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Application of Artificial Intelligence in Neuromarketing to Predict Consumer Behaviour Towards Brand Stimuli:

Case Study - Neurotechnologies vs. AI Predictive Model

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ABSTRACT

This research aims to analyse the current level of accuracy in predicting consumer behaviour in response to brand stimuli using artificial intelligence, comparing the results with an analysis conducted using neuromarketing biometrics. The study aims to determine the accuracy achieved in predicting consumer levels of attention and visual attraction towards visual stimuli, compared to the results recorded in a neuromarketing investigation with real users, through eye tracking. The implications of these comparative analyses are discussed in the final part of the article, concluding that the emotional intelligence tool provides very accurate predictions of consumer behaviour in response to visual stimuli. The results of this study revealed that the prediction of the percentage of users who would view each area of interest is very good, and regarding visual attraction (time until the first viewing of each area of interest), it is quite similar to the order observed by the consumer group; consequently, the level of approximation to reality of AI is very good.

KEYWORDS

Artificial Intelligence, Consumer Behaviour Prediction, Eye Tracking, Neuromarketing, Neurotechnology, Visual Stimulus

Prediction of human behaviour in response to brand stimuli involves understanding how individuals will emotionally and cognitively respond to various marketing signals, advertising, and brand experiences (Temesi et al., 2023). Repeated exposure to a brand can strengthen recognition and emotional associations (Ahn, 2022), while behaviour prediction involves assessing how familiarity and emotional associations will influence consumer purchasing decisions and loyalty (Vrtana & Krizanova, 2023). Emotions play a crucial role in purchasing decisions. Behaviour prediction involves analysing how marketing strategies and brand messages will evoke specific emotions in consumers,

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as these emotions can influence purchasing decisions and brand perception. Therefore, it is important to anticipate the effectiveness of certain visual elements, messages, and experiences in terms of capturing attention and generating interest.

The way consumers interact with the brand throughout their customer journey affects their perception and behaviour. Behaviour prediction involves evaluating how experiences at different touchpoints, from advertising to purchase and after-sales service, will influence customer satisfaction and loyalty (Vrtana & Krizanova, 2023). Brands that maintain a consistent image and message over time tend to build trust. Behaviour prediction involves assessing how brand consistency will affect consumers' perceptions and their willingness to interact and purchase. Actively monitoring consumer responses through social media comments, surveys, and other forms of feedback provides valuable information (Köker & Özer, 2023). Prediction involves analysing these responses to anticipate how consumers will react to future marketing initiatives.

Behaviour prediction is also influenced by evolving cultural and social trends (Katica et al., 2023), and understanding how these changes affect brand perceptions and consumer preferences is crucial for anticipating and adapting to the changing dynamics of the market. The ability of brands to personalise messages and offers on the basis of individual consumer preferences also affects behaviour prediction. Anticipating these preferences and delivering personalised experiences can increase the effectiveness of brand strategies. Therefore, predicting human behaviour in response to brand stimuli involves a deep understanding of emotions, neurological responses, and consumer experiences. Companies should employ a combination of market research, data analysis, neuromarketing techniques, and active monitoring to anticipate and proactively respond to consumer behaviour dynamics.

This study addresses a gap in the research on the application of artificial intelligence (AI) to the discipline of neuromarketing, an area in which little empirical research has been done. Researchers are now beginning to define new research questions and improve our understanding of the possibilities presented by neuromarketing, through the development of new methodologies and the acquisition of data that will help fill these gaps in our knowledge.

LITERATURE REVIEW

The study of consumer behaviour is focused on the actions and decisions individuals or groups take when selecting, purchasing, and using products, services, ideas, or experiences to satisfy their needs and desires (Bhavadharini et al., 2023). Understanding consumer behaviour is crucial for businesses, as it allows them to tailor their marketing strategies and meet market demands more effectively (Antonovica et al., 2023). Consumer behaviour is influenced by key elements such as cultural factors (values, beliefs, norms, customs, social class, and belonging to a specific cultural group, which greatly influence purchasing decisions; Coimbra et al., 2023; M. Pham et al., 2023), social factors (social relationships, reference groups, family, and other aspects of the social environment, such as the influence of friends and family; Qaiser et al., 2023), personal factors (age, gender, income, occupation, personality, and lifestyle; Boshoff, 2012), and psychological factors (perception, motivation, attitude, and decision making; Werth & Foerster, 2007; Yilmaz, 2023).

The consumer decision making process typically involves several stages, including problem identification, information search, alternative evaluation, decision making, and post-purchase evaluation. In the digital age, online presence, social media, and online reviews play a significant role in purchasing decisions, as consumers seek information online before making purchases and rely on feedback from other users (Hakami & Mahmoud, 2022). The quality of the customer experience, ranging from website navigation to interaction with customer service, may have a significant impact on consumers' loyalty and their willingness to recommend a brand (Sáez-Ortuño et al., 2023). Furthermore, consumers are increasingly making purchasing decisions based on ethical and sustainability considerations (Ogiemwonyi & Jan, 2023; Pradeep & Pradeep, 2023), forcing companies to adopt responsible business practices to gain preference among consumers conscious of these issues (Romero Valenzuela & Camarena Gómez, 2023).

