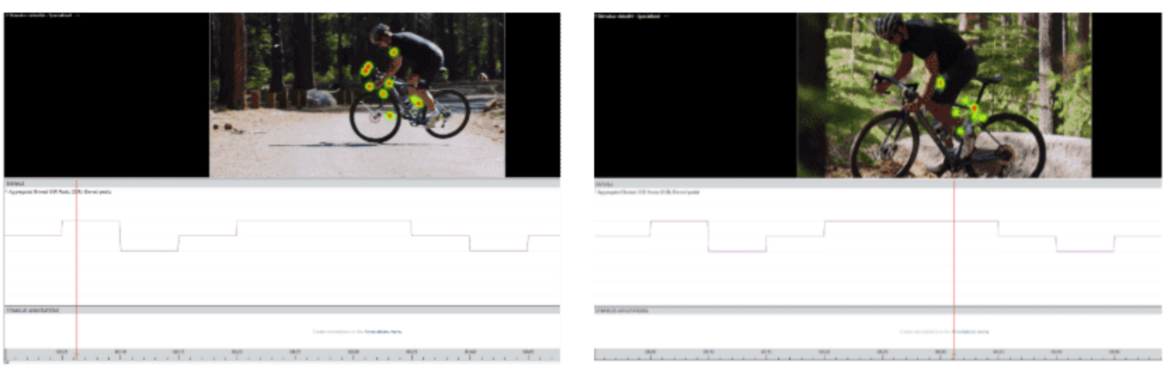
(a) Look



(b) Pinarello



(c) Trek



(d) Specialized

Figure 7 - Two scenes from each brand video ad with an eye-tracking heat map (ET-HM) and GSR peaks count for all the participants following the video timeline.

In Figure 7, two scenes from each brand video ad with an eye-tracking heat map (ET-HM) and GSR peaks count for all the participants following the video timeline. The scenes were selected right before or during GSR significant peaks to identify which type of exposition could create more emotional arousal in general.

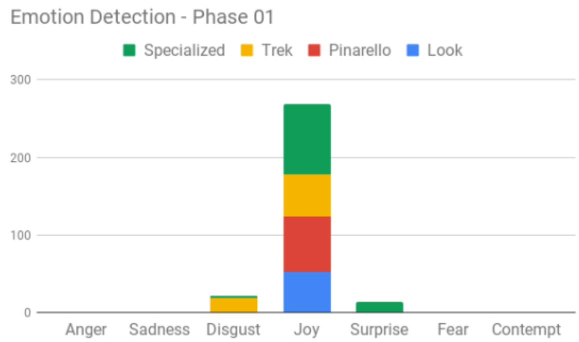
4.4 Results for Emotion Detection and Facial Coding (FC)

This subsection considers the emotion, attention, and engagement classification results based on facial expressions and coding. The seven emotions are specific indicators of the participants' responses, while the levels of awareness and engagement may reinforce the participant's interest in the stimulus.

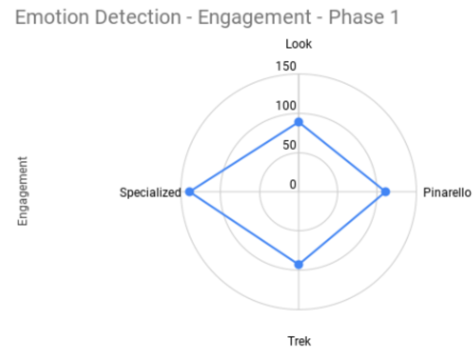
It is essential to highlight that the computerized identification of the seven basic emotions can be considered a first-level classification. Nevertheless, there are indications of at least 21 additional classes from mixed emotions and specific facial reading. This means that single classifications such as anger or disgust can be more explored in detail if necessary for the experiment under analysis. In this work, the seven basic emotions together with the estimation of engagement and attention are considered.

4.4.1 Phase 1

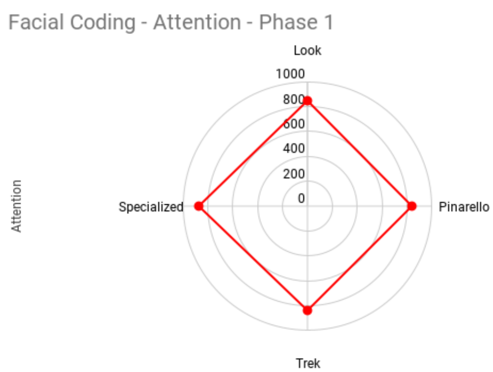
In Phase 1, as previously mentioned, the stimuli were exclusively the brand logo image ad, intending to capture the first impressions of each brand in general. Figure 8 depicts the results of emotion detection based on facial expressions during this phase. It is relevant to notice that in Figure 8-a, only three emotions were detected in all the participants: Joy, Disgust, and Surprise. All four brands aroused Joy, while Trek and Specialized aroused Disgust, and only Specialized aroused Surprise.



(a) Detected emotions



(b) Engagement



(c) Attention

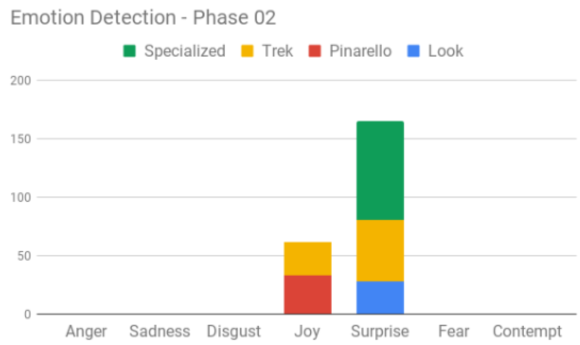
Figure 8: Emotions detected among all participants and results corresponding to Engagement Detection and Attention, based on facial expressions for each brand during Phase 1.

