POLITECNICO DI TORINO

Master's Degree in COMPUTER ENGINEERING

Master's Degree Thesis

Artificial intelligence tool for attention detection to be used in Neuromarketing

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Summary

Understanding humans and determination of human behaviour were always one of the focuses of humanity from early times. The market sector has spent fortunes to find out about client behaviour. However, it took more work to make accurate forecasts with modern approaches. *Neuromarketing* is a newly born field which is a combination of neuroscience, marketing and psychology. Neuromarketing has many different approaches to determining client behaviour.

Eye-tracking is one of them, Eye-tracking is a widely employed method for assessing visual attention. In the context of neuromarketing, the aim is to establish a connection between visual attention and consumers' thoughts and emotions. Eye-tracking and neuromarketing in the market analysis are gaining popularity, as it holds immense potential for assisting in various marketing areas such as market research, product innovation, advertising, sales, customer support, loyalty programs, and more.

The main objective of this thesis is to introduce a recently created artificial intelligence (AI) tool that can effectively handle diverse eye-tracking data obtained from a neuromarketing experiment. In collaboration with other students from different disciplines, the study explores various aspects, from post-processing to visualization, facilitating further analysis. Moreover, the development phase will specifically address the critical issue of data processing sensitivity, emphasizing the potential impact of errors during this stage on the accuracy of results. Ultimately, the experiment seeks to uncover insights into neuromarketing stimuli.

The literature review chapter will comprehensively examine neuromarketing, covering its history, conceptual framework, and the tools employed in this field. Additionally, the prospects and limitations of neuromarketing will be thoroughly discussed. Furthermore, the relationship between Data Science and Neuroscience will be explored, highlighting their strengths and weaknesses. Lastly, the chapter will conclude with an overview of the developed AI's concept, the rationale behind utilizing Python, and the central role of the OpenCV library.

The methodology chapter will focus on the methodology employed in the study:

- It will provide a detailed description of the experiment's methodology, including

the objectives, participants, a comparison between the original and mock-up websites, the specific methods used, materials and devices utilized, variables analysed, and the experimental environment.

• It will delve into the characteristics of the data collected, encompassing galvanic skin resistance (GSR) data, face recordings, eye-tracker data, and screen recordings.

• The methodology of the AI tool will be presented, discussing the previously adopted methodology, identifying weaknesses in prior work, and introducing the new methodology developed for this study.

Prior to the conclusion, the paper will provide a detailed explanation of the stages involved in the development of the AI tool. The post-processing chapter will comprehensively outline all the processing steps in two distinct topics. The first topic will focus on transforming raw data into intermediate metadata, while the second topic will address the subsequent transformation of this metadata into visualizations.

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Ve tüm sevdiklerime...

Can Karaçomak

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Acronyms

fMRI
: functional Magnetic Resonance Imaging

GSR
: Galvanic Skin Resonance

AoI
: Attention of Interest

EGG
: Electroencephalography

ERP
: Event-Related Potential

AI
: Artificial Intelligence

ML
: Machine Learning

DL
: Deep Learning

CSV
: Comma-Separated Values

IoT
: Internet of Things

Chapter 1

Introduction

According to Iloka and Onyeke (2020) [1], one of the most frequently asked questions in marketing today concerns what motivates consumers to select one product over another or how they interact with a particular brand. This questioning has led to a growing interest in studying the brain's reactions during decision-making. As a result, there has been an increase in the use of neuroimaging tools in real-world settings to investigate physical stimuli, which is the main focus of industrial neuroscience (Karmarkar & Plassman, 2019 [2]). However, to better grasp the concept, it is necessary first to comprehend what neuromarketing means. The term "Neuromarketing" refers to a field of research that utilises neuroscientific techniques to examine and evaluate human behaviours related to markets and marketing transactions (Lee et al., 2007 [3]).

The researchers (Iloka & Onyeke, 2020 [4]; Karmarkar & Plassman, 2019 [2]) have touched on the notable growth of neuromarketing research in the last decade. Diverse methods are used to analyse how the brain responds to different situations. The authors noted that recent scientific advancements have extended the application of these methods to various multidisciplinary research areas and addressed some of the issues that arose in these fields. As a result, researchers have been increasingly using neuroscientific techniques to study human behaviour in a wide range of fascinating contexts.

Eye-tracking is one of the options, with its pros and cons, that can be employed in determining neuroscientific marketing stimuli. Eye-tracking involves the analysis of individuals' eye movements to gain insight into their behaviours. Eye-tracking tools enable brands to perceive the world through the eyes of their potential customers, not only in laboratory settings but also during real-world purchasing experiences (Iloka & Onyeke, 2020 [4]).

Nowadays, eye-tracking devices are small and equipped with lights and can be worn by individuals while shopping or watching television. By using the data collected from these devices, brands can gain insights into a range of consumer behaviour-related questions, such as the level of attention paid to items promoted near the store's entrance, whether billboards and posters are read or glanced at, and how attention is distributed while choosing products from shelves. Additionally, eye-tracking can reveal the extent of attention paid to advertisements on TV. Therefore, the use of eye-tracking technology presents numerous opportunities for marketing research (Iloka & Onyeke, 2020 [4]).

The eye-tracking technique involves the measurement of the fixation or gaze point, the length of time the person fixates on the point, eye movements with the head, the number of blinks, and pupil dilation (Zurawicki, 2010 [5]). Another functional evaluation is the sequence of eye movements (saccades) from one location to another (Chae & Lee, 2013 [6]). Different technologies can be used to measure eye movements, most commonly tracking controlled stimuli at fixed points in photos, videos, and other user interactions displayed on a computer screen. More advanced technologies can also track the movement of the head in three-dimensional space based on an attached camera (Zurawicki, 2010 [5]). The measurement process is typically unobtrusive, as there is limited or no interaction between the subjects and the researchers.

Eye-tracking studies have been used for a while but offer unique perspectives in neuromarketing. With other tools, eye-tracking has become increasingly relevant in today's visually polluted business world, as it helps assess customers' attention (Zhao & Koch, 2013 [7]). Combinations of eye-tracking with other neuromarketing equipment can be used to measure cognitive responses, providing new insights into consumer behaviour and marketing communication. Researchers can accurately measure visual activity and connect specific emotional responses to stimuli by linking eye-tracking with facial coding. Moreover, combining eye-tracking with GSR (Galvanic Skin Response) is another option to determine emotional changes.

The thesis intends to present a newly developed artificial intelligence (AI) tool to process heterogenous raw eye-tracking data for a neuromarketing experiment. In collaboration, the investigation studies from post-processing to visualization for analysis by other disciplinary students. Additionally, the development phase will touch on a crucial topic, the sensitivity of data processing; how a mistake in the phase of data processing may induce inaccurate results. The experiment aims to discover neuromarketing stimuli.

The early version of the algorithm was already developed by an old master's student from Polito. Even though the algorithm was consistent with its assumptions, the assumptions were inadequate in a real-case situation. The algorithm's methodology could have been more efficient in handling the task that must be done. Therefore, a new methodology must be created with correct assumptions which suit the real-case scenarios.

In Chapter 2, neuromarketing will be explained in all detail, such as the history and concept of neuromarketing, the tools used for it, the future and the limitations of neuromarketing. Moreover, the relationship between Data Science and Neuroscience will be exhibited with all its strengths and weaknesses. Furthermore, finally, the concept of developed AI, the purpose of using Python and the core of the AI, which is the OpenCV library, will be touched on by the end of the chapter.

Chapter 3 is about the methodology. Firstly, the methodology of the experiment will be given by the topics; the aim, participants, the difference between the original and mock-up website, the method, the materials and devices used, analysed variables and the environment. Secondly, the characteristics of the data will be detailed for galvanic skin resistance (GSR) data, face recordings, eye-tracker data, and screen recordings. Lastly, the methodology of the AI tool will be exhibited by the previous methodology that was adopted, the weaknesses of previous work, and the new methodology.

Before the conclusion chapter (5) of the paper, the stages of the developed AI will be detailed. The post-processing chapter 4 shows all the processing steps in two topics, which cover the transformations from raw data to intermediate metadata and from this metadata to visualizations.

1.1 The Collaboration

The collaboration, which includes tutors and students from three universities, sets up the experiment. The universities are the University of Essex, the Polytechnic of Turin, and the University of Turin. It is a multidisciplinary collaboration of Computer Science, Mathematics, Psychology, and Marketing. The thesis student contributes to the collaboration with a data scientist role from a Computer Engineering background. The structure of the collaboration can be observed in figure 1.1.

The algorithm was developed in a team under the Development Group of Neuroscientific Tools, as illustrated in 1.1. The purpose of the algorithm is to link pupil coordinates produced by the eye-tracker with the screen recordings and prepare intermediate data to visualize for eye-tracking experiments. The group develops other tools for facial coding, GSR, and EGG experiments.

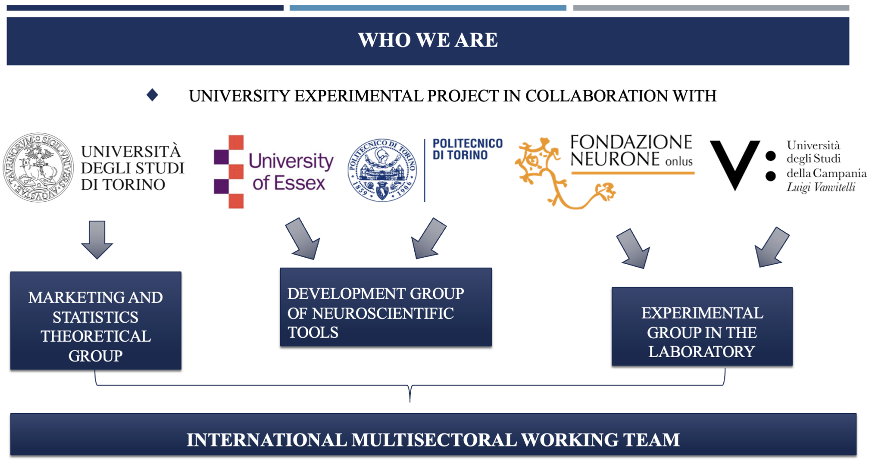

Figure 1.1: The contributors and their roles in the project.

Chapter 2

Literature Review

In this chapter, the place of neuromarketing in literature is shown by brief history 2.1, concept 2.2, tools 2.3, further improvements 2.5 and limitations 2.6 of neuromarketing. Additionally, in mid-section 2.4, the relationship between data science and neuromarketing is studied. Moreover, eye-tracking is scrutinized with details in subsection 2.3.1 for familiarity since a newly developed eye-tracker will be presented.

2.1 Brief History of Neuromarketing

Neuromarketing can be defined as studying customers' sensorimotor, cognitive, and affective responses to gain insight into customers' decisions, choices, and motivations. Moreover, it is a combination of neuroscience, neuropsychology, and marketing findings. The term "Neuromarketing" was taken place in the literature by different authors in 2002. However, research in the field was started by Gerald Zaltman (US) and Gemma Calvert (UK) in the 90s. In the same decade, Prof. Gerald Zaltman had a patent for the Zaltman metaphor elicitation technique [8].

The first publication was in an article [9] written by professor Ale Smidts in BrightHouse, a marketing firm based in Atlanta. Neurophysiologic research was started on nervous system functioning by the firm. And a business unit is constructed which uses fMRI scans for market research purposes. In 2004, this research gained attention in the market from big companies.