Understanding these aspects of consumer behaviour allows companies to anticipate the needs and expectations of their customers, adjust their marketing strategies, and offer products and services that resonate with their target audience. Market research, data analysis, and the application of AI are valuable tools for gaining deeper insights into consumer behaviour.

Predicting Consumer Behaviour

Predicting consumer behaviour involves the use of various techniques and tools to anticipate future actions and decisions of consumers. Some common strategies and approaches used in predicting these patterns of behaviour include historical data analysis, in which examining past consumer behaviour data can provide valuable insights into previous purchasing patterns, product preferences, identification of trends, and prediction of future behaviour. Machine learning algorithms can be applied to analyse large datasets to identify complex patterns, generate predictive models trained using historical data, and forecast future behaviour on the basis of new input (Juárez-Varón et al., 2020).

Classifying customers according to common characteristics makes predicting behaviour easier (Singhal, 2023). Each segment may have specific trends and preferences that can be used to personalise marketing strategies and services. Directly collecting information through surveys and customer feedback can provide valuable insight (Agag et al., 2023), as asking consumers directly about their intentions and expectations can help predict future behaviour. This method can be complemented with sentiment analysis tools (Punetha & Jain, 2023) to assess opinions and comments on social media, online reviews, and other sources, helping predict the public perception of a product or brand, which, in turn, will affect consumer behaviour. Recommendation models, commonly used in e-commerce platforms and streaming services (Lam et al., 2023), analyse user behaviour to predict products or content that may be of interest, enhancing customer personalisation and satisfaction.

Conducting experiments and A/B testing allows companies to test different approaches and strategies and to understand how consumers respond (Sheng et al., 2023), with the results of these experiments guiding future decisions. Considering the context in which consumers make decisions (for instance, factors such as season, current events, market trends, and economic changes) can be crucial in influencing consumer behaviour. Geographic location can play a significant role in predicting consumer behaviour, as geospatial data analyses can reveal regional behaviour patterns and help tailor strategies to specific locations (Alam et al., 2021). It is important to note that the combination of multiple approaches and data sources is often more effective in predicting consumer behaviour.

Neuromarketing

Neuromarketing is an interdisciplinary field that combines neuroscience, psychology, and marketing to understand how marketing stimuli affect consumer perception and behaviour (Kajla et al., 2023). Its goal is to use tools and techniques from neuroscience to analyse individuals' brain and physiological responses to marketing stimuli, such as advertisements, product packaging, and shopping experiences. Neuromarketing employs techniques such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and magnetic resonance imaging (MRI) to measure brain activity while individuals are exposed to marketing stimuli (Alsharif et al., 2023; Ouzir et al., 2024). This provides information about the activated areas of the brain and how they respond to different stimuli. In addition to brain activity, other physiological responses, such as heart rate variability, skin conductance, and eye tracking, can be measured (Gurgu et al., 2020). These responses can help us to understand consumers' emotions and level of attention during interactions with products or advertising messages.

Neuromarketing can help identify market segments on the basis of common neurological responses. This information allows companies to customise their marketing strategies to meet the specific preferences of different consumer groups. It focuses on mapping emotions to understand how certain stimuli generate emotional responses in consumers (Matsumoto et al., 2011). Neuromarketing seeks to identify which sensory elements (visual, auditory, tactile, etc.) generate positive or negative emotions that can influence purchasing decisions, and to understand how consumers experience different aspects of the purchasing and product usage process, which enables companies to enhance the customer experience. This can influence brand loyalty and product recommendations. By better understanding how the brain reacts to different brand messages, companies can optimise their advertising campaigns to be more effective by adjusting creative design, message tone, or ad format. Neuromarketing is also applied to packaging and product design by analysing brain responses to different designs, allowing companies to select visual elements that attract and captivate consumers at the point of sale.

The application of neuromarketing to predict consumer behaviour focuses on using neuroscience techniques and tools to understand how marketing stimuli affect individuals' minds and purchasing decisions (Alsharif et al., 2023). This application measures consumers' attention and engagement levels with marketing stimuli, providing insights into which elements capture attention most effectively. Understanding the emotions associated with specific marketing stimuli helps predict how consumers will respond to specific products, ads, or experiences. By analysing brain activity related to memory, neuromarketing can help predict which advertising elements are more likely to be remembered by consumers (Mashrur et al., 2022), with this information retention capacity being crucial for predicting the long-term effectiveness of a marketing campaign. Consequently, neuromarketing seeks to understand the connection between the brain and consumer behaviour to enhance marketing strategies and create more effective and engaging experiences for customers (Rodrigues et al., 2022).

