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RESEARCH ARTICLE

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Predicting consumer ad preferences: Leveraging a machine learning approach for EDA and FEA neurophysiological metrics

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Abstract

This research unveils to predict consumer ad preferences by detecting seven basic emotions, attention and engagement triggered by advertising through the analysis of two specific physiological monitoring tools, electrodermal activity (EDA), and Facial Expression Analysis (FEA), applied to video advertising, offering a twofold contribution of significant value. First, to identify the most relevant physiological features for consumer preference prediction. We integrated a statistical module encompassing inferential and exploratory analysis tools, which identified emotions such as Joy, Disgust, and Surprise, enabling the statistical differentiation of preferences concerning various advertisements. Second, we present an artificial intelligence (AI) system founded on machine learning techniques, encompassing k-Nearest Neighbors, Support Vector Machine, and Random Forest (RF). Our findings show that the RF technique emerged as the top performer, boasting an 81% Accuracy, 84% Precision, 79% Recall, and an F1-score of 81% in predicting consumer preferences. In addition, our research proposes an eXplainable AI module based on feature importance, which discerned Attention, Engagement, Joy, and Disgust as the four most pivotal features influencing consumer ad preference prediction. The results indicate that computerized intelligent systems based on EDA and FEA data can be used to predict consumer ad preferences based on videos and effectively used as supporting tools for marketing specialists.

KEYWORDS

advertising, consumer ad preferences, consumer neuroscience, emotions, explainable artificial intelligence, machine learning

1 | INTRODUCTION

Predicting consumer ad preferences poses a formidable challenge for measurement, anticipation, and generalization in marketing research. Preferences that influence decision-making are often shaped by unconscious choices, stemming from patterns of brain activity that elude measurement through conscious assessments, such as questionnaire responses (Dijksterhuis, 2004; Kawasaki & Yamaguchi, 2012).

Advertising plays a key role in consumer choices (Barroso & Llobet, 2012; Meenaghan, 1995). The hierarchy of the advertising effects model has significantly influenced the development of advertising research by providing a structured approach to understanding the impact of advertising on consumer behavior (Vakratsas & Ambler, 1999). Complementary, cognitive and affective appraisal theories (Smith & Ellsworth, 1985) on advertisements lead to emotional reactions either through peripheral or supporting cues, as the Elaboration Likelihood Model (ELM) shows (Petty & Cacioppo, 1986), and with lower levels of cognitions in low-order emotions than in high-order emotions (Poels & Dewitte, 2019). The influence of advertisements on emotions is well documented through explicit measures (see the meta-analysis by Eisend & Tarrahi, 2016), but less so with neurophysiological measures for unveiling how neuroscientific metrics predict consumer outcomes in terms of ad preferences (Guixeres et al., 2017; Venkatraman et al., 2015).

Neurophysiological monitoring for gauging emotions permits a closer examination of emotional activity, thus minimizing cognitive bias (Thompson et al., 2021). Casado-Aranda et al. (2023) suggest the relevance of brain imaging tools and advanced machine learning (ML) techniques in communication research. This approach offers valuable insights into how ad preferences influence consumer behavior (Cherubino et al., 2019; Sandy et al., 2013; Venkatraman et al., 2012). Nevertheless, harnessing the full potential of these advantages has its challenges. Although brain imaging tools, such as functional magnetic resonance imaging (fMRI), positron emission tomography and functional near-infrared spectroscopy are considered reliable sources of neurophysiological activity, collecting data on consumer ad preferences from video advertising presents challenges related to complexity of experimental design, cost of equipment (Yoon et al., 2009) and a temporal resolution of approximately 2–5 s (Venkatraman et al., 2015). Instead, neurophysiological tools related to the autonomous nervous system, such as electrodermal activity (EDA) and facial recognition, are easy and affordable to implement for studying responses to advertising (Alvino et al., 2020) providing relevant data for managers and researchers.