2.2 Concept of Neuromarketing

The initial step for companies promoting a product is gathering data on how the intended audience would react. Traditional techniques for market research include using focus groups or conducting large-scale surveys to assess the characteristics of the product being considered. In this type of study, some of the conventional research methods [10] employed include measuring the cardiac electrical activity (ECG) and the electrical activity of the skin (AED) of study participants. However, this approach can lead to an incompatibility between the findings of the market research and the actual behaviour displayed by the target market when making a purchase. Humans make decisions through both conscious and unconscious processes in the brain. Traditional research methods like focus groups and surveys successfully gathered consumers' explicit or conscious emotions. Still, they failed to tap into their implicit or unconscious emotions, which play a significant role in decision-making.

Neuromarketing offers significant understanding and progress in the field of market analysis, particularly in the examination of how consumers behave (Genco et al., 2013 [11]). Colaferro and Crescitelli (2014) [12] lend support to this claim by stating that neuromarketing offers a diverse array of skills, incorporating data on subconscious consumer behaviour into the decision-making process. As a result, neuromarketing research can assess various factors such as emotional involvement, recall, buying intent, novelty, brand recognition, product development and advancement, advertising performance, consumer choice-making, online interactions, and entertainment impact (Sebastian, 2014 [13]; Genco et al., 2013 [11]). Outcomes from neuromarketing research are significant and aid researchers in gaining a deeper understanding of consumers. When combined with other forms of qualitative data, neuromarketing can serve as a powerful predictor of consumer behaviour. By supplementing and reinforcing traditional research techniques, neuromarketing can also assist marketers in gaining a more thorough understanding of consumer preferences (Rehman et al., 2016 [14]). Neuromarketing holds great potential. By utilizing neuromarketing, marketers can develop and implement more sophisticated marketing tactics that will improve the efficiency of their marketing campaigns. (The paragraph adapted from Mansor and Mohd Isa, 2020, page:23-24, [15])

2.3 Tools of Neuromarketing

A significant drawback of conventional market research methods is the reliance on participants for accurate feedback and the incapability to uncover the unconscious thoughts of consumers. The conventional marketing techniques fall short in obtaining the unconscious insights of consumers (Calvert & Brammer 2012 [16]; Spanjaard et al., 2014 [17]), resulting in inaccurate predictions of consumer behaviour, which can lead to a discrepancy between the research findings and the actual actions taken by consumers during the buying process (Agarwal & Dutta, 2015 [18]). Lowenstein (2019) [19] emphasizes that it is crucial to understand the thoughts and feelings of the consumer in order for marketers to effectively shape, adapt, and convey their messages to the consumer.

The fundamental techniques used in neuromarketing can be classified into three groups; techniques that measure the metabolic activity of the brain, techniques that measure the electrical activity of the brain, and techniques that do not involve measuring brain activity (Zurawicki, 2010 [5]; Kenning et al., 2007 [20]; Calvert et al., 2014 [21]). Each of these approaches has unique advantages and disadvantages and is more or less suitable for different research scenarios. (Mansor and Mohd Isa, 2020, page:24, [15])

In the table 2.3, some of the common tools that used in neuromarketing and their benefits, limitations and management-relevant uses can be seen.

«

Commonly Used Consumer Neuroscience Methods			
Tool	Benefits	Limitations	Management-Relevant Uses
Electroencephalography (EGG)	• Can be used to measure rapid changes in neural activity on the millisecond scale • Minimally invasive and/ or commercial research packages available • Possible for participants to move around and engage in enriched/ social environments	• Difficult to pinpoint neural signals from particular brain areas (poor spatial resolution) • Does not measure from deep brain structures (e.g. nucleus accumbens)	• Can be used to monitor experience in stores and in social settings • Can detect positive/negative arousal, decision conflict, attention, language processing, some memory effects • Common in neuromarketing (applied) research
functional Magnetic Resonance Imaging (fMRI)	• Ability to resolve activity in small structures • Differentiates signal from neighboring areas • Whole-brain measurement	• Physically restrictive; participants lie on their backs in the scanner and cannot move around • Expensive and equipment intensive	• Response to marketing stimuli such as brands and price • Localization of neural processing during decision-making, consumption experiences, socially relevant stimuli, and value learning • Prediction of market-level and/or population-level behaviour

Eye tracking	• Offers strong nuanced data on visual attention and gaze pathways, and can be integrated with pupillometry	• Does not measure inferences, valence of the response, thoughts, or emotions	• Evidence of overt attention • Shelf layout and packaging and advertising • Website usability • Can be applied to attention and information seeking in interpersonal communication and social scenes
Biometrics: skin conductance response (SCR), heart rate, pupil dilation	• Simple; well validated • Unobtrusive equipment; allows for more natural interactions with environment	• Cannot distinguish between positive and negative arousal	• Response to communication stimuli (e.g., commercials and/or persuasive and signaling messages) • Inferences of emotional engagement/arousal during choice processes • Inferences of emotional engagement/arousal during interpersonal interactions with others of varying status
Facial electromyography (fEMG), facial affective coding	• Dynamic tracking of emotional (potentially unconscious) responses to ongoing stimuli/information • Available automatic facial encoding software/algorithms	• Requires attaching electrodes directly to the face (in a lab)	• Valence of response to marketing stimuli, in particular commercials • Inferences of emotional valence of information processing during choice and processes like negotiations

Transcranial magnetic stimulation (TMS)/tDCS	• Can be used to show causality	• Limited to investigating function of surface brain areas • Can only generally lower (TMS/tDCS) or raise (tDCS) neural activity generally; cannot test for specific "levels" of activity or influence specific circuits	• Studying causality of specific brain regions for specific mental processes (e.g., preferences, brand choice) by temporarily taking them "offline" • Can be used to upregulate and downregulate brain areas relevant to self-control and social conformity

Table 2.1: The table is taken from Karmarkar and Plassman (2019) [2]

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2.3.1 Eye-Tracking

An approach used to assess visual attention is eye-tracking. Regarding neuromarketing, the goal is to connect visual attention to how consumers think and feel. And the popularity of utilizing eye tracking and neuromarketing in market analysis is on the rise. It has a lot of potential for helping with market research, product innovation, advertisement, sales, customer support, loyalty plans, and other marketing areas.

Eye tracking assesses where the user is focusing their attention (the point on the screen where they are looking), the movement of the eyes in relation to the head, and the changing size of the pupils (Zurawicki, 2010 [5]). Various eye tracking systems have the ability to calculate where the user's eye is fixed on a computer screen or in a store and can identify precisely where the user's attention is focused (Duchowski, 2003 [22]). According to Hoffman and Subramaniam (1995) [23], eye movements can be used as a tangible indication of where a person's attention is directed and can aid in the process of sorting through visual information.

Eye tracking assesses where the individual is focusing their gaze, how long they are looking at a certain point, how their eyes move in relation to their head, the changing size of their pupils, and the number of times they blink (Zurawicki, 2010 [5]). In addition to measuring the fixation point, eye tracking can also evaluate the order in which the individual's eyes move from one location to another (Chae & Lee, 2013 [6]). Various technologies are used to measure eye movement. The most widely used are those that measure the viewing of controlled stimuli at specific points in videos, images, and when a user interacts with a computer screen.

Eye tracking technology has become increasingly important in today's world, where there is a lot of visual information competing for consumers' attention. Understanding the ways in which consumers choose specific points of interest in an image (attention patterns and predicting areas of most significant interest) has many applications in the business world (Zhao & Koch, 2013 [7]). Thus, eye tracking can give insight into what is more likely to capture attention as it relates to visual fixation patterns in various marketing contexts (Fiszman, Velasco, Salgado-Montejo, Spence, 2013 [24]). While eye-tracking tools effectively study consumer behaviour, some challenges come with using these neuromarketing tools. One such challenge is that the eye-tracking system can only tell researchers what a person is looking at, but not why they are looking at it or how they perceive it. Additionally, these tools cannot provide information about the emotional response accompanying visual attention, whether positive or negative. Another challenge is that webcam applications of eye-tracking tools may need to be more precise and accurate than in-lab solutions (Iloka & Anukwe, 2020 [4]).

However, eye tracking can also be combined with other equipment to measure cognitive reactions, thereby providing new insights, particularly regarding consumer behaviour and marketing communications. And it means the lack of emotional response in eye-tracking can be handled by a combination of tools. When used in conjunction with facial coding, the results reveal the precise level of visual activity and link specific emotional responses to different elements of a stimulus. The correlation between emotional response and visual focus provides a dependable way to understand what is causing reactions to a particular stimulus (Hill, 2011 [25]). This is of immense value, particularly for TV commercials, in which a large amount of information is presented every millisecond, which can make it challenging to identify what the viewer actually liked or what caught their attention positively or negatively. (The subsection 2.3.1 is adapted from dos Santos, Renê de Oliveira Joaquim, et al., 2015 [26]) Another combination tool of eye-tracking would be Galvanic Skin Response (GSR).

2.4 Data Science in Neuromarketing

Is it necessary for research in neuromarketing to adopt the techniques and approaches for analysis and forecasting that are commonly used in other fields, such as data science, computer science and engineering? Moreover, are the data-science-based approaches on appropriate usage to collect accurate results?

In this section, due to the lack of research in the literature, electroencephalography (EGG) will be the neuromarketing tool that distinguishes between traditional and data-science-based predictions.

The section 2.4 is adapted from Hakim & Levy, 2019 [27].

2.4.1 Introduction to Electrophysiological

EEG, or electroencephalography, is a method used to measure the electrical activity of the brain by attaching electrodes to the scalp. When neurotransmitters bind to receptors on neurons, changes in the flow of ions can cause fluctuations in post-synaptic potentials. These potentials can be caused by activity in multiple neurons and can be measured by the electrodes on the scalp. However, while EEG recordings are precise in timing, it is difficult to determine the specific location within the brain where the activity comes from. (Haas, 2003 [28]; Buzsáki, Anastassiou & Koch, 2012 [29])

Analyses of EEG recordings typically fall into two categories: "ERP" and "spectral analysis." ERP, or event-related potential, refers to the voltage changes in response to a specific event, such as a stimulus or button press. This type of analysis is commonly used in psychological and cognitive experiments and involves averaging multiple responses to the same event to obtain a more apparent voltage time series. On the other hand, Spectral analysis examines the different frequencies present in the electrical signal. The power spectrum is used to determine the power of each frequency component in the time-series signal, and many studies report changes in the power of specific frequencies or frequency bands as their findings.

2.4.2 Abstracts of Research Papers on EGG with ML

This subsection will present some of the articles' abstracts as examples of the machine and deep learning techniques used to classify EGG outputs.

«An investigation by Koelstra et al. (2012) [30] employed EEG to predict a value-related concept by recording the electrical activity of the brain, facial expressions, and physiological signals while participants viewed 40 music videos. Based on the participants' ratings, the study posed three binary classification problems: predicting low/high arousal, low/high valence, and low/high liking. The accuracy of the EEG features used in the study varied, ranging from chance level to 62%. The accuracy was improved when they combined EEG features with those from other modalities, such as auditory and visual-based features, which they referred to as multimedia content analysis. However, the study did not evaluate population metrics or aim to predict beyond traditional methods.»

«Two studies in this category employed advanced machine learning models to make predictions. For instance, Yadava, Kumar, Saini, Roy, Prosad Dogra (2017) [31] applied a hidden Markov model on EEG signals of 40 participants while they were viewing images of 14 different products to predict their like or dislike of the products. They also tested various other models, such as support vector machine, random forest, and nearest neighbour, with varying results. Using their proposed method, they were able to achieve a prediction accuracy of 63.5-70.3% using a leave-one-out testing method. The use of machine learning models is becoming increasingly popular in the market and academia, and their utilization represents a promising strategy, although it is still in its early stages. Another study conducted by Murugappan, Murugappan, Balaganapathy, Gerard (2014) [32] applied a probabilistic neural network and k-nearest neighbour prediction models in their experiment. They had participants view four commercials per four different vehicle brands and extracted spectral energy (SE), power spectrum density (PSD), and spectral centroid (SC) of the alpha band as predictors and participants' self-assessments as a response. Using a 10-fold cross-validation technique, they were able to reach a 96.62% accuracy rate at their highest. However, interpreting these high prediction accuracies is problematic and very limited since it was achieved when predicting only one vehicle brand (Toyota) with a single feature (PSD) and not the entire dataset. In the study, the researchers found that the Toyota brand was the most popular among the participants. Therefore, their high accuracy rate in predicting responses to Toyota commercials is likely due to the generally positive response to the brand rather than its specific favorability or likability. Furthermore, the authors of these studies did not evaluate their predictions using population-wide metrics and did not attempt to predict beyond traditional measures.»