Artificial Intelligence

AI is a field of computer science that focuses on the development of systems and computer programs capable of performing tasks that typically require human intelligence (Carrozza et al., 2019). These tasks include learning, reasoning, problem solving, visual perception, speech recognition, and decision making. One of the main branches of AI is machine learning, which focuses on developing algorithms and models that enable machines to learn from data (Badrulhisham et al., 2023). Instead of following programming rules, machines can improve their performance as more information is provided (Costa-Climent et al., 2023). Another branch is artificial neural networks, which are inspired by the functioning of the human brain. These are deep learning systems used in many AI applications (N. T. Pham et al., 2023), such as image recognition, natural language processing, and games. Natural language processing (NLP) focuses on the interaction between computers and human language (Ning, 2022), enabling machines to understand, interpret, and generate human language in a meaningful way, with applications like chatbots, automatic translation, and sentiment analysis.

Computer vision deals with teaching machines to interpret and understand visual content (Sharrab et al., 2022). It is used in applications such as facial recognition, image classification, and autonomous vehicles. Expert systems are computer programs that mimic the ability of a human expert in a specific field to make decisions based on predefined data and rules, while intelligent agents are software or hardware entities that observe their environment and take actions to achieve goals (ranging from a simple chess program to a complex autonomous vehicle) (Adewale & Lee, 2023). AI has applications in a wide variety of fields, from healthcare and education to industry and entertainment. As technology continues to advance, the integration of AI into various aspects of human life is likely to increase.

Artificial Intelligence Applied to the Prediction of Consumer Behaviour

AI plays an increasingly significant role in predicting consumer behaviour. Through the analysis of vast amounts of data, AI can identify patterns, trends, and correlations that help forecast how consumers will behave in the future. Some applications of AI to the prediction of consumer behaviour use big data analysis, in which large amounts of data from various sources such as social media, online transactions, browsing histories, etc. are processed, identifying consumer behaviour patterns and preferences (Davahli et al., 2020). AI utilises machine learning algorithms to analyse a consumer's past behaviour and predict their future preferences, enabling businesses to customise product recommendations, advertising, and offers to align with the individual interests of each customer (Jupalle et al., 2022). With customer segmentation, AI can group consumers according to their behaviour and preferences, helping businesses to better understand their audience and adjust their marketing and sales strategies to cater to each segment. On the basis of this information and with the assistance of advanced algorithms, AI can forecast product or service demand, which is crucial for inventory management and supply chain planning, as companies can adjust their stock levels based on AI predictions.

AI-powered chatbots can interact with consumers in real time, providing quick answers to questions and assisting in the purchasing process. Additionally, they collect data on user interactions, which can be fed into predictive models. On an emotional level, AI can analyse natural language on social media, product reviews, and other online comments to assess consumer sentiment towards a specific brand or product (Magni et al., 2023). This sentiment analysis provides valuable insights into consumer perception and can help predict trends and even anticipate the likelihood of a customer's leaving a brand, enabling companies to implement proactive customer retention strategies, such as personalised loyalty programs or targeted marketing campaigns (A. A. A. Ahmed et al., 2022). In summary, the application of AI in predicting consumer behaviour provides companies with the ability to make more informed decisions and customise their strategies to meet the changing needs of customers in a dynamic market.

MATERIALS AND METHODS

The objective of this research is to determine the level of accuracy and precision achieved by AI in predicting levels of visual attention and attraction in consumer behaviour resulting from visual stimuli. The research relies on the measurement, through neurotechnology, of a neuromarketing study with real consumers using eye tracking.

Objectives

This research aims to analyse the current level of prediction of consumer behaviour resulting from brand stimuli by AI, comparing the results with an analysis conducted using neuromarketing tools. The study records consumers' levels of attraction and visual attention to static advertising stimuli. The main objective is to compare the prediction of human attention behaviour with the actual recorded data, using AI for prediction and neurotechnology for the empirical part.

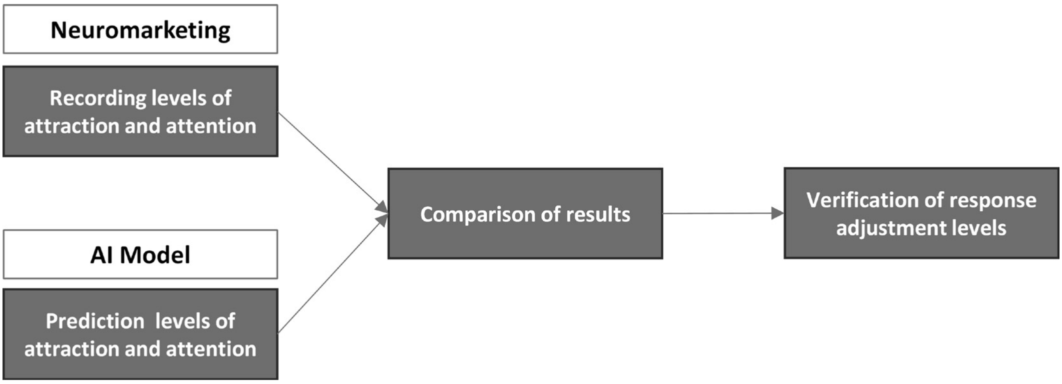
Specific objectives include the following:

- Quantitatively evaluate levels of attraction and visual attention to static brand stimuli by consumers using neurotechnologies.
- Quantitatively predict levels of attraction and visual attention to the same static brand stimuli by AI.
- Compare the results obtained for the recorded and analysed variables.
- Verify the degree of agreement between the responses provided by AI and the values recorded through neurotechnology measurement.