Until recently, researchers primarily relied on descriptive and inferential statistical methods, including regressions and specialized software for processing such data (Casado-Aranda et al., 2023; Mañas-Viniegra et al., 2020). Nevertheless, with the increase in data dimensionality and complexity, integrating different sources such as surveys with physiological data, there is a need to consider nonlinear and multidimensional analysis, which is almost impossible with conventional statistical analysis. In this context, the use of artificial intelligence (AI), with ML or deep learning (DL) techniques, has proven instrumental in providing reliable and effective predictive accuracy for models (Ngai & Wu, 2022).

ML algorithms in conjunction with neurophysiological tools have benn attracting research attention (Gill & Singh, 2022; Hakim et al., 2021; Juárez-Varón et al., 2020; Zeng et al., 2022), which is reflected in a systematic review of Electroencephalogram (EEG) (Byrne et al., 2022). Further, Mashrur et al. (2022) proposed a two-stage ML approach using a support vector machine (SVM) for feature selection and classification of consumer preferences while monitoring EEG and eye-tracking and particularly in predictive modeling in advertising (Guixeres et al., 2017; Venkatraman et al., 2015), in marketing (Chen et al., 2015) and brand perception (Chen et al., 2015; Marques dos Santos & Marques dos Santos, 2024).

Following the significant growth in AI adoption, a set of techniques identified as eXplainable AI (XAI) is dedicated to developing strategies that enable end-users to understand, trust, and effectively manage the results presented by different AI systems (Barredo Arrieta et al., 2020; Longo et al., 2020). It should be considered an additional computational tool for supporting marketing practitioners and researchers to deploy practical applications and interpret results provided by AI-based solutions (Senoner et al., 2022).

Built on two neurophysiological tools and the use of inferential analysis, ML and XAI, this research aims to detect drivers of ad preference. The monitoring tools adopted, create a minimal direct intervention, allowing a comfortable and natural environment for the participant during the data collection. Thus, the detection of emotional arousal based on EDA, which only requires two sensors in two fingers of the participant, which are not susceptible to noise, and Facial Expression Analysis (FEA), collecting frames of images from the participant's face using a webcam accurately, facilitates accurate data collection. Further, according to our knowledge, prior research has not yet explored the combination of EDA and FEA exclusively in tandem with ML algorithms. Also, a noticeable gap exists in studies that consider the use of XAI techniques to elucidate the outcomes produced by AI and ML classifiers or predictors. XAI is dedicated to developing strategies that enable end-users to understand, trust, and effectively manage the emerging era of AI systems (Barredo Arrieta et al., 2020).

Considering the problem under study, two research questions are defined: (i) Which emotions and emotional arousal features are the most relevant for consumer ad preference prediction? (ii) How can ML techniques support marketing strategies for predicting consumer ad preferences based on FEA and EDA physiological monitoring tools?

This study contributes to the literature in two ways: (i) to identify the most relevant features concerning the predictive analysis of consumer ad preferences using a two-step process, inferential statistics to discern statistically significant variations in brand preferences, and an XAI based on ML to measure the relative importance of each monitored feature in predicting consumer ad preferences; (ii) developing a computerized intelligent predictive system based on ML to predict consumer ad preferences based on EDA and FEA features.

It is important to note that the proposed approach does not replace current marketing tools, which have a well-established role in consumer ad preference predictions, but rather adds an additional layer of analysis on the monitoring of consumer reactions to advertising based on neurophysiological tools.

2 | LITERATURE REVIEW

2.1 | Predicting consumer ad preferences

The dynamics of consumer responses to advertising are addressed through two primary approaches (Tellis, 2004). The first is a modeling approach that accounts for budgetary and exposure variables in relation to sales. The second is a behavioral approach, which examines consumer responses to creativity-related variables such as message, execution, source, and strategy (Eisend & Tarrahi, 2016). Vakratsas and Ambler suggested a hierarchy of effects starting from the input variables involving the message, followed by filters such as motivation, and ability to process, then, consumer cognition, and affect, and ending with consumer choices. Rosengren et al. (2020) distinguish between immediate and outcome responses. The former refers to affect transfer, processing, and signaling, while outcomes responses relate to attitudinal, memory responses, and sales. A review of the existing literature, particularly the aforementioned meta-analytic studies, suggests a series of interconnected effects that culminate in a preference for an advertisement, manifested as either an effect or likeability towards the ad. This perspective will inform our research approach. We propose that consumer preferences for advertisements can be inferred from emotional and arousal responses, which are linked to immediate reactions that ultimately determine preference as an outcome.