«A study by Guixeres et al. (2017) [33] aimed to predict the effectiveness of Super Bowl commercials using EEG signals by measuring the global field power (GFP) of cerebral activity in each band. They also used a pleasantness index based on hemispheric asymmetry and an interest index based on the number of peaks in beta and theta bands during a commercial. Together with data from eye tracking and heart rate, they used a neural network model and achieved an average accuracy of 82.9% in predicting the number of YouTube views for each commercial. The model also included questionnaire responses, which made a small contribution to prediction. However, the study did not examine the accuracy of the predictions without the traditional measures; therefore, the contribution of the neural measures beyond traditional measures could not be determined.»

«Another study guide by Hakim et al. (2018) [34] in their lab used a variety of EEG measures for preference prediction. Participants watched six different product commercials while their EEG was recorded. Afterwards, they completed a binary choice task and a marketing questionnaire to measure their preference. They also collected YouTube metrics and a questionnaire answered by an online cohort to measure the commercials' success in the general population. They used various machine learning models and were able to achieve 68.5% accuracy in predicting the most and least preferred products in the subject pool when using both EEG and questionnaire measures. This was higher than the accuracy achieved by the questionnaire alone, showing the contribution of EEG measures in predicting individual preferences beyond traditional measures.»

«Several studies have attempted to make predictions based on EEG data by using in-house indices that were created by the researchers themselves. However, it can be challenging to determine the validity of these in-house measures, as they have not been tested or validated in previous literature, and the robustness of the results is not reported. For example, in a study conducted by Baldo et al. (2015) [35], the team from neuromarketing Labs used EEG signals to predict the success of shoe sales using their custom-made "preference index computed through an internally developed algorithm loosely associated with parameters from basic emotional neuroscience." They reported that they achieved 80% accuracy with their testing procedure, which was higher than the prediction accuracy from a questionnaire, which reached only 60%. A similar study was conducted by Sands Research, but they did not provide test results, the actual prediction models were not provided, and the data could not be examined in the published papers. These studies did not include predictions based on their sample pool, making it hard to evaluate the validity of their claims.»

«In a study by Telpaz et al. (2015) [36], the researchers had 15 participants view images of 10 consumer products while their brain activity was being recorded. The participants then completed a binary choice task where they selected their preferred product from all possible pairs. Using the N200 component and the theta power band from the EEG recordings of product viewing, the researchers were able to predict the participants' subsequent choices to a certain degree with a neural random utility model. However, the study did not aim to predict population metrics, and the predictions were made only within the subject pool without a held-out test set.»

In the following table 2.2, a summary of the mentioned papers will be shown with authors, year, EGG predictors, standard predictors, ML or DL model, stimuli, response, number of subjects, and accuracy by per cent of successful prediction.

Summation of current findings in EEG-based preference prediction								
Authors	Year	EEG predictors	Standard predictors	Prediction model	Stimuli	Response (within/population)	Subjects	Success (fit/test)
Telpaz et al. [36]	2015	N200, theta band power	None	Neural random utility model	10 products	Within: binary choice rankings	15	Test: 59–60% accuracy
Baldo et al. [35]	2015	Preference index	Questionnaire	1D linear classifier	30 shoe products	Pop: successful/unsuccessful sales	40	Test: 80% accuracy
Yadava et al. [31]	2017	DB4 wavelet coefficients (power bands)	None	HMM (SVM, RF, NN)	14 products * 3 image variations each	Within: likes/dislikes	40	Test: 63.5–70.3% accuracy
Koelstra et al. [30]	2012	Theta, slow alpha, alpha, beta, and gamma spectral powers and asymmetry	None	Gaussian naive Bayes classifier	40 music videos	Within: arousal, valence, liking	32	Test: 50–62% accuracy
Murugappan et al. [32]	2014	Alpha band SE, PSD and SC	None	K-NN, PNN	16 vehicle commercials	Within: self-assessment	12	Test: 96.62% highest accuracy
Guixeres et al. [33]	2017	GFP per band	Liking, recall	Neural network	8 TV Super Bowl commercials	Pop: online views on YouTube	35	Test: 82.9% average accuracy
Hakim et al. [34]	2018	ISC, power bands, hemispheric asymmetry	Questionnaire	SVM, regression, decision trees, K-NN, KDL	6 product commercials	Within: binary choice rankings	31	Test: 68.5% accuracy

Table 2.2: «GFP: global field power; HMM: hidden markov model; ISC: inter-subject correlation; KDL: kernel discriminant learning; K-NN: k-nearest neighbours; NN: neural network; PNN: probabilistic neural network; PSD: power spectrum density; SC: spectral centroid; SE: spectral energy; SVM: support vector machine; RF: random forest; RMSE: root mean square error.»

2.4.3 Conclusion of the Section

Neuromarketing is a relatively new field, and early attempts to make predictions have shown some promise and opened up new areas for further research. However, there are still not enough studies that can accurately predict what marketers want to know - which version of a marketing message would be the most successful out of two or three variations of a stimulus. Additionally, even when predictions are successful, there is still a long way to go in understanding the advertising message and why some succeed while others fail. It is crucial to gain more knowledge in this area to help marketers plan their campaigns and for researchers to understand the fundamental principles that influence subject choice and value.

Additionally, current studies in neuromarketing lack transparency in their methods and results, making it difficult to replicate their findings and build upon them. In order to improve the field and increase the validity and generalizability of its findings, it is important for researchers to adopt a more standardized and rigorous approach to data collection and analysis and to report their methods and results in a clear and transparent manner. This will also help to increase the visibility and credibility of the field and to attract more high-quality researchers to the field. (Lee, Chamberlain & Brandes, 2018 [37])

One of the main objectives of neuromarketing is to utilize EEG data in order to predict consumer preferences. To achieve the goal, it is crucial for the field to adopt widely accepted methodologies used in data science, as these methodologies have been proven effective in dealing with similar challenges in other domains. This includes the use of rigorous statistical techniques, the creation of large and diverse datasets, and the use of robust machine learning algorithms. Additionally, it is essential to ensure that the predictions made are validated through rigorous testing procedures, such as cross-validation, to ensure that the results are generalizable and not just specific to the sample population. By utilizing these established methodologies, neuromarketing will be able to make more accurate predictions and gain a deeper understanding of consumer preferences (Jordan & Mitchell, 2015 [38]).

2.5 Future of Neuromarketing

Neuromarketing, which has been a rapidly growing field in the marketing industry in recent years, is expected to continue to expand with the increasing availability and affordability of advanced technologies such as IoT. The use of these technologies, such as "always on" sensors and devices, has the potential to significantly improve the retail shopping experience for both consumers and manufacturers by providing real-time tracking and feedback on interactions with products.

IoT technology can make focus groups more efficient by allowing for remote participation and providing more accurate and effective consumer sentiment analysis through the use of eye-tracking and emotion detection. This development can reduce participant incentives, recruitment, travel, accommodations, and staff costs. Additionally, in conjunction with neuromarketing techniques, web cameras and biometric sensors can standardize and measure consumer reactions by identifying eye movements, facial expressions, and emotions.

The use of facial identification technology in retail stores allows marketers to offer personalized and event-driven promotions in real-time based on the shopper's profile and loyalty status. This approach differs from traditional promotions based on historical information and is offered to a broad audience. This technology enables retailers to proactively offer discounts, bundled promotions and other incentives at the right time and place using digital signage, mobile and other channels. Retailers can also use real-time analysis of inventory turnover, historical buying habits, and in-store sales projections to offer even more personalized promotions.

Neuromarketing has the potential to significantly influence brand association and customer loyalty by measuring consumer behaviour in real-time, as well as testing non-verbal and verbal responses to new products, advertisements, promotions, and pricing. In the long term, it is both an art of measuring consumer emotions and a science of measuring marketing effectiveness. As technology advancements like Big Data, Artificial Intelligence, Machine Learning, and Cloud Computing continue to develop, the possibilities for what can be achieved through their integration with neuromarketing will also expand. (Erevelles et al., 2016 [39]; Arthmann & Li, 2017 [40])

2.6 Limitations of Neuromarketing

In this section, the limitations of neuromarketing will be shown in 3 subsections; (For future readings: Mileti et al., 2016 [41]; Fortunato et al., 2014 [42])

2.6.1 Cost of Experiments

The high cost of neuroimaging technology poses a challenge for researchers as it limits the funding for long-term studies. Additionally, individual researchers often require the support of companies to conduct their research (Hubert Kenning, 2008 [43]). With hourly costs reaching $500 or more (Perrachione & Perrachione, 2008 [44]), using these machines necessitates using a limited testing time, basic experimental designs, and small sample sizes of 10-20 subjects (Kenning, Plassman, & Ahlert, 2007 [45]). These limitations make it difficult to detect changes in brain activity over time and to study rare events essential for accurate diagnosis.

The costs are different for brain-imaging and non-brain-imaging approaches. Non-neuroimaging techniques are relatively cheap compared to neuroimaging techniques, which require more sophisticated and expensive tools.

For neuroimaging technology, the high cost poses a challenge for researchers as it limits the funding for long-term studies. Additionally, individual researchers often require the support of companies to conduct their research (Hubert Kenning, 2008 [43]). With hourly costs reaching $500 or more (Perrachione & Perrachione, 2008 [44]), using these machines necessitates using a limited testing time, basic experimental designs, and small sample sizes of 10-20 subjects (Kenning, Plassman, & Ahlert, 2007 [45]). These limitations make it difficult to detect changes in brain activity over time and to study rare events essential for accurate diagnosis. The numbers below must be changed in time because of improvements in technology. However, the life cycle cost of an MRI scanner is estimated at around 815,033 dollars for ten years in recent research papers. (Sahu & Vikas & Sharma, 2020 [46]) Moreover, the current average price of 1.5 MRI machines is from 100.000 to 600.000 dollars depending on the models.

For non-neuroimaging approaches, in this case, for eye-tracking tools, the price of eye-trackers can change between 100 dollars to +10,000 dollars. (For details.) The cost of an eye-tracker is variated due to its flexibility, mobility of usage, and sampling quality. All the details of the eye-tracking tools used for this research can be found in section 3.2.3.

Therefore, the cost would be a limitation primarily for brain-imagining neuromarketing experiences.

2.6.2 Lab-Based Experiments

Another significant limitation in neuromarketing research is the reliance on laboratory experiments, which lack real-world conditions and fail to consider consumer behaviour's social, situational, and experiential aspects (Arnould & Thompson, 2005 [47]). The role of emotions in consumer behaviour makes the limitations of laboratory experiments even more apparent in neuromarketing studies. Neuroimaging technology provides a cutting-edge and advanced perspective on emotion theories. However, laboratory experiments' artificial and controlled settings clash with the natural integration of emotions in purchasing decisions, which diminishes the validity of neuroimaging experiments.