In Figure 8-b, it is possible to find a higher level of engagement in the Specialized ad while the level of attention was similar among the four brands, as can be seen in Figure 8-c.

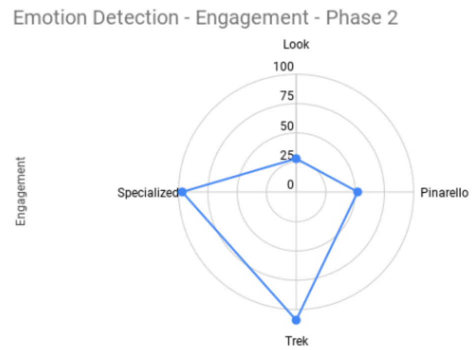
4.4.2 Phase 2

In Phase 2, detecting emotions based on facial expressions for each brand, Figure 9 depicts the range of emotions. In this phase, only two emotions were detected, Joy and Surprise. Look, Trek and Specialized aroused Surprise, with only Trek and Pinarello arousing Joy.

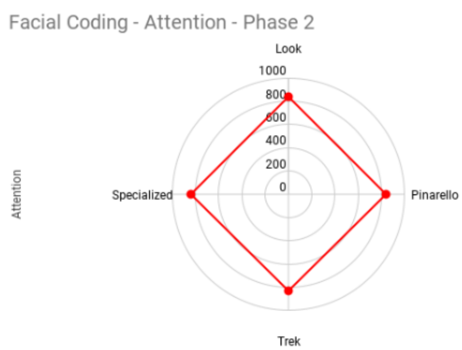
Specialized and Trek achieved a much higher attention level than Pinarello and Look in this phase, as presented in Figure 9-b. Again, the level of attention can be considered similar among the four brands, as shown in Figure 9-c.



(a) Detected emotions



(b) Engagement



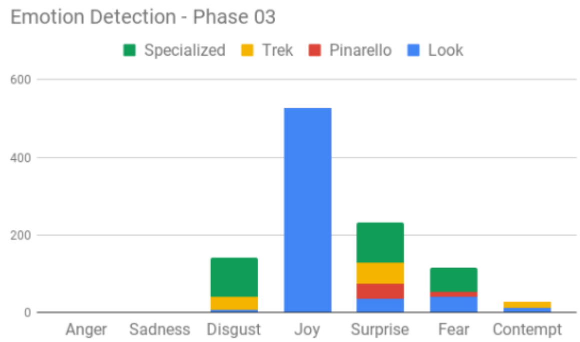
(c) Attention

Figure 9: Results Corresponding to Emotion Detection based on facial expressions for each brand during Phase 2

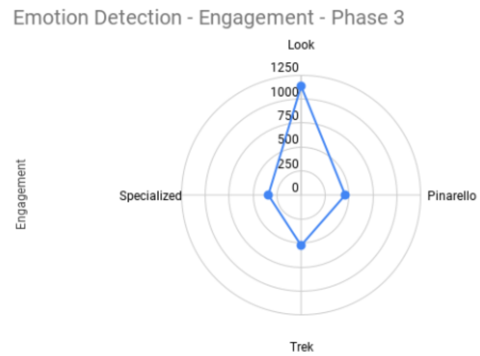
4.4.3 Phase 3

In Phase 3, detecting emotions based on facial expressions for each brand, Figure 10-a depicts a broader range of emotions. In this phase, only Look aroused Joy at a higher degree, although it also aroused Surprise and Fear at a lesser degree, and Contempt and Disgust to an even minor degree, along with Trek. All four brands evoke Surprise. Specialized, Look and to a minor extent, Pinarello aroused Fear. Notably, Specialized aroused similar degrees of Disgust, Surprise, and Fear.

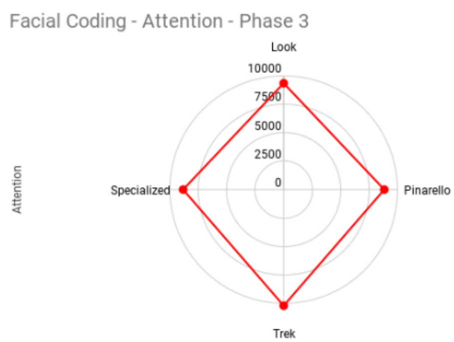
In Figure 10-b, the brand Look achieved an outstanding level of engagement when compared to the other three brands. Specialized reached a notably lower level of engagement. The level of attention was higher for the brands Trek and Look, as presented in Figure 10-c.



(a) Detected emotions



(b) Engagement



(c) Attention

Figure 10a: Results corresponding to Emotions Detection based on facial expressions for each brand during Phase 3.

4.5 Hypothesis Testing

After presenting the results, the analyses of the proposed hypothesis are presented. For both tests, according to the sample size, considering the Mann-Whitney-Wilcoxson test with a confidence interval of 95% (α=0.05), the critical value is 17.

First, considering the independent variable "Attention Count," the following null and alternate hypotheses are tested:

H_0: The effectiveness of attracting consumers' attention to a brand's video ad is the same as that of image ads when measured through physiological monitoring.