Research Instrument

The combination of neuroscience with traditional research (qualitative or quantitative) has given rise to the relatively new research discipline of neuromarketing (Juárez-Varón, Bellido-Garcia, et al., 2023). Technological advancements are allowing this field to go beyond traditional quantitative and qualitative research tools, focusing on consumers' brain reactions to stimuli (Juárez-Varón, Mengual-

Figure 1. Graphical Representation of the Proposed Approach (Source: Prepared by the authors)



Recuerda, et al., 2023). Research with neurotechnologies aims to connect neuronal system activity with consumer behaviour, offering a wide range of applications for brands, products, services, or communication. This research can determine purchasing intent, preferences, novelty level, knowledge, or generated emotions. Butler (2008) proposes a research model connecting marketing researchers, professionals, and stakeholders, emphasising the need for more research to establish the academic relevance of neurotechnologies.

Theoretical research with neurotechnologies is grounded in neuroscience, utilising neuroimaging techniques in this emerging field to test hypotheses, enhance existing knowledge, and examine the effect of marketing stimuli on consumers´ brains (Mengual-Recuerda et al., 2020). Research has established that brain activity patterns are closely related to behaviour and cognition. Therefore, the research technique used in this study is neuromarketing, using eye tracking. Its purpose is to measure the levels of attention and visual attraction generated by the areas of interest of the stimuli projected to users. The neurodata used are based on eye tracking, which records the movement of the pupils and their fixations on stimuli.

Sample Characteristics

In the present research, the sample consisted of male and female university students in their final year of undergraduate and master's programs, aged between 22 and 25 years old. A total of 30 individuals (50% men and 50% women) participated randomly and voluntarily as study subjects after meeting the criteria. The selected city was Valencia, Spain. The sample size (composed of 30 individuals) was suitable for a neuromarketing study (Cuesta-Cambra et al., 2017). After conducting the empirical study, 2 users were excluded (1 male and 1 female), leaving 28 users. The work was focused on the first moments of observing a graphic stimulus, so the profile of the sample is not as influential, because the mental patterns are similar, and this is how the AI predictive model has been trained.

Data Collection and Analysis

The neuromarketing research phase with images was performed using the eye tracker model Gazepoint GP3HD, with a 150-Hz sampling rate. For data collection, Gazepoint Analysis UX Edition v.6.11.0 software was used. The AI research phase with images was performed using Decoditive Spark v.1.0 software, from the Decoditive software manufacturer. Statistical analysis of the data was conducted using R software, v.3.6.3. The independent variable was the sex of the participants, with a similar sociocultural profile in all of them, and determined by the main profile of the company’s target. The dependent variables were the level of attention and attraction recorded in response to the observed stimuli. The sample size involved in neurotechnology studies is not large enough to be able to incorporate metrics of statistical significance or confidence intervals. The reliability of the results can be analysed when a quantitative study is combined with neuromarketing. In studies based on neurotechnologies, sample sizes are small (focused on the specific requirements of each biometric), and scientific validation is determined by mental patterns.

Different AI models have been used based on image processing, and a combination of AI and computer vision. Image-processing AI models have the ability to understand, interpret and manipulate visual data, much like the human visual system. One of the main algorithms in image processing is convolutional neural networks (CNN). CNNs are deep learning algorithms used to analyse and classify images; they are particularly useful for image recognition tasks such as object detection, image segmentation, and facial recognition. The neuromarketing tools used were eye tracking neurotechnologies. These models have been trained with data from people who have been looking at different sources (around 20,000 images in total) while eye tracking was performed with hardware in neuromarketing laboratories. Its validation was carried out by measuring the effectiveness of the output generated by the AI model, compared with the data provided by the eye tracking study with real users who were measured with one of the most precise hardware devices on the market, showing very positive results. The models are images with saliency maps superimposed, which indicate the points of attention within the image and which have been collected during the study in the laboratory. With those images, whose maps have been translated into numbers, a model was trained that allows the reverse process to be done; that is, when an image enters it, it outputs that image with the saliency map from which the heat map is drawn and all the other neuromarketing variables are obtained.