2.6.3 The Moral, Social & Ethical Challenges

Neuromarketing is being actively pursued by academics and has become a source of profit for over 200 companies worldwide, which has grown significantly in recent years. However, academics and industry players have different goals and approaches when it comes to neuromarketing research. Academics prioritize the dissemination of knowledge through peer-reviewed publications, while industry players focus on developing a competitive advantage through private data collection and proprietary analysis methods. Academics tend to evaluate their results using stringent thresholds to protect against the possibility of chance results. At the same time, industry players prioritize forecasting and may take calculated risks when managerial decisions involving significant financial implications are at stake. As a result of these different priorities and approaches, both academic and industry neuromarketing researchers may face significant ethical challenges. (Stanton et al., 2017 [48])

The field of "neuroethics" has emerged as a result of the study of brain mechanisms (Roskies, 2002 [49]; Vlasceanu, 2014 [50]), which encompasses both the ethical considerations related to the design and implementation of neuroscience research and the examination of concepts such as free will, self-control, personal identity, and intention from a neural perspective (Roskies, 2002 [49]). The development of neuroethics is partly driven by the growing public concern and opposition to neuromarketing (Ulman et al., 2015 [51]). Neuromarketing research has been criticized for its potential to manipulate consumers and influence their purchasing decisions and for its potential negative impact on human dignity and violations of bioethical principles and individual rights such as autonomy, self-determination, confidentiality, and privacy (Ulman et al., 2015 [51]).

The ethical issues and debates surrounding neuromarketing are centred around the concept of human dignity, which should serve as the foundation for ethical principles such as autonomy, self-determination, privacy, confidentiality, protection of vulnerable groups, and the reliability and honest interpretation of research findings, in light of the potential risk of manipulation by commercial actors. (Ulman et al., 2015 [51])

Several governmental and non-governmental bodies, experts, scholars, and various groups in society have raised concerns. It is crucial to incorporate public policies based on human rights laws and the bioethical value of human dignity and integrity into research in this field. Evaluation and monitoring by bioethics committees and review boards are recommended, and a multi-faceted dialogue process involving various stakeholders, including the public and academic circles, policymakers, specialists, and experts, should be established to develop effective policies on neuromarketing. Bioethics discourse and ethical decision-making can provide a medium for acknowledging the human participant’s dignity and autonomy to be protected from harm. Ultimately, the rational and beneficial use of these technologies should be based on scientifically and ethically contemplated public policies prioritizing the welfare and health of all living beings on Earth. Moreover, it is the ethical duty of professionals to inform and educate the public and shape public policy concerning the use of neurotechnologies. (Ulman et al., 2015 [51])

2.7 Python

Python is an interpreted programming language that operates at a high level, featuring a straightforward syntax, contributing to its readability and appeal to novice and experienced users. Python was initially created by Guido Van Rossum and publicly introduced in 1991, marking its first release. His intention of developing was to create a programming language that prioritized simplicity and aesthetic appeal.

The characteristics of Python can be enumerated by:

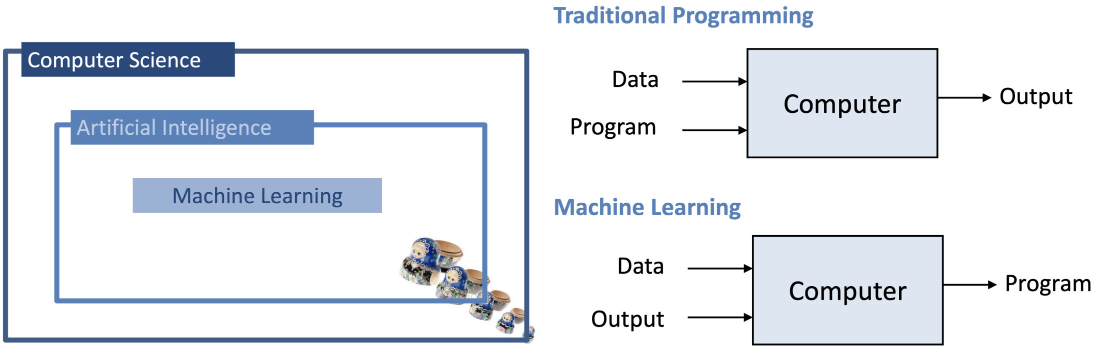
- Being easy to read
- Being open source: Available for download, enabling users to modify it according to their needs and utilize it in any desired manner.
- Being portable: Python code can run on any operating system with a Python interpreter.
- Being extensible: Flexibility to write the code in alternative languages, like C++, allowing them to incorporate low-level modules into the Python interpreter to customize and optimize their tools.
- Having a comprehensive standard library: Openly accessible to all users, eliminating the need to write code from scratch for every function.

With the above-mentioned characteristics, Python can be an adequate candidate for data manipulation in various fields such as research, reporting, predictive analytics, regression analyses, and more. Python is also one of the top languages for developing AI. Frequently employed libraries such as NumPy [52], Pandas [53], and Matplotlib [54] offer automated functionality for tasks like data cleaning, transformation, and visualization.

2.8 Artificial Intelligence

Artificial intelligence (AI) is a technology that allows the design of intelligent systems capable of imitating human-like intelligence. These systems can learn, reason, perceive, and make decisions based on data and algorithms, aiming to replicate or surpass human cognitive abilities in various tasks. However, there needs to be more understanding of the AI systems. Because the confusion between AI and self-learned models like a machine and deep learning models may mislead what AI is.

As visualized in figure 2.1a, AI is a superset of Machine Learning (ML). ML models are characterized by their learning abilities 2.1b. In traditional programming, the program that will process the input must be supplied to the computer. However, machine learning can create its program by providing inputs and outputs. In other words, it can learn its task/duty by cause and effect relationship. The AI programs do not have to mimic this kind of learning skills of intelligence. Simple statistics and given tasks/duties/programs can also imitate learning skills of intelligence. An AI system can be created by both traditional programming and machine learning.



(a) Clusters of Computer Science

(b) Traditional Programming & Machine Learning

Figure 2.1: Position of Artificial Intelligence

The other confusion in AI is between deep learning models. Deep learning (DL) uses artificial neural networks to simulate intelligence. DL is a subset of ML with the same characteristics. Their differences come from the design of models, the maths behind them, and deep learning can perform more complex decision makings.

In this paper, the proposed AI algorithm belongs to the group of traditional programming.

2.9 OpenCV

OpenCV [55] is a substantial open-source library with significance in computer vision, machine learning, and image processing. For better understanding, computer vision is a specific domain within AI that enables computers and systems to extract meaningful information from digital images, videos, and various other types of visual inputs. It contains the capacity to apprehend and interpret visual data, empowering computers to perform actions or offer proposals based on the insights acquired from these inputs. It is possible to perform image and video processing tasks that involve identifying and recognizing various elements such as objects, faces, and even human handwriting. Integrating libraries like NumPy [52] with Python enhances its ability to analyse the array structure of OpenCV, enabling advanced processing and analysis of images and videos.

OpenCV offers interfaces for multiple programming languages, including C++, C, Python, and Java. It is compatible with various operating systems, such as

Windows, Linux, macOS, iOS, and Android. The design of OpenCV heavily prioritizes real-time applications, ensuring efficient computational processing. The implementation of OpenCV is predominantly written in optimized C/C++ code, which takes advantage of multicore processing to enhance performance.

Chapter 3

Methodology

In this chapter, we will dig into eye-tracker experiments by discussing methods used in data collection through data processing with a newly developed tool. Furthermore, the characteristic of data and previously done work will be detailed in this chapter for a better understanding of the study.

3.1 Data Collection

This research included two types of experiments for data collection and thorough analysis. The first was a lab experiment, and the second was an online experiment. Participants in the lab experiment were selected and took part in the experiment under the supervision of lab staff. Meanwhile, data for the online experiment was gathered through an internet platform. Additionally, the lab and online experiments were each divided into Mockup website and Original website categories, which will be discussed later in the report. In this paper, lab experiments will be discussed in all detail. The online experiment has occurred via the RealEye platform; for the details of it, the link can be visited.

In this section, the data collection protocol will be touched by the topics of aim, participants, creation of the mock-up website, method, materials & devices, analysed variables and environment, equipment mounting & condition control.

3.1.1 Aim of Experiment

The goal of the experiment is to address usability problems with websites and enhance their visual appeal.

Figure 3.1: The image illustrates the ideal laboratory setup.

3.1.2 Participants

The study requires 20 to 30 healthy individuals (male and female), ranging in age from 20 to 50 years, to participate voluntarily. The participants must be regular internet users, which is an essential requirement for the experiment, but they do not need to know the purpose of the study. Before participating, each participant must complete and sign an informed consent form. (14 participants are used in this experience from both genders.)

3.1.3 Creation of the Mock-up Website

A mock-up of the original website was created based on user experience guidelines. By comparing the mock-up and the original website, the experiment aims to determine which website is more user-friendly and appealing to the audience.

3.1.4 Method of Experiment

The experiment has three parts:

1)The first part involves setting up EEG, GSR, a facial coding camera, and eye-tracker calibrating.

2)During the second part, the participants will be asked to browse or perform

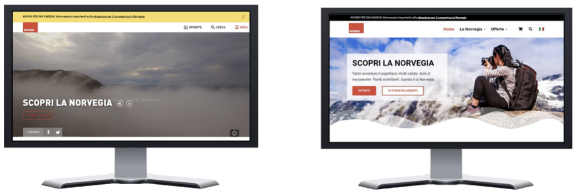


Figure 3.2: On the left: the original website; on the right: the mock-up website created according to UX guidelines.

tasks on both the original and mock-up websites, without knowledge of the study's aims.

3)In the final part, after biomarker recordings, each participant will complete a questionnaire on Google Forms.

The questionnaire can be found in Appendix A.

3.1.5 Materials & Devices

Eye tracker: to determine which parts and elements of the websites grab the participants' attention and which ones are ignored.

Galvanic Skin Response (GSR): to assess sweat gland activity, which reflects emotional arousal, to detect the participant's emotional stimulation, intensity, and type during the experiment.

Computer screen and Desktop application: on which the websites will be displayed, and data of participants will be collected. (The neuromarketing application development team developed the application.)

Electroencephalogram (EEG): to capture the brain activity of the participants while browsing the websites.

Facial Coding: to identify facial emotions by analysing facial expressions using AI algorithms.

Google Forms: to gather the participants' views on their website browsing experience through a questionnaire covering familiarity with websites, initial impression, and the visual impact of various website elements (colours, images, visual hierarchy, etc.).

3.1.6 Analysed Variables

For eye tracking (Tobii T60 or Tobii Pro Nano), after defining AOIs (Areas of Interest), the following metrics will be generated:

•Heatmaps: display the most and least viewed areas of the stimulus using a colour-coded system.

•Fixation Points: show where participants focused their gaze.

•Gaze Plots: illustrate the order, location, and duration of gaze on a stimulus.

•Time Spent (dwell time): the duration spent in an AOI.

•TTFF (Time to First Fixation): the time elapsed between the appearance of the visual stimulus and when the participant first viewed it. Number of Participants: the total number of participants who viewed the AOI.

For GSR(Galvanic Skin Response):

•The signal trend and peak values were measured by the GSR sensors.

For EEG (Electroencephalogram):

•The electrical activity in specific brain regions to evaluate the arousal aspect of emotions.

For Facial Coding:

•Classification of facial emotions using a machine learning algorithm that predicts two emotional dimensions: arousal and valence.

3.1.7 Lab Environment, Equipment Mounting & Recording Condition Control

The participants are asked to sit comfortably on a reclining chair, facing the computer screen at a distance of 60 cm. The room should be quiet, dimly lit, and have a temperature between 23 and 26°C. The operator logs into the desktop application, and each participant signs up by providing their personal information and is assigned a unique ID code for privacy. The operator sets up the Tobii equipment and prepares the participant by cleaning their skin with an antiseptic solution before applying the EEG and GSR electrodes. The experiment begins with the display of websites, and the levels of attention, emotion, and memory will be analysed. After the experiment, the subject will be linked to a questionnaire to gauge their preferences.