H_1: The effectiveness to attract consumers' attention to a brand's video ad is more significant than image ads when measured through physiological monitoring.

For this first hypothesis, the U-value is 0, and the critical value is 17, resulting in a p-value equal to 0.00042, rejecting the null hypothesis and supporting the alternative hypothesis.

For the second case, the independent variable "GSR Peak Count" is considered, and the following null and alternate hypotheses are tested:

H_0: Customer's emotional arousal is not influenced during video ads compared to image ads of similar brands.

H_1: Customer's emotional arousal during video ads is more significant than image ads of similar brands.

For this case, two statistical tests were performed. Firstly, the test between phase 1 (image ad) and phase 3 (video ads). The U-value is 6.5, and the critical value is 17. The p-value is 0.00308, rejecting the null hypothesis and supporting the alternative hypothesis. The second test was between phase 2 (image ad) and phase 3. The U-value is 3.5, and the critical value is 17. The p-value is 0.00128, rejecting the null hypothesis and supporting the alternative hypothesis.

4.6 Data Analytics Module

In addition to the hypothesis testing, the Data Analytics Module was designed to provide the first level of computational interpretation to support the decision-making and analysis of the proposed experiment. First, linear correlation analysis is performed within one phase and between different phases. Secondly, a two-component PCA is performed for phases 1, 2, and 3, and possible interpretations are presented. Finally, the graphical results for calculating the Feature Importance (FI) are shown. The most relevant features that may support the participants' responses during each experiment are discussed.

4.6.1 Correlation Results

The exploratory analysis started with determining eventual correlations between the collected data features. The linear correlation index (Pearson) was considered for each feature, and the matrices are presented in Figures 12 and 13.

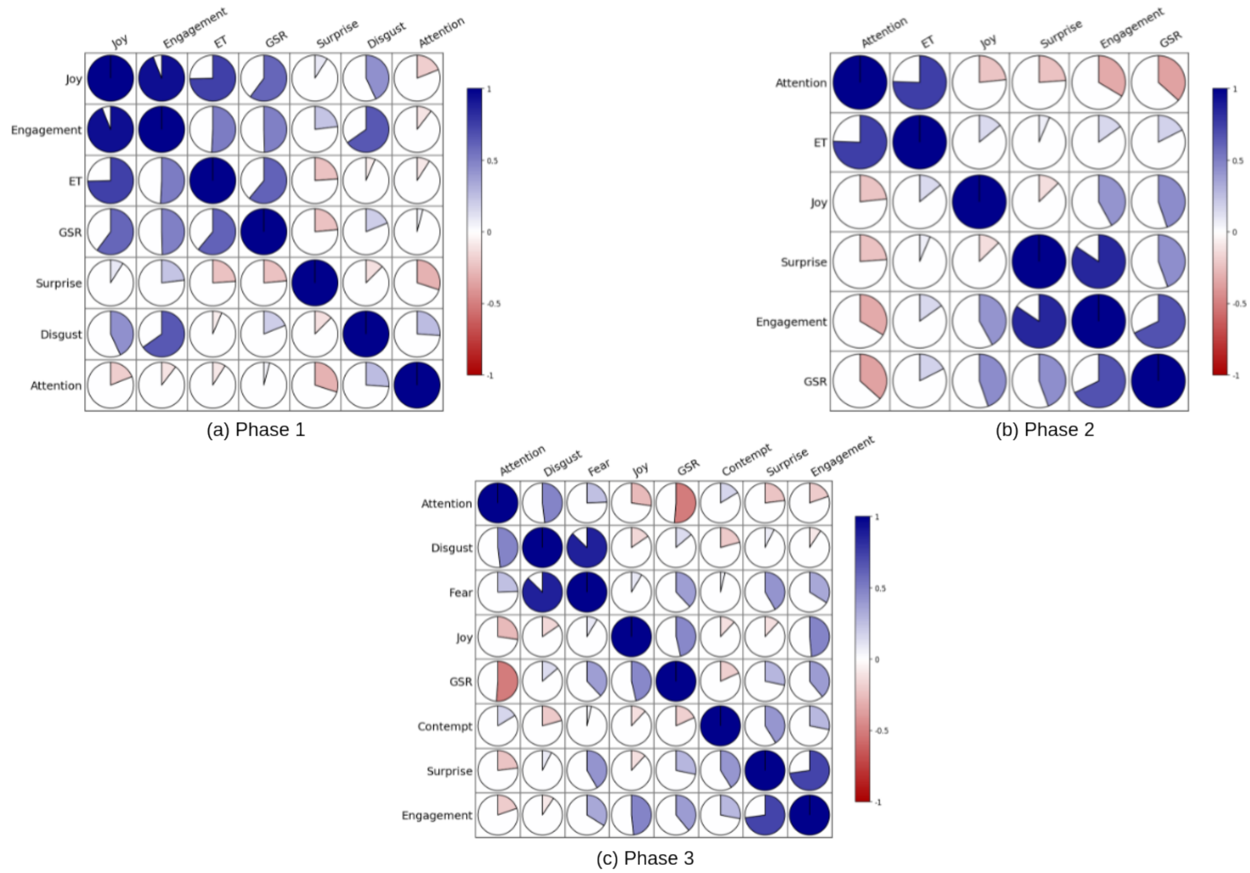


Figure 12 - Correlation matrix between features. (a) Phase 1; (b) Phase 2; (c) Phase 3.