A Gazepoint GP3HD desktop eye tracker was used, with a 150 Hz sampling rate. The use during the empirical part was based on an individual calibration per user, and the same stimuli were projected that were incorporated as inputs in the AI-based predictive model. Quantitative data analysis was used to evaluate the seconds that elapsed between the appearance of the stimulus and the first fixation, or the time first fixation (TFF); the total number of seconds of attention to each area of interest; the percentage of views; and the order of visualisation. The qualitative evaluation was performed using thermal maps of the attention registered by the eye tracker.

The study is based on two global metrics: a comparison of the AOIs (areas of interest) identified manually and their equivalents identified by the AI model (success in automatic identification of AOIs), and, on the other hand, the attraction and visual attention measurement metrics of each AOI, expressed as AOI % views (%), AOI average time to first view (sec), and AOI Average time viewed (sec). The differences relating to visual attraction (time recorded for first viewing) are justified by the order differences predicted by the AI. However, regarding visual attention (average viewing time of each area of interest), the AI predicts very similar behaviour, with similar times. On the basis of the AI's history of creative stimuli, the model predicts a greater attraction (time elapsed until they look at it) towards the protagonist's face and less attraction towards the commercial message. Similarly, it predicts greater visual attention to the face and less attention to the commercial message. Reality, for this stimulus, indicates that the line and the face are viewed at practically the same time (you see the face first, but you immediately look at the commercial message) and that more time is spent on the first line of message than on the face. This may be justified because we are analysing the first moments, in which the user is tracking the objects of the stimulus, visualising the images more quickly than the texts.

RESULTS

Comprehensive Analysis of Attention

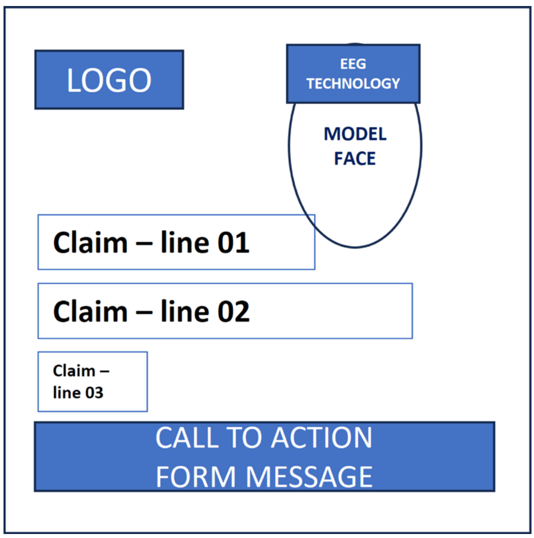
The visual stimulus used is an image extracted from a social network (Instagram), belonging to an advertisement from the company Brain User Experience, S.L., with the company's authorisation (Figure 2).

Table 1. Description and Coding of Manually Proposed AOIs

AOI Name	Coding
AOI 01 – Logo	AOI 1
AOI 02 – EEG device worn by the protagonist of the ad	AOI 2
AOI 03 – Line 1 of the ad's claim	AOI 3
AOI 04 – Line 3 of the ad's claim	AOI 4
AOI 05 – Line 2 of the ad's claim	AOI 5
AOI 06 – Face of the ad's protagonist	AOI 6
AOI 07 – Rectangle of the form message	AOI 7

Source: Prepared by the authors.

Figure 2. Scheme of Elements of the Original Image (Source: Prepared by the authors)



The manually proposed AOIs with the Gazepoint eye-tracking program are shown in Table 1. The description of each AOI is indicated in Table 1.

The importance of AOIs is based on the graphical and textual elements that appear in the stimulus.

The automatically proposed AOIs by the AI, using the Decoditive Spark program, are shown in Table 2. The description of each AOI is indicated in Table 2.

Below are the results for the heat map generated by the eye tracking program after the complete viewing of the user group, and the results for the heat map generated by AI in predicting visual attention (Figure 3 and Table 3). The heat maps match the visual attention areas, with a higher distribution of attention towards the form rectangle in actual behaviour, compared to a greater visual attention towards the "claim" in the AI prediction.

Table 3 shows the visual attention and attraction data generated by the eye tracking software, after aggregating the data from 28 users:

Similarly, Table 4 displays the predicted visual attention and attraction by the AI:

Table 2. Description and Coding of AOIs Proposed by the AI

AOI Name	Coding
AOI 01 – Logo	1AOI
AOI 02 – EEG device worn by the protagonist of the ad	2AOI
AOI 03 – Line 1 of the ad's claim	3AOI
AOI 04 – Line 3 of the ad's claim	4AOI
AOI 05 – Line 2 of the ad's claim	5AOI
AOI 06 – Face of the ad's protagonist	6AOI
AOI 07 – Rectangle of the form message	7AOI

Source: Prepared by the authors.

Figure 3. Heat Maps Generated by Eye Tracking Technology (a) and AI Model (b) (Source: Prepared by the authors)

The differences between the percentage of users who viewed the AOIs, with the eye tracking software (neuromarketing study) and the values predicted with the AI software are shown below (Table 5):

The level of approximation of the AI's behaviour prediction was quite tight, being minimal in the case of the logo (0.30% difference) and higher in the face of the protagonist of the ad (25.00% difference). Regarding the texts, differences ranged between 3.77% and 10.61%. Overall, the average difference was 8.64%.