3.2 Characteristic of Data

Eight male and six female participants have been attended the lab experiment, a total of fourteen participants with the age interval 25 to 50, and all participants were workers. Staff members supervised all the experiments. An application developed by the neuromarketing application development team was used to collect data. Moreover, all the data collection was occurred explained in section 3.1.

In this section, the data collected will be detailed by topics of GSR data, face recordings, screen recordings, and eye tracker data. Furthermore, it has to be mentioned that all the data exists both for original and mock-up webpages.

3.2.1 Galvanic Skin Resistance (GSR) Data

Galvanic Skin Response (GSR) is a metric for the conductivity of human skin and reflects changes in the sympathetic nervous system (SNS). There is a long history of research linking variations in GSR to stress and SNS arousal (Selye, 1956 [56]). Increased stress leads to higher GSR, while lower stress results in a decrease in GSR. The potential use of GSR to indicate stress and cognitive activity was initially explored in (Miller & Shmavonian, 1965 [57]). Recent studies have established a connection between GSR and cognitive activity (Boucsein, 2012 [58]) and showed a correlation between stress and cognitive functions (McEwen & Sapolsky, 1995 [59]). These works support using GSR to evaluate cognitive load and its fluctuations.

There has been a growing focus in recent years on using GSR (Galvanic Skin Response) to objectively assess human-computer interactions' usability. This is extensively discussed in (Lin et al., [60]; Mandryk & Inkpen, 2004 [61]) with comprehensive reviews. (Shi et al., 2007 [62])

3.2.2 Face Recordings

During the experiment, the face of the participant was recorded by a webcam to detect the emotion. All the recordings are 180 seconds and stored in MPEG-4 format. The resolution of the videos is 640x360. This data helps to be aware of the participant's emotional state for each object observed on the websites by the audience.

3.2.3 Eye-Tracker Data

The eye-tracker devices, which are named Tobii Pro Nano and Tobii T60, were used for the experiment. Both devices are developed for on-screen research. The Tobii Pro Nano link and Tobii T60 link can be visited for detailed specifications.

Briefly, Tobii Pro Nano can be used with all external screens. Moreover, it is suitable to use outside the lab since it is portable. However, meanwhile, Tobii T60 uses its screen for research. Both have 60 Hz as the sampling frequency.

The data output of devices is a timestamp, gaze origin, gaze point, pupil diameter and validity code for each eye. Moreover, it is stored as a matrix in the "tsv" format. It is worth having more details about timestamp, gaze points and validity codes since they will be mentioned in section 2.

• **Timestamp**: is a unique identifier that represents the exact time that recording happens.

• **Gaze points**: are described by coordinates in the y and x axes. They can have continuous values from zero to one for each axis and each eye. 0 (zero) represents the left-most point of the screen for the x-axis while the top-most point of the

(a) Tobii Pro Nano on external device

(b) Tobii T60

screen for the y-axis. Furthermore, 1 (one) represents the right-most point of the screen for the x-axis while the bottom-most point of the screen for the y-axis.

• **Validity code**: can be 0 or 1 to represent the validity of the observation. The validity code can be 0 just in cases of undetected pupils.

All the features of eye-tracking data can be found in Appendix B.

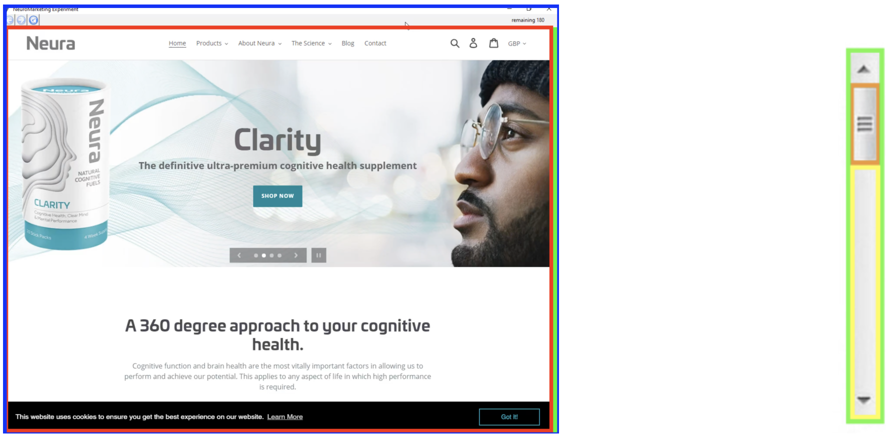
Note: When looking outside the screen, the coordinates can be minus or higher than one value while the validity code is still 1. In this case, the data have to be cleaned by the analyst.

3.2.4 Screen Recordings

The recorded screen videos are 180 seconds in MPEG-4 format. The resolution of the videos is 1280×1024 pixels. The components of the observed screen must be mentioned for better understanding in section 3.3 since the calculation for analysis is made by these components.

For the figure 3.3a, the area represented by blue borders is the screen borders which are right-left-most and top-bottom-most points. The area represented by the red area is the webpage that is analysed. Moreover, the green line represents the scrollbar area.

For the figure 3.3b, the orange area represents the scrollbar, and the area with the yellow border represents the scrollbar rail. Finally, the area with the green border represents the scrollbar wrapper.



(a) Sample of the screen **(b)** Sample of scroolbar

Figure 3.3: The components of the observed screen

3.3 Methodology of Algorithm

In this section, the previous data processing algorithm will be scrutinized by all steps of its methodology, and all the details of it will be shown in subsection 3.3.1. Then, the mistakes made due to wrong assumptions about the structure of the websites will be indicated in subsection 3.3.2. Finally, the new methodology developed by the thesis student is demonstrated in section 3.3.3.

3.3.1 Previous Work

An algorithm developed by the previous student who wrote his thesis in the neuromarketing analysis team and recently graduated from Politecnico di Torino was used in the analysis. For clear understanding, it would be better to describe the algorithm in two topics: its purpose and methodology for processing.

All the exposition is materialized by the original website. However, all is valid for the mock-up website in section 3.3.

Purpose of Algorithm

The algorithm aims to process the data to have three outputs. The first output is a video that includes the screen recordings and a spot on the screen which represents the observed point. The other outputs are intermediate data that includes matrices in CSV format; one matrix to virtualize the heatmap of webpages (durations) and the other one to virtualize fixation points on the webpages. In other words, the algorithm links the coordinates that are produced by the eye-tracker with the screen recordings.

Methodology of Calculations

Since a part of a webpage can be observed in a specific time, and different webpages can be observed in one experiment, two things should be determined to calculate the new coordinates on the webpages.

The web pages visited & visiting periods: to determine which periods belong to which webpage. For example, if there are ten web pages visited in 180 seconds and only the first three are visited with the periods of the first 50 seconds for the first page, the next 60 seconds for the second page and the next 70 seconds for the third webpage, the web pages and the periods should be known to link the coordinates with these web pages. (How to handle: Web Page Determination 3.3.1)

The position on the webpage that is observed at a specific time: to calculate the new coordinates according to the position and link them with a web page. (How to handle: Position Determination 3.3.1)

Web Page Determination

Identification of the current page is occurred by the size of the page scrollbar. The scrollbar size information for the pages comes from a configuration file already prepared by the developer. This size information is tried to match with the size of the detected scrollbar on the screen recording.

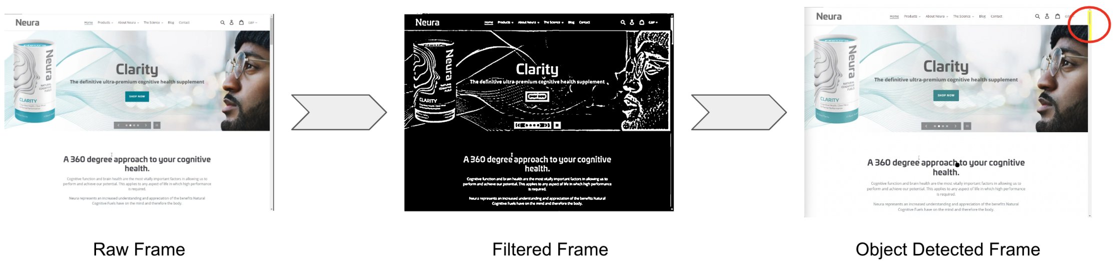


Figure 3.4: Object detection steps

Object detection: the identification of a specific object on the screen. In this case, it is the scrollbar. For this operation, the general location of the object would help the identification process, like the right-most 60 pixels of the screen. Moreover, the OpenCV [55] library is used in this operation. The operation steps; I) Adaptive pixel threshold is used to filter the frame to make objects more visible. II) Object search is done on the right-most of the page.

With the size information of the detected object and the scrollbar's size information that comes from the configuration file, if there is a match between these two pieces of information, the web page currently visiting can be determined.

Position Determination

The scrollbar height and the present web page height information are used to calculate the currently observed area on a web page. The web page height information is fetched from the configuration file as the scrollbar size.

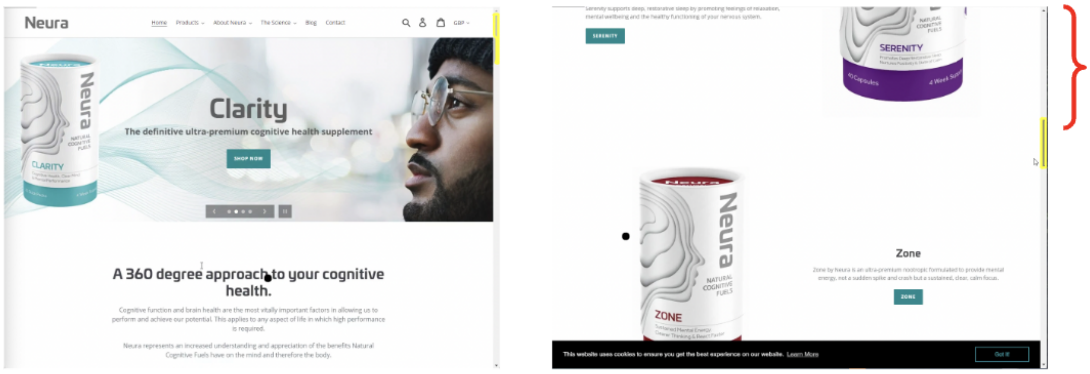


Figure 3.5: Position calculation visualization

As shown in figure 3.5, to know how many pixels that scrolled down, the y-axis coordinate of the scrollbar wrappers top should also be known. This data is statically determined in the algorithm code, and it would be hard to generalize for other experiments without knowing the language used in the algorithm and without familiarity with the code.

3.3.2 Incorrect Assumptions & Ideal Assumptions

The previous assumption was; there are three pages and sizes (scrollbar and webpage heights) about these pages. These pages can be seen in figure 3.6.

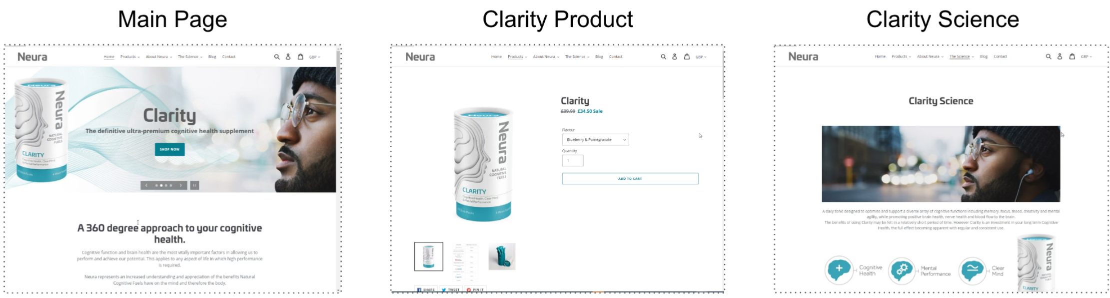


Figure 3.6: All the web pages that are expected to visit in previous work.