In Figure 12, Phases 1, 2, and 3 are represented by Figures 12-a, 12-b, and 12-c, respectively. During phase 1 (Figure 12-a), it is possible to highlight a strong positive correlation between the Joy emotion with Engagement and Eye-Tracking fixed duration time (ET). A positive correlation between Joy and the number of GSR peaks (GSR) is also found. A weak negative correlation was found between Attention coding and Surprise emotion.

In Figure 12-b, representing correlations in Phase 2, it is possible to indicate three positive correlations: ET and Attention; GSR and Engagement; Surprise and Engagement. A weak negative correlation was found between Attention coding and GSR monitoring.

Finally, during phase 3, strong positive correlations can be found between Fear and Disgust and between Engagement and Surprise. Weak positive correlations are found between Disgust and Attention, Joy and GSR; Engagement and Joy. On the other hand, weak negative correlations can be found between the level of Attention and the number of GSR peaks.

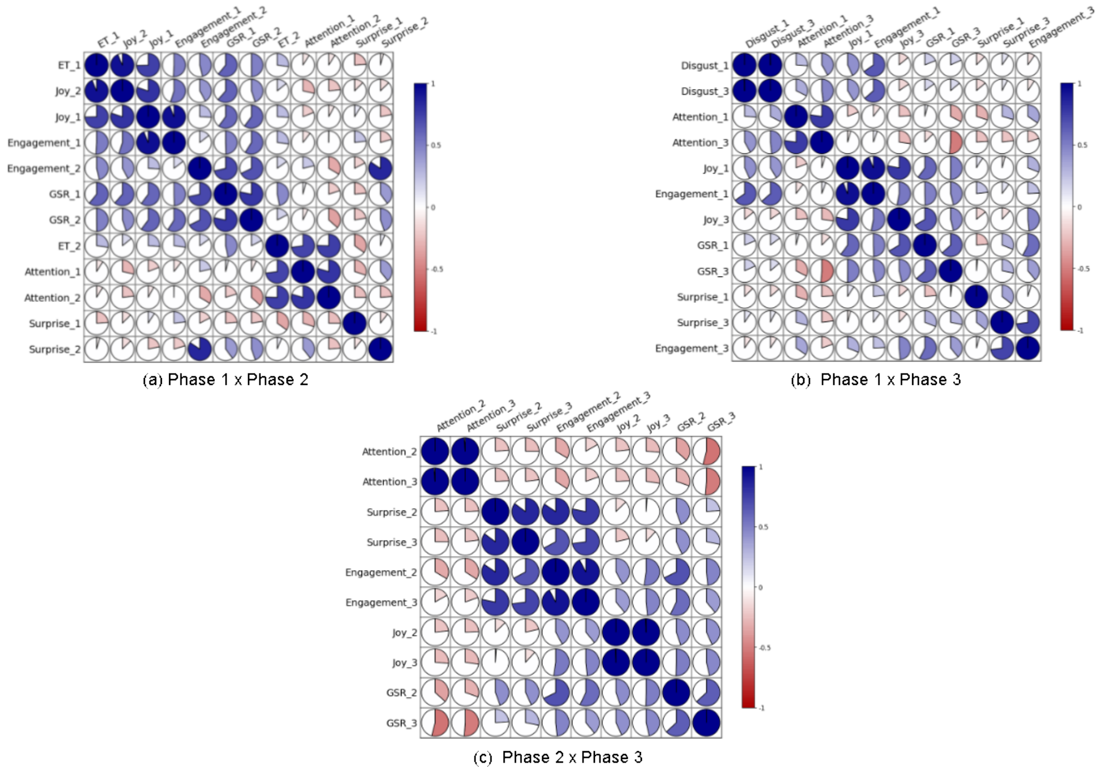


Figure 13 - Results for the feature correlation implementation between phases.
(a) Phase 1 x Phase 2; (b) Phase 1 x Phase 3, and (c) Phase 2 x Phase 3.

In Figure 13, the correlation indexes between features in different phases are presented as follows. In some cases, the correlation might not add a valuable discussion, such as the ET fixed duration time in phase 1 and emotions in phase 2. Still, correlation analysis of emotions in different phases might indicate trends in consumer behavior and help analyze decisions.

Comparing phases 1 and 2 (Figure 13-a), besides many positive correlations, it is possible to highlight many strong positive relevant correlations: Joy_1 and Joy_2; Attention_1 and Attention_2; Surprise_2 and Engagement_2; GSR_1 and GSR_2. In Figure 13-b, the correlation analysis is between phases 1 and 3. Relevant positive correlations are; Joy_1 and Joy_3, while strong negative correlations could not be found between these specific phases. Finally, Figure 13-c presents the correlation between phases 2 and 3. Relevant positive correlations are Surprise_2 with Surprise_3 and Engagement_3. As previously mentioned, GSR peaks and attention showed negative correlations even between phases.

4.6.2 Principal Component Analysis - PCA

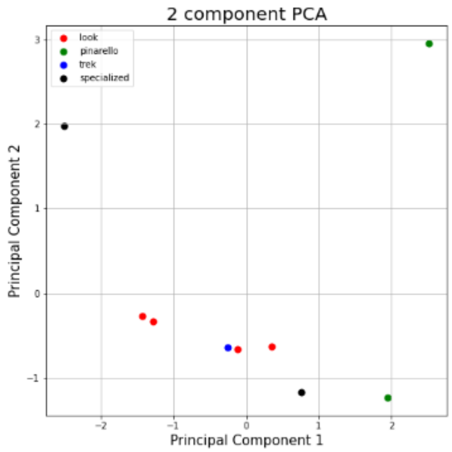
As previously introduced, when a model has a large number of attributes considered to perform a classification task, dimensionality reduction can be considered to identify the most relevant contributors to achieve satisfactory results and simplify the computational implementation. In this work, it is regarded as the technique known as PCA (Principal Component Analysis).