Below are the results for the fixation maps generated by the eye tracking program after the complete viewing of the user group and the fixation map generated by AI in predicting visual attraction (Table 6). The order established by visual attraction in the consumer group is shown in Figure 5, compared to the forecast generated by the AI software, shown in Figure 5b. Following this, Table 6 shows the display order, based on the visual attraction generated, for the consumer group and by the AI behaviour prediction.

The AI shows a prediction of seven fixations, which is why the first seven fixations measured in neuromarketing research have been shown in the table. This is the order followed by the gaze for the

Table 3. Visual Attention and Attraction Data Generated by the Eye Tracking Software

AOI Name	Viewers (%)	Avg. Time to 1st View(sec)	Avg. Time Viewed (sec)
AOI 01 – Logo	45.00%	1.08	0.64
AOI 02 – EEG device worn by the protagonist of the ad	75.00%	1.41	0.91
AOI 03 – Line 1 of the ad's claim	100.00%	0.95	0.90
AOI 04 – Line 3 of the ad's claim	75,00%	2.23	0.71
AOI 05 – Line 2 of the ad's claim	100.00%	2.96	0.37
AOI 06 – Face of the ad's protagonist	75.00%	1.45	0.49
AOI 07 – Rectangle of the form message	100.00%	4.22	1.55

Source: Prepared by the authors.

Table 4. Visual Attention and Attraction Data Generated by the Eye Tracking Software

AOI Name	Viewers (%)	Avg. Time to 1st View(sec)	Avg. Time Viewed (sec)
AOI 01 – Logo	44.70%	0.75	0.45
AOI 02 – EEG device worn by the protagonist of the ad	69.60%	2.25	0.35
AOI 03 – Line 1 of the ad's claim	89.39%	1.75	0.78
AOI 04 – Line 3 of the ad's claim	78.77%	2.00	0.73
AOI 05 – Line 2 of the ad's claim	91.85%	1.00	0.85
AOI 06 – Face of the ad's protagonist	100.00%	0.50	0.95
AOI 07 – Rectangle of the form message	93.04%	0.25	0.88

Source: Prepared by the authors.

visualisation of the stimulus, for the group, according to the fixation map. Comparative consumer registry - AI behaviour prediction.

The order established by the AI differs in the first, fourth and seventh element looked at, coinciding in the second, third, fourth and fifth element. The AI centred the first element to be displayed (initial

Table 5. Difference in the Percentage of Users Who View the AOIs, Between Neuromarketing and AI

AOI Name	Viewers (%)		Difference (%)	
	Real Eye tracking	IA Eye tracking	Absolute Difference	Relative Difference
AOI 01 – Logo	44.70%	45.00%	0.30%	0.67%
AOI 02 – EEG device	69.60%	75.00%	5.40%	7.76%
AOI 03 – Line 1 of the ad's claim	89.39%	100.00%	10.61%	11.87%
AOI 04 – Line 3 of the ad's claim	78.77%	75.00%	3.77%	4.79%
AOI 05 – Line 2 of the ad's claim	91.58%	100.00%	8.42%	9.19%
AOI 06 – Face of the ad's protagonist	100.00%	75.00%	25.00%	25.00%
AOI 07 – Rectangle of the form message	93.04%	100.00%	6.96%	7.48%

Source: Prepared by the authors.

Table 6. Order Followed by the Gaze, According to the Fixation Map, Comparing Neuromarketing With AI

Order followed	1	2	3	4	5	6	7
Consumer behaviour	AOI 03	AOI 06	AOI 01	AOI 06	AOI 05	AOI 07	AOI 04
A.I. prediction order	AOI 07	AOI 06	AOI 01	AOI 05	AOI 05	AOI 07	AOI 03

Source: Prepared by the authors.

Table 7. Differences in Attraction and Visual Attention Between Neuromarketing and AI

AOI Name	Visual Attraction Avg Time to 1st View(sec)			Visual attention Avg Time Viewed (sec)		
	Real Eye tracking	IA Eye tracking	Absolute Difference	Real Eye tracking	IA Eye tracking	Absolute Difference
AOI 01	1.08	0.75	0.33	0.64	0.45	0.19
AOI 02	1.41	2.25	-0.84	0.91	0.35	0.56
AOI 03	0.95	1.75	-0,80	0.90	0.78	0.12
AOI 04	2.23	2.00	0.23	0.71	0.73	-0.02
AOI 05	2.96	1.00	1.96	0.37	0.85	-0.48
AOI 06	1.45	0.50	0,95	0.49	0.95	-0.46
AOI 07	4.22	0.25	3.97	1.55	0.88	0.67

Source: Prepared by the authors.

attraction element) on the form, ending again with the form and the first line of text. Research in neuromarketing tells us that the group of consumers started with the first line of text (which is logical, since it is in the centre of the image), ending with the form and the first line of text again. Due to the order changes at the beginning and end of the fixation map, there is a difference in times (times until the first fixation) between the displayed elements. The differences in attraction and visual attention between neuromarketing measurements and AI prediction are shown below (Table 7):

The differences relating to visual attraction (time recorded for first viewing) are justified by the order differences predicted by the AI. However, regarding visual attention (average viewing time of each area of interest), the AI predicts very similar behaviour, with similar times.