However, The actual number of pages that can be visitable is more than 10. The pages are shown in figure 3.7. Furthermore, the major difficulty is that some of the pages' scrollbars are identical or have only 2-4 pixels differences in their heights.

Figure 3.7: The pages that are visitable.

Therefore, while the object detection methodology is valid and achieves its duty, the final outputs were incorrect and were causing misleading visualization for the final analysis.

3.3.3 New Approach

In this subsection, the new methodology and algorithm will be presented with two topics: compilations that realized and affected the final form; and a two-step strategy: identify the website and then process.

Compilations

Three difficulties will be addressed in this topic. The final remedy attempts to solve these challenges with a generalizable method, not an ad-hoc approach.

1) As touched on, some pages of scrollbars have identical sizes. Therefore, scrollbars alone cannot be used to determine the current web page.

2) At the first beginning of uploading each web page, some anomalies may happen, like; web pages may be initialised with a blank white screen, and the scrollbar size would get significantly smaller because web pages are loaded part by part, which affects scrollbar size directly.

3) All the behaviours of participants must be considered, like visiting the same page more than once (the durations should be aggregated in this case) and so on.

Two-Step Strategy

This two-step strategy requires two iteration of all the participants' data. First iteration for identification of the website;

Identify the website; since some web pages share identical scrollbar sizes, scrollbar sizes cannot be used to determine pages. A different approach should handle recognizing the web pages. The thesis student proposes that webpage screenshots can be used for recognition of the whole webpage.

In this proposal, the developed algorithm automatically takes screenshots at the beginning of all possible web page changes. All likely page changes are discerned by the detection of scrollbar size differences between the frames of the screen recording.

Figure 3.8: Screenshot 0_1.jpg is labelled as main.jpg and stored in the website_images file as the other page screenshots.

Then, these extracted screenshots of pages are labelled and stored in a file, as in figure 3.8. This operation has to be managed by a person since there would be more than one extracted screenshot for some pages due to hardships in 3.3.3.

Second iteration for process to accomplish the purpose (3.3.1);

Post-Process; of data is performed by the following steps iteratively until the screen recording ends:

1) **The first-page identification**: There happen comparisons between the current frame of the recording and the screenshots in the prepared folder. If any comparison results in success, in this case, success is a similarity between them; the labelled screenshot is picked, and it determines the webpage by its name.

The parity score is calculated like object detection is applied to both JPG files then all the detected objects are compared by size. An object is counted as a shared object if there is a match according to size. The ratio between the number

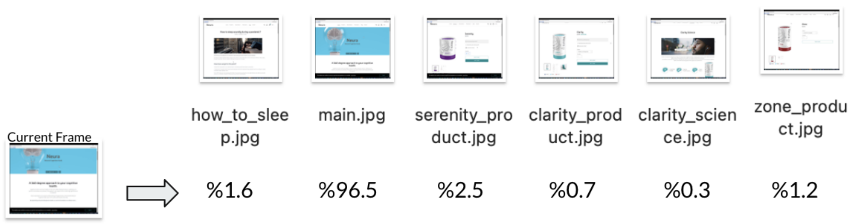


Figure 3.9: The best similarity is with the main page by %96.5 parity. The most similar page is chosen, or the page has a higher parity score than a given threshold.

of shared objects to the number of total objects in the JPG file has a higher number of objects. This operation will be called "similarity search" after now on in this paper.

$$\frac{\text{the number of shared objects}}{\text{the total number of all objects in "crowded" file}}$$

2) **Object initialisation**: After the current page determination, necessary objects are created and initialised;

I) Page object with attributes; Name, ID number, height, the percentage of the visited area by participant... to collect essential information of the current page.

II) Scrollbar object with attributes; ID number, height, coordinates, scrollbar wrapper height... to gather important information about the current page's scrollbar.

III) "Detected scrollbar in screen" object with attributes, coordinates & size to use for detection of page changes.

IV) Lists of old pages and scrollbars objects to detect the revisitings to the previous pages.

3) **Preparation of required outputs**: While surfing the page;

I) There happens calculation eye coordinates comparison by position on the page. They are stored for the output matrices.

II) The currently observed point is marked on the video.

III) Keep track of the position on the page. If scrolled down, extract a frame as in 3.10. The purpose of this operation will be given in chapter C.

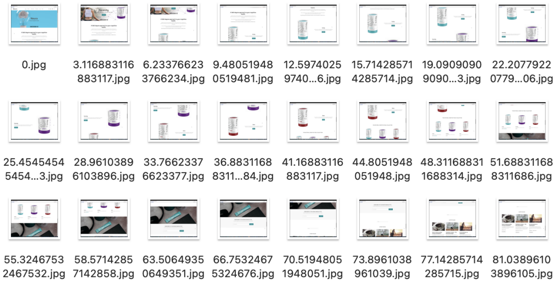


Figure 3.10: The sample of extracted screenshots while scrolling down and their percentage of visited area. For this example, extraction ensues if more than 3% of the page is newly visited.

(This step iterates itself until the fourth step happens.)

4) **New-old page detection**: If any change is traced by differences between the scrollbar and "detected scrollbar on screen" objects;

I) The search occurred by comparing the sizes of historical scrollbars. If the current page is an old page that was visited, the old page and scrollbar objects are loaded again. Then go to step 3.

II) If the current page is a new one, the similarity search arises between the current frame and the screenshots in the folder. Then go to step 2.

Chapter 4

Post-processing

This chapter will show the steps during the post-processing with all details. Specifically, data transformations and new algorithm 3.3.3 will be the focus. For better understanding, a participant, the subject with the code 6200, is selected to exhibit the post-processing steps.

4.1 Raw Data to Meta-Data

First, the website should be identified if it was not identified. The first step of the algorithm 3.3.3 is initialized to detect all the pages visited by Participant 6200 on the website. After extracting all the first frames in each page change, they are labelled, and we are ready for post-processing.

Screen recording (MP4 video) and gaze coordinates (CSV file) are needed to produce the meta-data. Each row in the CSV file stands for one frame of the screen and video recordings. Since the experiment set-up is 60 fps, there should be a 10800-frame video recording (3 minutes) and the same number of rows in the gaze-coordinate CSV file. Screen recording is 3 minutes, as expected. However, the CSV file has 12195 rows.

Furthermore, all the other patients have various numbers of rows in their CSV files. The reason is that before the experiment, calibration happens. Therefore, additional rows in the CSV files stand for the calibration phase. The last 10800 rows belong to the experiment. Because of that, the last rows are extracted for necessary columns from the file. The necessary columns are timestamps and coordinates (if they are valid) for both gazes. After this step, screen recording is started to iterate frame by frame with the following function.

```
    while cap.isOpened():
        ret, frame = cap.read()
```

Right after, the first frame is taken for the similarity search 3.3.3. When a match is found, the scrollbar, page and "detected-object" objects are initialized by information like the name of the page and scrollbar size...

Now, we are ready to estimate spent time at the coordinates on the whole webpage with the position information 3.3.1 and given grid ratio. Grid ratio is the ratio of requested rows to columns for page separation. For example, if the grid ratio is 28x8, we separate the page into 224 cells for 28 rows and eight columns. Then, we calculate the time spent for each cell.

A	B	C	D	E	F	G	H	I	J
	start time	end time	start x	end x	dx	start y	end y	dy	duration
0	0	0	0	4	4	0	1	1	0
1	0	0,116667	4	3	-1	1	1	0	0,116667
2	0,116667	0,133333	3	4	1	1	1	0	0,016667
3	0,133333	0,233333	4	3	-1	1	1	0	0,1
4	0,233333	0,25	3	4	1	1	1	0	0,016667
5	0,25	0,35	4	3	-1	1	1	0	0,1
6	0,35	0,366667	3	4	1	1	1	0	0,016667
7	0,366667	0,416667	4	3	-1	1	1	0	0,05
8	0,416667	0,433333	3	4	1	1	1	0	0,016667
9	0,433333	0,45	4	3	-1	1	1	0	0,016667
10	0,45	0,483333	3	4	1	1	1	0	0,033333
11	0,483333	0,633333	4	3	-1	1	1	0	0,15
12	0,633333	0,65	3	4	1	1	1	0	0,016667
13	0,65	0,833333	4	3	-1	1	1	0	0,183333
14	0,833333	0,85	3	4	1	1	1	0	0,016667

main | product | clarity_product | +

Figure 4.1: Meta-Data: Integer positions for rows and columns for the visited pages are indicated below. The float positions also exist for specific positions on the page.

During this procedure, a video is prepared to indicate the gaze points on the screen recording. An example of video can be found here.

4.2 Meta-Data to Visualizations

For visualization, the Seaborn library [63] has been used. The Seaborn library is used to create statistical visualizations in Python programming language [64]. It offers a convenient interface to Matplotlib [54] and is well-suited to work with data in Pandas [53] format, in which all the intermediate data is transformed. Seaborn's functions provide a straightforward, data-focused API (application programming interface) that enables users to turn questions about their data into graphical representations that provide answers.

The following piece code calculates the total time spent in each cell.

```
file = pd.read_excel(f, desired_page_name, index_col=0)
x = list(file['start x'])
y = list(file['start y'])
duration = list(file['duration'])
```

```
tempdf = pd.DataFrame(list(zip(x, y, duration)), columns=['start x', 'start y', 'duration'])
tempdf = tempdf.drop(tempdf[tempdf["start x"] < 0].index)
tempdf = tempdf.drop(tempdf[tempdf["start y"] < 0].index)
tempdf = tempdf.drop(tempdf[tempdf["start x"] >= params[1]].index)
tempdf = tempdf.drop(tempdf[tempdf["start y"] > params[0]].index)

# rounding-off startx and starty
tempdf2 = pd.DataFrame(list(zip(tempdf['start x'].apply(np.floor),
tempdf['start y'].apply(np.floor),
tempdf['duration'])), columns=['start x', 'start y', 'duration'])

# Grouping by the dataframe and shrinking the dataframe down and getting the sum of duration
tempdf2 = tempdf2.groupby(['start x', 'start y'], sort=True).sum().reset_index()

# Converting the dataframe to given ratio matrix
tempdf2 = tempdf2.pivot('start y', 'start x', 'duration')
# print(f"temporal dataframe: {tempdf2}")
if duration_matrix.empty:
    duration_matrix = tempdf2
    fixation_matrix = tempdf
else:
    duration_matrix = pd.concat([duration_matrix, tempdf2]).groupby('start y').sum()
    fixation_matrix = pd.concat([fixation_matrix, tempdf])
```

After the necessary information is calculated, we can visualize our findings. Duration matrix can be used for heatmaps. Fixation matrix can be used for scan paths.

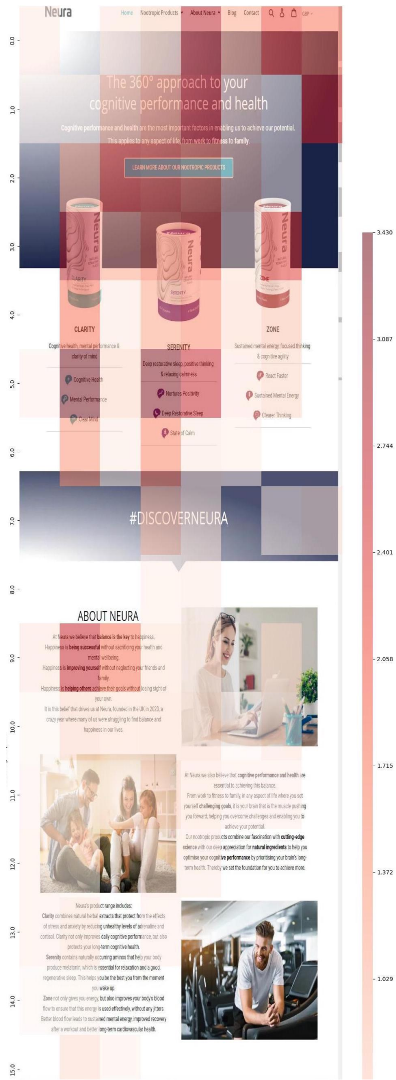
For the figure 4.2, two things can be said;

Firstly, participant 6200 spent a maximum of 5.75 seconds in a cell on the original website; this number decreased to 3.43 for the mock-up website. The maximum time spent in a cell is longer in the original website, with more than 2 seconds. Therefore, the original website has a better design than the mock-up. The loss of concentration is less on the original website.