The dimensionality reduction to two dimensions was considered. It is possible to represent the attributes in two-dimensional plots (Principal Component 1 x Principal Component 2), as presented in Figure 14.

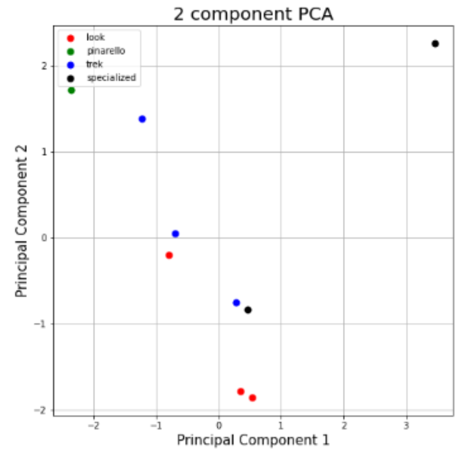
Regarding the first phase (Figure 14-a), Pinarello, Trek, and Specialized classes can be linearly separated when considering the two main components. Note that the explained variance for these two components is about 69.4%.

In Figure 14-b, representing Phase 2, Pinarello, Trek, and Specialized can be linearly classified, while the brand Look can also be classified with the simple application of a two subclasses technique. Note that the explained variance for these two components is about 74.2%.

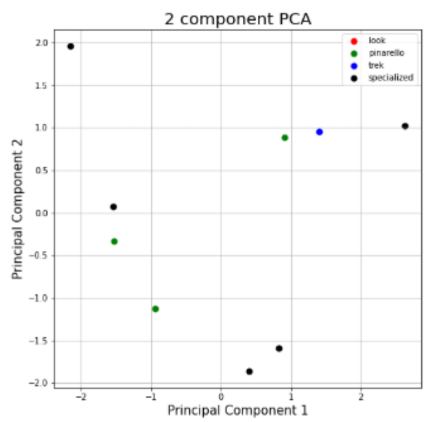
Finally, during phase 3, the PCA representation could not generate linearly separable classes. The increasing complexity of the physiological monitoring during video ads demands the implementation of more advanced nonlinear classifiers, such as Artificial Neural Networks (ANN). The classifiers implementation is beyond the scope of this work, which is focused on the exploratory analysis.



Phase 1



Phase 2



Phase 3

Figure 14 - Results for the PCA implementation based on two main components. (a) PCA for phase 1, (b) PCA for phase 2, and (c) PCA for phase 3.

4.6.3 Feature Importance

Figures 15-17 depict the Feature Importance (FI) implementation results for phases 1, 2, and 3, respectively, using Random Forest, based on the mean decrease of impurity (MDI), which measures the disorder of a set of elements. It was calculated as the probability of mislabeling an element, assuming that the element is randomly labeled according to the distribution of all the classes in our set.

As presented in Figure 15, Age, ET-MFD, and Engagement have higher correlations with the brand choice in phase 1, while in phase 02, the three main features are Age, ET-MFD, and the number of GSR peaks, which increased in importance and achieved a higher index than Engagement (Figure 16). Finally, in Figure 17, which represents phase 3, the three main features are the same as in the previous phase, but with a higher index for the Surprise feature and the Fear emotion.

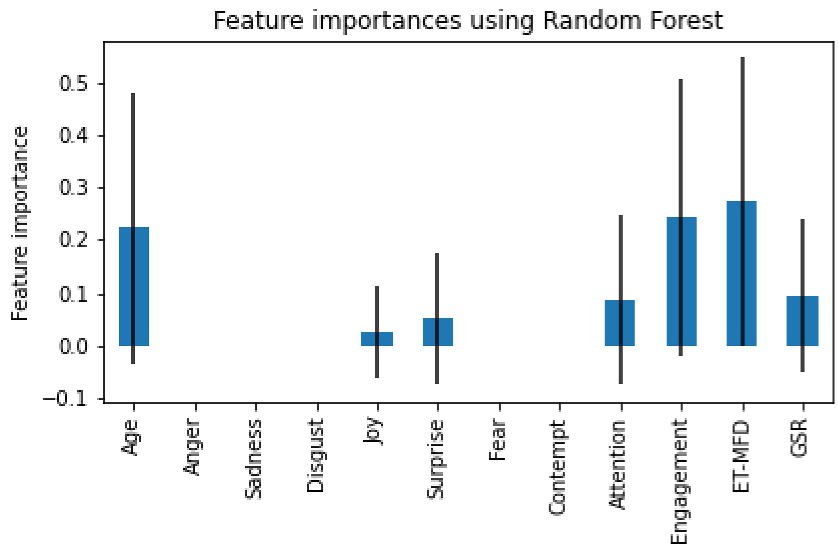


Figure 15 - In Phase 1, age, ET-MFD, and Engagement have higher importance to correlate with the brand choice in this phase