DISCUSSION

Predicting consumer behaviour involves the use of various techniques and tools to anticipate the future actions and decisions of consumers. This prediction, in response to brand stimuli, involves understanding how individuals will react emotionally and cognitively to various marketing signals, advertising, and brand experiences. Predicting behaviour entails assessing how experiences at different touchpoints, from advertising to purchase and post-sale service, will influence customer satisfaction and loyalty. This requires a profound understanding of emotions, neurological responses, and consumer experiences. Companies must use a combination of market research, data analysis, neuromarketing techniques, and active monitoring to anticipate and proactively respond to consumer behaviour dynamics.

The goal of neuromarketing is to use tools and techniques from neuroscience to analyse the brain and physiological responses of individuals to marketing stimuli, such as advertisements, product packaging, and shopping experiences. Its purpose is to identify which sensory elements (visual, auditory, tactile, etc.) evoke positive or negative emotions that may influence purchasing decisions. By understanding how consumers experience different aspects of the purchasing and product usage process, companies can enhance the overall customer experience. AI is playing an increasingly significant role in predicting consumer behaviour. By analysing vast amounts of data, AI can identify patterns, trends, and correlations that assist in forecasting how consumers will behave in the future.

In terms of its empirical contribution, this study compares the results of an AI tool designed to predict consumer behaviour in response to visual stimuli with the outcomes observed, using neuromarketing as the research technique, in a group of consumers exposed to the same stimuli, The analysis focused on a visual record of attraction and attention, using eye tracking to provide data on the percentage of users who viewed each area of interest, the time taken to view the areas (attraction), and the time spent looking at them (attention). The differences relating to visual attraction (time recorded for first viewing) are justified by the order differences predicted by the AI. However, regarding visual attention (average viewing time of each area of interest), the AI predicts very similar behaviour, with similar times. On the basis of the history of creative stimuli of the AI, the model predicts a greater attraction (time elapsed until they look at it) of the protagonist's face and less attraction towards the commercial message. Similarly, it predicts greater visual attention to the face and less attention to the commercial message. Reality, for this stimulus, indicates that the line and the face are viewed at practically the same time (you see the face first, but you immediately look at the commercial message) and more time is spent on the first line of the message than on the face. This may be justified because we are analysing the first moments, in which the user is tracking the objects of the stimulus, visualising the images more quickly than the texts. The study is framed within the validation of AI tools for predicting human behaviour in response to visual stimuli presented by brands (Ferruz-Gonzalez et al., 2023). To align both methods of consumer behaviour analysis, the sample, size, and stimulus were configured in the same way. The research technique used in this study is neuromarketing, monitored with eye tracking neurotechnology. Its purpose is to measure the cognitive processing of the response to a visual stimulus from a commercial brand.

Visual behaviour allows humans to comprehend and interact with a vast amount of information, a capacity challenging to replicate in AI systems. The success of predicting the scan path depends largely on whether this image information can provide a sufficiently rich representation for prediction. We worked with a representation of gaze behaviour that focused on regions of interest in images, defined by natural and collective gaze behaviour. These regions (referred to as interest-based regions) can be used to segment images for semantic labelling and to provide a basis for shared representation among observers. Without any additional labels or image information, we achieved highly accurate sequence prediction using this interest-based image representation (Guo et al., 2023).

The neurodata used was based on eye tracking, which records levels of visual attraction and attention in cognitive perception of stimuli. Overall results, as observed in group behaviour, revealed that the values predicted by AI aligned well with those recorded by the neuromarketing technique. This research aims to examine a neural network (AI) as an alternative model for investigating the phenomenon of neuromarketing. Neuromarketing is comparatively new as a technique for designing marketing strategies, especially advertising campaigns. Currently, only large companies can access neuromarketing studies, so SMEs cannot access information that allows them to grow and know their customers more quickly and deeply. With this software, based on an image-processing AI model, they can obtain similar information with a much lower budget than traditional neuromarketing studies. Findings suggest that a neural network (AI) is an alternative to traditional neuromarketing tools (R. R. Ahmed et al., 2022). Consequently, the evolutionary state of AI tools for predicting consumer behaviour in response to visual stimuli is approaching the level of results offered by neuromarketing.