Secondly, we can observe a harmonic surfing on the original website. From top to bottom, all the captions of products are read sequentially. It seems there is no confusion while surfing. However, for the mock-up website, we can observe some confusion at the top of the page. Moreover, it is hard to see a harmonic surfing on the page.

Appendix C can be read for further information on the readability of visualizations, the possible visualizations, and some analysis types.

(a) Original website



(b) Mock-up website

Figure 4.2: Heatmap of main pages for original and mock-up websites.

Chapter 5

Conclusion

By digging into this eye-tracking experiment from literature to post-processing, all the findings, challenges and limitations were exhibited step by step in this study. There needs to be a tact for researching to reach the absolute truth. Even a little mistake may lead the results to fallaciousness easily.

The experiment's conclusive conclusion should be done by someone other than the thesis student with a role of a data scientist in this collaboration. Since multidisciplinary research groups have become crucial in this complex modern world, all team members should do their own duty with perfection to make the research accurate. Every single wheel must work properly to show the actual time in a clock. Each member must know her/his responsibility and contribute to her/his team without any mistakes.

A data scientist must be sure that any mistake has yet to happen in all data processing steps. The raw data must be checked for validation and well-known to sense possible outputs in the next steps of processing. The data should be cleaned cautiously to increase its quality and enable precision. The methodology used in data processing must be created with correct assumptions, and the integrity of processed data must be controlled.

The only disadvantage is that it has to iterate all the participants twice; if no "control user" is used to identify the website by visiting all the possible web pages. Besides the disadvantage, it could handle all the challenges mentioned and produce mistakeless intermediate data to visualize.

However, except for the drawbacks, the AI tool achieved to process the heterogeneous raw data into metadata that can be used in visualizations. The methodology that was created proved its usability, applicability and generalizability. Furthermore, the visualizations successfully hold the knowledge about the website and make the information human-readable.

Most crucially, with the consideration of IoT's future in our life, the experiments are run on the user interface (UI), and usability optimization can gather huge success with gaze-point analysis in future. It can be said that eye-tracking will be in our life more frequently.

Appendix A

Questionnaire

First Questionnaire

1. Do you consume any nutrition supplements on a regular basis?
2. Do you consume caffeine on a regular basis?
3. Why do you consume caffeine?
4. How many hours do you work/study during a typical weekday?
5. How stressed or irritable do you feel when you are ...? (working/studying, with friends, with family, running errands)
6. How stressed or irritable do you feel after you have been ...? (working/studying, with friends, with family, running errands)
7. After a busy day ...? (how easily can you fall asleep?, wow well do you sleep?)
8. Do you use any supplements or medications on a regular basis to help you with sleep?
9. How many days a week do you typically exercise?
10. Do you consume any sports supplements on a regular basis?
11. Please list the names of your favourite influencers in the box below.
12. Do they promote any nutrition supplements?
13. Which aspect of the daily life do the nutrition supplements sponsored improve?
14. Have you ever heard of Nootropics (nutrition supplements) before?

15. Have you ever purchased them?
16. Gender?
17. What is your age?
18. In which country do you currently reside?
19. What is your ethnic background?
20. What is the highest educational qualification you have completed successfully?
21. What is your marital status?
22. How many dependants (e.g. children) do you have?
23. What is your current employment status?
24. If you are a worker, what is your personal annual income?

Second Questionnaire

1. How many products does Neura offer?
2. Which of the following are products offered by Neura? (Serenity, Clarity, Edge, Zone, Boost)
3. How much do you think Neura's products would help improve your ...? (potential at work, fitness, family life, sleep, overall wellbeing)
4. Do you think Neura is ...? (professional, high quality product, premium, scientific, trustworthiness, sustainable, expensive)
5. Having viewed the website, do you think you have enough information about nootropics?
6. How likely are you to purchase the following nootropics supplements from Neura in the future? {Clarity (Cognitive health, mental performance & clarity of mind), Serenity (Deep restorative sleep, positive thinking & relaxing calmness), Zone (Sustained mental energy, focused thinking & cognitive agility)}
7. How likely is it that you would buy a nootropic supplement from any brand in the next year?
8. How much usable the website is for you?

Appendix B

Eye-Tracker Data Column Names

1. device time stamp
2. system time stamp
3. left gaze point on display area x
4. left gaze point on display area y
5. left gaze point in user coordinate system x
6. left gaze point in user coordinate system y
7. left gaze point in user coordinate system z
8. left gaze origin in trackbox coordinate system x
9. left gaze origin in trackbox coordinate system y
10. left gaze origin in trackbox coordinate system z
11. left gaze origin in user coordinate system x
12. left gaze origin in user coordinate system y
13. left gaze origin in user coordinate system z
14. left pupil diameter
15. left pupil validity
16. left gaze origin validity

17. left gaze point validity
18. right gaze point on display area x
19. right gaze point on display area y
20. right gaze point in user coordinate system x
21. right gaze point in user coordinate system y
22. right gaze point in user coordinate system z
23. right gaze origin in trackbox coordinate system x
24. right gaze origin in trackbox coordinate system y
25. right gaze origin in trackbox coordinate system z
26. right gaze origin in user coordinate system x
27. right gaze origin in user coordinate system y
28. right gaze origin in user coordinate system z
29. right pupil diameter
30. right pupil validity
31. right gaze origin validity
32. right gaze point validity

Appendix C

Analysis

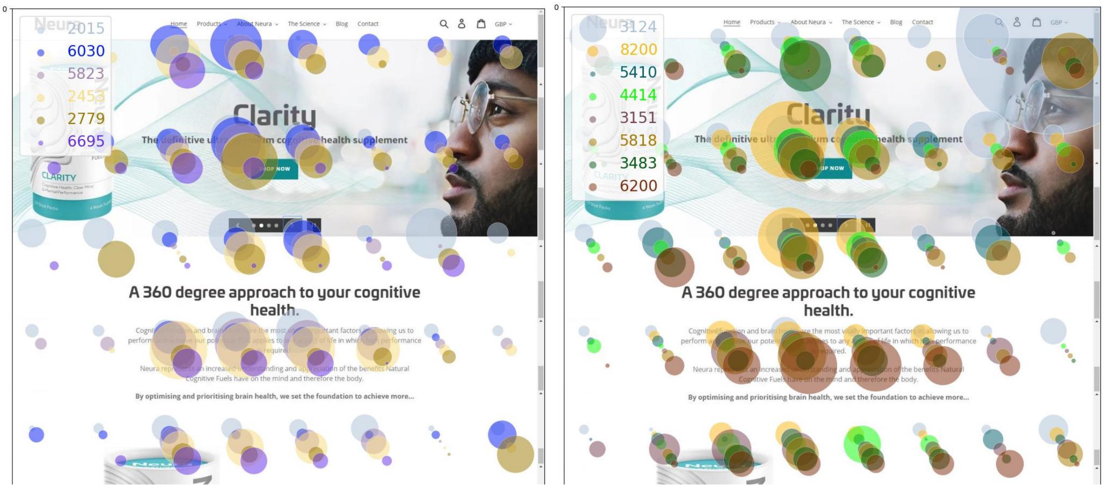
In this chapter of appendix, the conclusive visualizations produced to analyse by people from other disciplines (in this case, psychologist colleagues) will be detailed in four sections. In the first section, exploratory data analysis will be shown. In the second section, reliability in data processing will be touched on to indicate problems that may arise with its impact. The third section will discuss possible visualizations that can be produced with the data to analyse visual attention—additionally, some details of visualization types. This chapter will be finalized by comparative analysis, which is the experiment's target mentioned in subsection 3.1.1.

C.1 Exploratory Data Analysis

Visualizing data is an essential step in the data-cleaning process, as it helps to explore the structure of data, identify any outliers or unusual groups, uncover trends and clusters, and detect local patterns. Additionally, data visualization is helpful in evaluating the output of data models and presenting results. In exploratory data analysis, visualizing the data is crucial in ensuring data quality and allowing analysts to gain a better understanding of a dataset.

For the experiment, heatmaps are needed to analyse (for more detail, C.3 and C.4). However, there was a heatmap cell with the longest spent time on the top-right on the main page in the early heatmaps, even if there was no context that could take time to consider at that corner. This situation made the heatmaps hard to read and analyse due to the time spent domination on the duration scale. The reason for this situation should be detected to increase the quality of visualizations. An algorithm can be used to detect the participants that have spent time in that area more than a threshold. However, figure C.1 has been produced for the educational purpose of identifying an outlier and unusual behaviour.

In figure C.1b, as can be seen clearly, participant 3124 spends more time in the



(a) Female participants

(b) Male participants

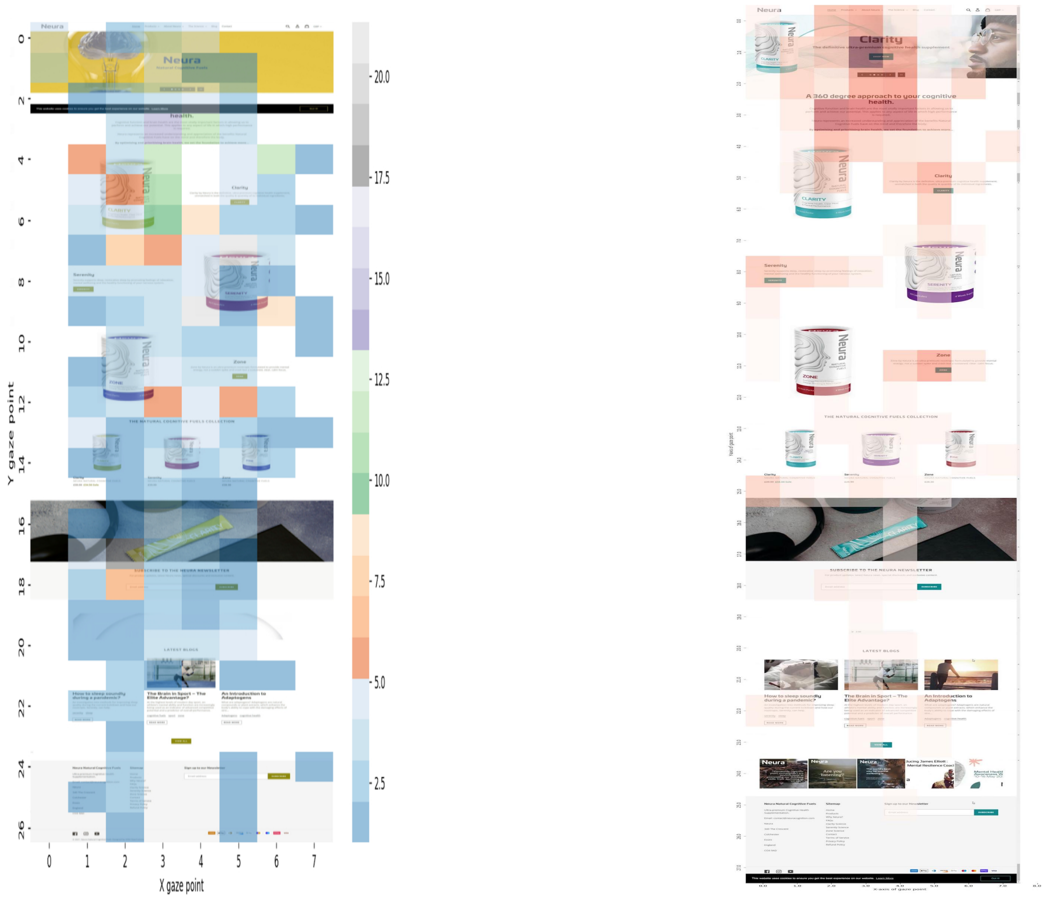
Figure C.1: Spent time on the top of the main page of the original website: Each circle represents one participant's view duration at that area. Colours and slight shifting of circles are used to distinguish the participants. The circle's size represents the participant's duration in that area. Note: Since nothing is exciting and educational on the rest of the page, just the top is shown to increase visuality.

top-left corner of the page dramatically than anyone else spends in other areas. As said before, this causes a reduction of quality in visualizations. Therefore, it needs to be removed. In the following sections, the participant will not be considered and joined in the visualizations. On the other hand, in figure C.1a, no particular instance affects the quality and must be removed.