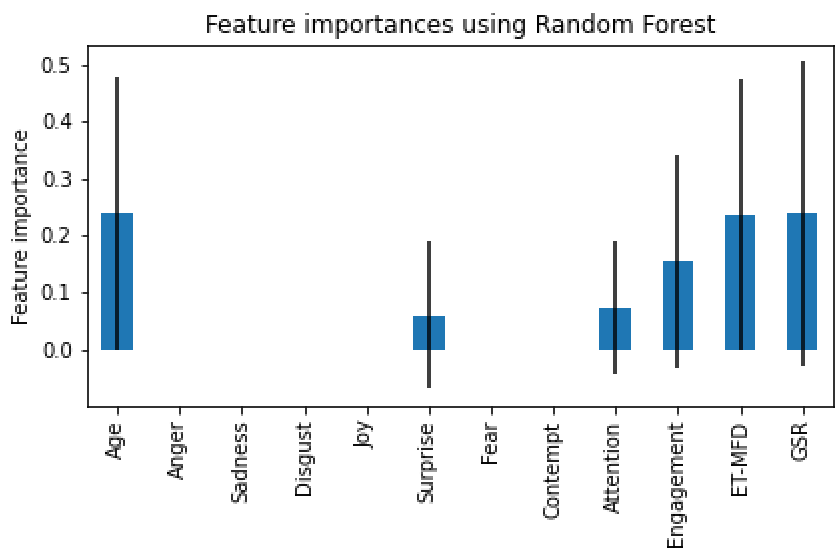


Figure 16- In Phase 2, the three main features are Age, ET-MFD, and the number of GSR peaks, which increased in importance and achieved a higher index than Engagement

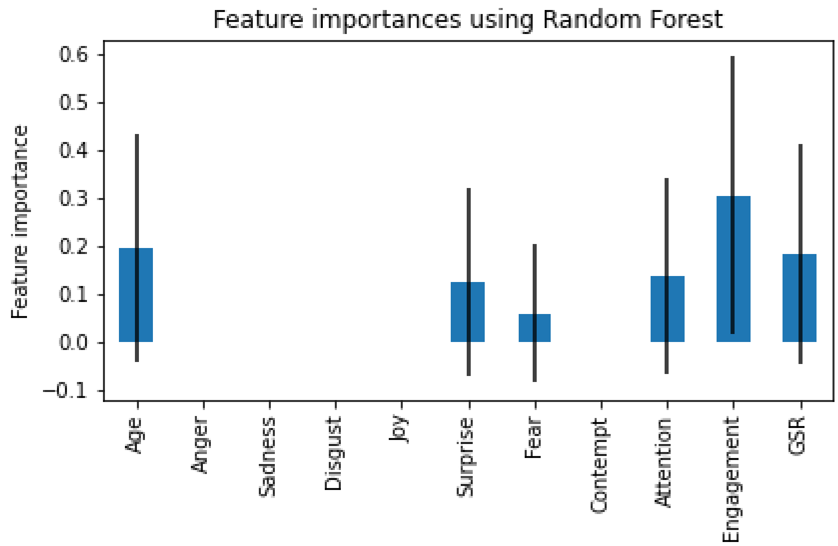


Figure 17 - In Phase 3, the three main features are the same as in the previous phase, but with a higher index for the Surprise feature and the Fear emotion

V. Discussion, Conclusions, Limitations, and Future Research

The past decade has seen a remarkable effort by neuroscientists and economists in applying neurophysiological and neuroimaging techniques to understand brain activity. At the same time, experimental tasks that involve behavioral or economic decisions are being performed. In this study, we tried to best understand the preferences of customers regarding four international bicycle companies, two American (Specialized and Trek), one Italian (Pinarello), and one French (Look). We presented emotional and behavioral reactions to stimuli related to these bicycle brands while outlining various components (features) related to individual responses and decision-making in brand selection.

Understanding these preferences from the neuromarketing perspective alone can be limited. We argue that neuromarketing data and analysis must be combined with behavioral economics and choice behavior theories that consider global multicultural aspects and socioeconomic ones. Behavioral economics has a normative factor that prescribes consumers' decisions to optimize the payoffs. However, psychology concepts offer descriptive theories of decision-making that have evolved that describe the kinds of judgments and decisions consumers make in practice. Cognitive, motivational, and affective factors limit the rational behavior approach taken by normative theories.

Several factors may skew such data from the consumer's perspective when choosing and reacting to stimuli. Some of these factors are discussed next.

5.1. Discussion

While brain imaging techniques demonstrate the involvement of a brain area during the performance of a behavioral task, these techniques cannot tell us whether a particular brain area is essential for the concerned behavior (Chandrasekhar, 2005; Miyapuram, 2008). Typically, analysis of choice behavior is based on revealed preference: if an alternative A is chosen over alternative

B, the consumer prefers A over B, for whatever reason. The expected utility theory (Von Neumann and Morgenstern, 1953; Bernoulli, 2011) attaches a subjective value or utility to each alternative and suggests that consumers make choices that maximize their expected utility. Hence, when a consumer prefers A over B, A's utility is more significant than B's.

Another factor must be considered when consumers make decisions, however. Most decisions under uncertainty are either risky or ambiguous. Risky decisions are taken when the probabilities of uncertain outcomes are known, whereas ambiguous decisions are taken when uncertain results are unknown (O'Neil and Kobayashi, 2009). While the consumers in this research experiment likely did not feel they were at risk, they certainly faced ambiguity. Behavioral evidence illustrating the distinction between risk and ambiguity in decision-making was first depicted by Ellsberg (1961). He observed that subjects responded differently to risky and ambiguous choices. They primarily selected options with risky outcomes, which could explain choices of Surprise, Fear, and Disgust in this experiment. Such choices demonstrate the existence of ambiguous averse consumers who would like to choose uncertain outcomes with only known information.