An enhancement option for the analysis of this work is the application of big data in neurotechnology, which allows us to leverage large datasets related to brain activity to enhance understanding of consumer decision making (Gupta et al., 2023). Analysing large sets of functional neuroimaging data, EEG, magnetoencephalography (MEG), and other neurophysiological data can help researchers better understand brain function and the underlying mechanisms of various consumer behaviours. Analysing large datasets of brain signals can improve the ability of BCIs to interpret user intentions and translate them into specific actions. In summary, the application of big data in neurotechnology has the potential to revolutionise our understanding of consumer emotional behaviour by leveraging the vast amount of available data to gain meaningful insights and improve predictions of brand stimulus response.

CONCLUSION

This work can be considered a contribution to the development of empirical research aimed at gaining a better understanding of AI tools for predicting consumer behaviour, crucial for evaluating how brand consistency will impact consumer perception and their willingness to interact and make purchases. Through neurotechnology, the cognitive perception evaluation of final-year undergraduate and master's students, aged between 22 and 25, was collected in response to a visual advertising stimulus from a brand. A neuromarketing research approach was used, utilising neurotechnologies that allowed the analysis of visual attraction and attention. The objective was determine how closely current AI tools designed for predicting human behaviour align with actual consumer behaviour when consumers are exposed to visual stimuli, taking into account their initial or normal state. Attraction and visual attention values were recorded for AOIs; user responses during visualisation were also analysed, and the brain activity generated was captured.

The most significant aspects of the analysis were the percentage of users who viewed the AOIs and the visual attention. Regarding the difference in the percentage of users who viewed the AOIs, the level of approximation of the AI's behaviour prediction was quite close. The order established by the AI differed in the first, fourth and seventh elements looked at, coinciding in the second, third, fourth and fifth element. The AI centred the first element to be displayed (initial attraction element) on the form, ending again with the form and the first line of text. Research in neuromarketing tells us that the group of consumers started with the first line of text (logical, since it is in the centre of the image), ending with the form and the first line of text again. Due to the order changes at the beginning and end of the fixation map, there was a difference in times (i.e., times until the first fixation) between the displayed elements. Finally, the differences relating to visual attraction (time recorded for first viewing) were justified by the order differences predicted by the AI. However, regarding visual attention (average viewing time of each area of interest), the AI predicted very similar behaviour, with similar times.

The results of this study revealed that, regarding the predicted percentage of users who would view each area of interest, the AI's level of approximation to reality is very good, with similar values except for the protagonist's face and the first line of the commercial message. Concerning visual attraction (time until the first viewing of each area of interest), based on the fixation map, the order predicted by AI was quite similar to the real order observed in the consumer group. Historical data recorded by AI allows for a fixation map very similar to reality to be generated, with variations primarily in the initial and final areas of interest. It is worth noting that AI requires more data to make predictions, especially of the initial visual behaviour. Finally, regarding visual attention (time spent viewing each area of interest), the times predicted by AI were very similar to those recorded in the neuromarketing study using eye tracking. As a result, specific research objectives have been addressed, concluding that the percentage of users viewing areas of interest was similar, the times needed for the first viewing differed due to changes in the order predicted by AI, and the times spent viewing each AOI showed minimal differences. Thus, some differences are evident between predictions of emotional intelligence related to visual attraction and those recorded through neurotechnology, but the emotional intelligence tool made very accurate predictions of consumer behaviour in response to visual stimuli.

The findings achieved thanks to the predictive AI visual attention model are focused on validating the stimuli created by brands for their communication, thus optimising their efficiency in commercial strategies and campaigns. Only those creative stimuli that are aligned with the communication strategy (promoting a brand or product) will be used in advertising campaigns.

LIMITATIONS AND FUTURE RESEARCH

The limitations of the AI predictive model are based on the time spent (only the first moments) and the lack of recording of emotional activation. However, improvements planned for future versions include a user profile and more extensive exposures, as well as an emotional activation registry based on facial recognition. This is possible thanks to current training work through profile registration, longer times, and facial recognition. Similarly, future work will consider external factors that could have influenced the results of AI and neuromarketing studies, such as the context of the advertisement or the characteristics of the product being advertised. Consumer diversity, as well as cultural factors, are key in the attentional and emotional response of users. However, this AI tool focuses on predicting visual attraction and attention in the first moments, where the visual pattern is common to all users.

The improvements to the AI predictive model are aimed at using longer dedicated times and incorporating a record of emotional activation. Regarding the use of neurotechnologies, future improvements are aligned with the use of online software, based on the use of the webcam, which facilitates the relocation of the study. The model is highly scalable, since it is completely predictive and does not necessitate analysing people in physical settings, such as laboratories, which was the standard practice until now. The model simply receives an image, processes it, and returns the final outputs in a matter of seconds. It can be applied to any visual content, both image and video, and in most sectors.

ETHICAL CONSIDERATIONS

The use of AI does not imply having knowledge of real user data, so there are no ethical or privacy implications. Regarding the study that uses neurotechnologies, all participants have been duly informed of the project, the objectives, the technologies and the protection of their data.

COMPETING INTERESTS

The authors of this publication declare that there are no competing interests.

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