C.2 Importance of Trustworthy Data Processing

Any mistake during data processing or misassumption would dramatically change the absolute consequences. Especially if these intermediate outcomes are used for analysis to have an understanding of indeterministic beings, in this case, it is human behaviour; all the interpretations may lead the analysis in the wrong direction. Even in critical cases, it may induce irreversible results.

It should be noted before talking about figure C.2 that the web page images behind the heatmap are not the same. The website has been updated many times from when the experiment was performed. Because of that, finding an identical page to the original one is challenging. Since the developed algorithm extracts the screenshots while the experiments are running, producing the web pages seen by the participants is feasible and effortless by concatenating them. The methodology



(a) Heatmap old version **(b)** Heatmap new version

Figure C.2: All the female participants on the main page of the original website.

of it is as follows.

Producing identical pages: This operation is similar to the similarity search mentioned previously. Only the difference is the objects selected with the same size and x-axis but not the y-axis. The difference between objects' y-axis gives us the overlapping distance of the concatenation operation. This operation is applied to all the screenshots extracted sequentially to produce an identical image of the web page visited by the participants.

Moreover, the colour palette selection of heatmaps has been modified because of the purpose of readability. In figure C.2a, grey is picked to represent the most viewed area, while the darkest tone of red is chosen in figure C.2b. Different and uncollated colours are selected to represent the levels of attraction in figure C.2a; meanwhile, the lighter versions of red are decided for the same objective in figure

C.2b.

As can be observable in figure C.2, the reliability of the intermediate data can be revealed by the consistency of visualization. While there is a correlation between the heatmap and context of the webpage in figure C.2b since the texts are the most viewed areas and the initialization area of the website (the top of the main page) is more viewed than the bottom part (because all participants do not scroll down), there is no detectable correlation and is the dominance of randomness in figure C.2a. The developed algorithm produces the intermediate data with good preciseness.

C.3 Visual Attention

Data visualization involves creating visual representations to present data. These representations usually focus on raw data and essential summaries and may incorporate displays of transformed data using complex transformations. What one person considers statistics, another person may see as raw data. Therefore, having a shared set of concepts and terminology is essential when working with graphics. Ultimately, the main objective is to use data visualization to interpret displays and gain insights from the information presented.

(a) Main page **(b)** Science of behind the product **(c)** Product description

Figure C.3: All participants' average duration heatmaps on three web pages. Note: These heatmaps are not generated for comparison purposes. Therefore, they show the scale of durations from min to max for their selves.

Heatmaps: can be used in order to analyse user behaviour and website structure by visualizing AoI (attention of interest). In figure C.3, the "main", "science", and "description" pages of a product are shown to study the learning process of general users.

In figure C.3b, the participants' attention decreases to the product components information in the long text while reading it. All the information about the ingredients is read at the top, but while going through the bottom of the text, the attention disappears, and only the short texts are read, like the ingredient's name.

Scanpaths: refer to the record of eye movement information gathered by a gaze tracking device. This information includes the path of the eyes as they scan the visual field, analyse visual information, and view it. The needed data typically includes the position of old-new coordinates and the duration of fixations as produced.

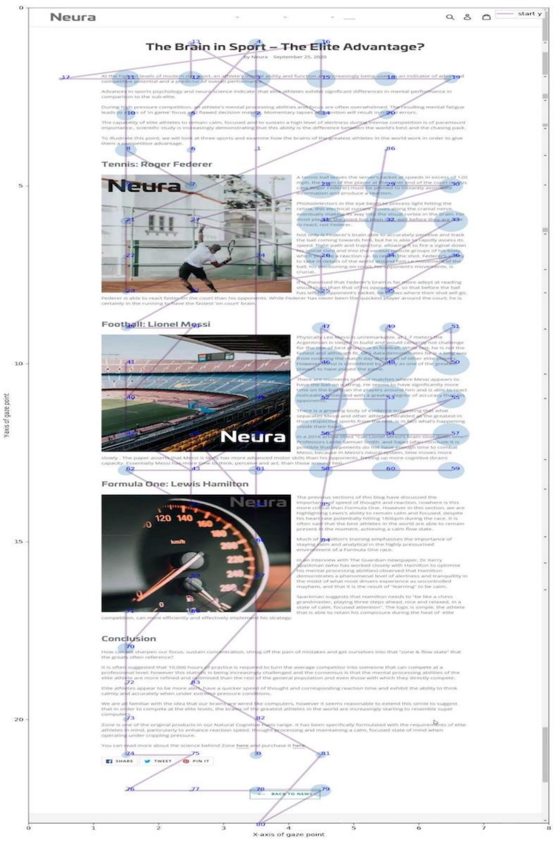


Figure C.4: Participant: A 24-year-old male student who does fitness; Page: "The brain in sport" page, which includes information about products' effects on sports and examples from famous athletes.

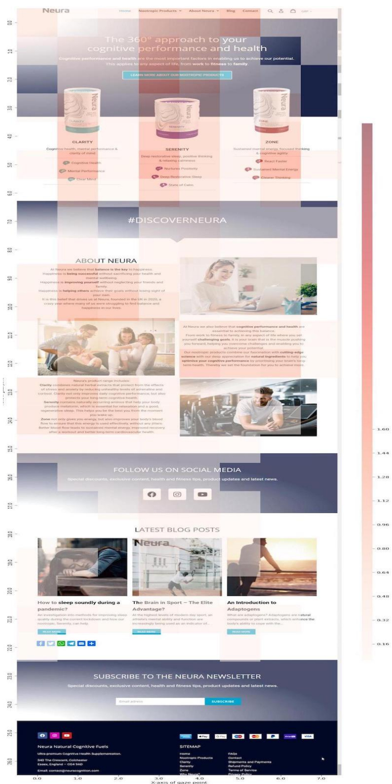
In figure C.4, the example of a scanpath from experiments reveals the demeanour of the participant on the page. The blue circles symbolize the time spent in that area, directly proportional to their size. Also, all the circles are labelled by their order to track the order of sight.

In this example, it is evident that Lionel Messi engages the attention of the subject. He spends much more time on information about this athlete than all the other details. He reads the text about the athlete more carefully without eyes away even a second. By the information of his indicated favourite athlete, Cristiano Ronaldo, his attention to this detail reaches significance.

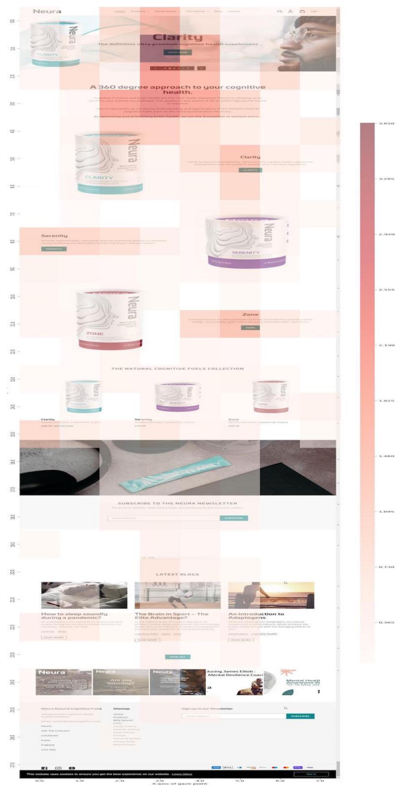
C.4 Comparative Analysis

As a thesis student who contributes to the team in a data scientist role, the duty must be to generate trustable visualizations to make the analysis of colleagues from other disciplines more effective. Therefore, some of the possible visualizations for comparative analysis will be mentioned without conclusive inference in this section.

Mock-up vs Original Website



(a) Mock-up website



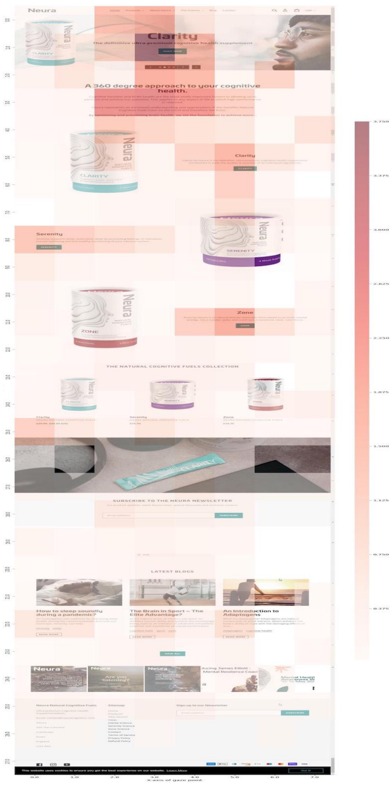
(b) Original website

Figure C.5: Main pages

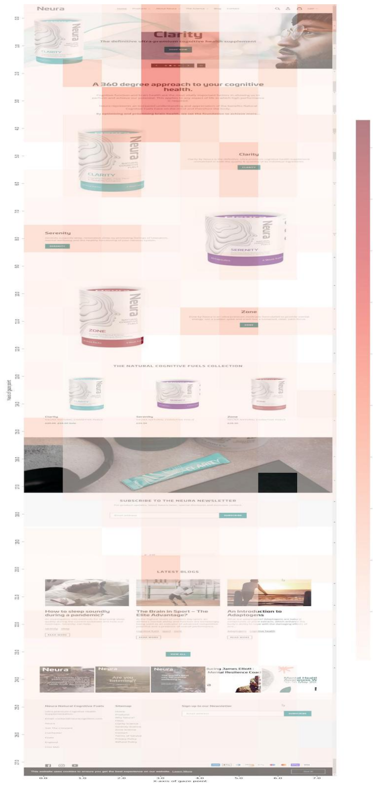
For the figures above, the heatmaps show AoI of all participants in areas. The same colour palette is used to represent the duration differences. The scale bars for each heatmap are set from most prolonged duration in both to zero to increase the quality of the analysis. Additionally, higher amounts than observable duration in the heatmap are not displayed in the bar to avoid confusion since these amounts cannot be observable in one of the heatmaps, as in figure C.5a.

It is evident that the maximum duration in an area differs between the mock-up and the original website. The maximum duration of 3.65 on the original website is more than two times higher than the maximum on the mock-up website, with 1.6 seconds.

Female vs Male Participants



(a) Females



(b) Males

Figure C.6: Main pages

In figure C.6, the comparison between genders is shown. Some attention differences can be observed between heatmaps undoubtedly. Furthermore, many more alternatives of this comparison can be visualized, like young-old, sporty-non-sporty participants.

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