Most decisions under uncertainty are either risky or ambiguous. Risky decisions are taken when the probabilities of uncertain outcomes are known, whereas ambiguous decisions are taken when uncertain outcomes are unknown (O'Neil and Kobayashi, 2009). While the consumers in this research experiment likely did not feel they were at risk, they certainly faced ambiguity. Behavioral evidence illustrating the distinction between risk and ambiguity in decision-making was first depicted by Ellsberg (1961). He observed that subjects responded differently to risky and ambiguous choices. They mainly selected choices with risky outcomes, which could explain Surprise, Fear, and Disgust choices in this experiment. Such observation demonstrates the existence of ambiguous averse consumers who would like to choose uncertain outcomes with only known information.

It is important to note that the aroused emotions expressed (decisions) by the subjects of this experiment also incorporated disappointment (e.g., Fear, Contempt, and Disgust) or elation (e.g., Joy and Surprise) signals. Disappointment is a reduction in utility from a lousy outcome purely due to an unfavorable realization of a random variable. When the stimuli (in this experiment, the logo poster, logo+product, or video with an experience) is lower than expected, subjects might feel disappointed (Roese, 1977; Loomes and Sugden, 1991). Elation is the opposite to that of disappointment and analogous to rejoicing. The experimental conditions of neuroeconomic studies such as the one we performed and many others already listed here are designed based on partial feedback to investigate neural correlations of emotional arousals, whether disappointment or elation.

5.1.1. Reliability of Results: Physiological, Socioeconomic Status, and Racism

Lesions to specific brain areas allow the determination of whether a particular brain region is necessary for a particular cognitive function. In humans, patients with well-defined lesions caused by an injury, for instance, can be studied but are less precise due to the varied nature of lesions. Hence, consumers with any brain lesion may react to a stimulus or experience emotion in less predictable ways.

Aside from physiological variation of stimuli and emotional reactions, no human brain exists out of context, for a human's past experiences affect how the brain and body react. Because of this, neuromarketing researchers should consider how socioeconomic status (SES) and racism affect the brain and biometric activity. For example, functional magnetic resonance imaging (fMRI) tests have proven that SES has an impact, finding distinctions in the way brain systems are deployed for the executive function that has not been observed in behavioral studies" (Farah, 2017).

Through diffusion-weighted magnetic resonance imaging (dMRI), a recent study demonstrated that the effects of SES indicators on cerebellum cortex microstructure and integrity diminish in blacks versus white groups. These findings are supported by the Marginalization-related Diminished Returns (MDRs) phenomenon. Assari and Boyce (2021) argued that under racism, social stratification, segregation, and discrimination, individual-level economic and non-economic resources, and assets, have weaker effects on development for marginalized, racialized, and minoritized families. Another study found "in response to being socially excluded by Whites; Black participants appeared to be more distressed showing greater social pain-related neural activity and reduced emotion regulatory neural activity" (Masten, Telzer, & Eisenberger, 2011).

Knowing that brain activity cannot be uniquely based on physiology, neuroscientists and neuromarketing researchers should focus on more diverse human test sampling to achieve legitimate results. Despite being a challenge, such a concern is rarely mentioned or investigated in the neuromarketing community. "Researchers risk reproducing scientific racism through the omission of racial experiences that do not fit or are too tricky to understand in neurobiological calculations" (Rollins, 2021). Since the average neuromarketing research participant comes from white middle-class strata, primarily representatives of western, educated, prosperous, and democratic societies, it is reasonable to assume that past and current research findings may offer incomplete and biased results due to a lack of diversity in the sampling. Farah (2007) argued that such reactions to stimuli aroused emotions and behaviors cannot be generalized to the large segments of humanity living under different circumstances.

5.1.2. Ethical Issues

Neuromarketing is still a relatively new field in the consumer research discipline, quickly evolving. Neuromarketing brings some powerful insights and techniques into the consumer research domain, offering a unique approach to market research based on novel knowledge from brain science. As some would argue, neuromarketing is not a tool to identify the consumer's "buy button," often coming across as not well understood, but it is controversial (Genco, Pohlmann, & Steidl, 2013).

The ethics of neuromarketing can also be interpreted as an issue. While neuroscience technology promoting commercial interest is not in itself unethical, the use of such technologies for testing the inner processes of the human brain can be significantly beyond what can be disclosed in traditional behavioral tests, which may raise significant ethical issues. The issues may be broken down into two areas: a) protection of various individuals that could be exploited or harmed by neuromarketing practices and b) the protection of consumers' autonomy (Murphy, Illes, and Reiner 2008). For some, neuromarketing raises questions regarding the extent to which marketing professionals, advertising agencies, and market researchers, to name a few, should be allowed to access consumers' privacy and the supposed powerful insights it may give them, including the possibility of manipulating consumers' choices and buying decisions (Lewis, 2005). Scholars and practitioners should be aware and careful with ethical aspects when using brain scans and neuroscience advances to understand consumers' decisions for all these reasons.

5.2. Conclusions

The main objectives of this investigation were to examine whether the effectiveness of brand video ads versus image ads could be measured through physiological monitoring, whether customer's reactions and emotions evolve when exposed to different visual presentation strategies, serving as the best predictor of a product choice, and whether other age groups' preferences can be correlated to the type of ads. Despite the small population sample, the results of this research use multiple stimuli approaches, methodologies for monitoring participants' reactions to stimuli (ET, GSR, and face coding/emotional detection). Variances in consumer's age analysis (e.g., to experience different emotional arousal, to experience various experiences with brand stimuli) offer evidence to confirm all three hypotheses with statistically significant results. Therefore, a significant takeaway from this research is that a progressive mix of brand stimuli, instead of a single type of stimulus, will impact consumer's reactions to a brand, which can be measured through physiological monitoring, and different age groups' preferences will vary according to the type of stimuli they are exposed.

5.2.1. Theoretical and Managerial Contributions

This work makes several theoretical contributions. First, it extends the experiential literature of neuromarketing and global branding reaction analysis based on real-time monitoring of multiple consumers' biosignals and emotions to a new domain—the use of numerous staggered types of brand stimuli in sequence multiple concurrent levels of monitoring. As shown in Table 1, past work in this literature attempted to understand and predict consumers' preferences and decision-making processes based on their emotional reactions when exposed to advertisements and their effects on them. However, none of these studies considered an experimental design that took a *progressive* and *evolving* approach to view different stimuli, such as the one we adopted in this investigation.

Second, this study also adds to the knowledge of interactive marketing. Researchers in interactive digital media (Hanna et al., 2011; Petit, Velasco, & Spence, 2019) have given considerable attention to the experiences consumers have in this domain, as the social media environment is centered on consumer experiences, which is echoed by global (and digital) marketing professionals. This study shows that, in theory, and practice, the idea of consumer experience matters not only for what consumers say they want and how they feel about a brand—their experiences while interacting with the brand— but also for what they are not aware of in terms of emotions and feelings related to a brand, detectable and monitorable—the subconscious experiences they have when exposed to a variety of brand stimuli. This study also offers global marketing managers tools to motivate consumers to engage with their brands, primarily through innovative digital marketing techniques.

The knowledge presented in this paper is relevant for product manufacturers, service providers, retailers, brand developers (and owners), and global marketing managers for various reasons, many beyond the scope of this research, but mainly for competitive advantages. For instance, due to circumstantial events, such as rebranding strategies, product/service changes, or resource constraints, companies may miss sales unless consumers are willing to exert a level of effort, such as trusting the brand, waiting for a new and improved version, forgive shortcomings, etcetera. Hence, it is helpful for the manager to know consumers' emotional arousal related to various aspects of the brand, product/service features, or any negative emotions they trigger. For example, companies could employ automated consumer stimuli device tracking, such as eye-tracking or face coding, to detect and identify consumers' reactions and sentiments related to their products or services. Using eye-tracking technology, retailers can understand where customers' attention is drawn and derive first-hand insight into how their environment impacts their shopping behavior.

Finally, undoubtedly obtaining information from neuromarketing is more accurate because it takes into account not only the sociological and psychological profiles of customers but also the cognitive. Thus, neuroscience gives global marketing professionals the ability to explore more of each group and segment the market on a more solid basis (Braidot, 217). Studies using neuro-imaging methodologies provide insight into real-time consumer response to a specific stimulus. As shown in this research, a brand's image can arouse emotions that can be more powerful than the effect of the product itself. In other words, a strong brand image alters the perception of the product (Dragolea et al., 2011). Hence, the importance of knowing the underlying processes of customers in ways that enterprises develop valuable skills and resources to generate targeted strategies.

This study reveals that consumers' conscious and unconscious mental states allow consumer products companies to be more effective in reaching out to the consumer. By considering that consumers' habits change, organizations must design proposals for each contact they make to achieve a more significant customer perception through all the brand aspects. Godin (2015) argued that the age of mass production and marketing is over. Global marketing professionals must be able to market to various and distinct tribes across the globe.

5.3. Limitations

This study has several limitations, some of which point to opportunities for future research. Although this investigation examines various consumers' reactions to visual brand stimuli, the data do not speak to a myriad of other types of reactions (and efforts) that consumers may experience. Such reactions may include adaptation and familiarization to a brand, de-attachment from a familiar brand, and bargaining process, including those related to herd mentality, particularly in a digital environment where certain stimuli can go viral. Although theoretically, the authors do not expect the findings to be generalizable, as the sample was small, future research more extensive in scope could expand and further examine the merits of this study.

5.4. Future Research

While this study examined experiential response to visual stimuli, future research could take a more nuanced view of the classes and features explored. For instance, are there identifiable sub-categories of features and classes that are uniquely capable of inducing positive emotional arousal in consumers' subconscious experience with a brand? Also, several scholars have long argued (Nicolao et al., 2009; Carter & Gilovich, 2010; Caprariello & Reis, 2013) that consumers' experiential reactions differ along other dimensions besides visual stimuli.

Future research could also test the boundaries of the experiment model advanced here. It is possible, as argued by Pennebaker et al. (2015), that certain consumer or situational factors render different emotional reactions from those in this study, where results could be attenuated or strengthened. For instance, visual stimuli such as those adopted in this research experiment could be less relevant to introverts than extroverts (Goldberg, 1990). They could be less applicable when the stimuli are connected to a counterfeit brand product (Commuri, 2009). In addition, although this research was conducted in person, future research could examine whether the same experiment carried out digitally (remotely), via video-conferencing, would alter the effects observed in this research.

6. References

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