How can advertisers effectively predict which immediate variables affect consumer ad preferences? The answer is usually by using self-report techniques, qualitative tools, or applied advertising tools that capture only one part of an emotional experience, which can be classified as the subjective part (Mauss & Robinson, 2009; Shaw & Bagozzi, 2018). Compared to neuroscientific tools, questionnaires are easy to design, scalable, affordable, and allow access to large subject cohorts (Birmingham & Wilkinson, 2003).

Despite the widespread use of self-assessment tools, marketers face the fact that customers are unskilled at retrospection (Shaw & Bagozzi, 2018). This is because conventional marketing research usually only permits the examination of customer responses to marketing stimuli after they occur (Wang & Minor, 2008). Furthermore, because participants may misremember their experiences or give into social desirability bias, self-report methods may produce data that is inadequate or biased (Wang & Minor, 2008). This limitation is exacerbated by the fact that many processes occur subconsciously (Camerer & Yoon, 2015). As a result, alternative techniques, such as neuroscientific tools, are becoming increasingly popular (see for a review Casado et al., 2023). Therefore, neuroscience tools that measure physiological responses can provide insights that are unavailable using traditional consumer behavioral data, which is free of cognitive bias (Eijlers et al., 2020; Plassmann et al., 2015). Consequently, alternative methods that allow to measure unconscious reactions have been gaining prominence. The subjective component of an emotional experience may include physiological changes and behavioral reactions, such as facial expressions (Caruelle et al., 2019). Emotions are initially felt physically (facial expression, heart rate changes, and sweating), and an individual becomes conscious of emotion only when the intellect interprets these physiological changes. The Stimulus-Organism-Response (SOR) approach (Mehrabian & Russell, 1974) aligns well with the sequence of effects from a neurophysiological perspective (Bigne et al., 2020; Kakaria et al., 2023). In this framework, stimuli are associated with advertisements, while organism changes, derived from emotions (FEA) and arousal (EDA), leading to ad preference as a response. Preferences that influence decision-making are often shaped by unconscious choices, stemming from patterns of brain activity that elude measurement through conscious assessments, such as questionnaire responses (Dijksterhuis, 2004; Kawasaki & Yamaguchi, 2012).

2.2 | The role of emotions in consumer ad preferences

Emotions have long been regarded as robust predictors of advertising effectiveness, given their profound influence on an individual's response to incoming messages (Batra & Stayman, 1990; Geuens et al., 2011). Furthermore, emotions play a vital role in human cognitive processes, as they strongly correlate with Attention, memory, and decision-making (Ekman, 1992; Otamendi & Sutil Martín, 2020) and their interplay between cognition and affect, as explained by the Affect Infusion Model (Forgas, 1995). Given their substantial impact on decision-making (Kemp et al., 2020), advertisers often craft campaigns to elicit specific emotional responses from consumers. Leveraging an emotional tone in advertising captures the audience's Attention, potentially enhancing the appeal of a product. It's worth noting that emotional advertisements tend to be more memorable than their rational counterparts (Otamendi & Sutil Martín, 2020).

Psychological theories on emotions (Frijda et al., 1989; Roseman et al., 1994; Zeelenberg & Pieters, 2006) suggest that a person's future behaviors are greatly influenced by the type of emotion they are experiencing. Furthermore, research has shown that emotions are essential for rational thinking and behavior (Poels & Dewitte, 2006). As the ELM shows, attitudinal responses to advertisements may focus either through peripheral or supporting cues (Petty & Cacioppo, 1986). Consumers' psychological processes range from low elaboration, where mere exposure is needed (i.e., peripheral route), to high elaboration, with more cognitive effort (i.e., central route). Building on these discoveries, academics from various fields—including marketing and advertising—have highlighted how crucial emotions are to understanding human behavior and decision-making, establishing that emotions reveal and can predict consumers' attitudes and behavior (Laros & Steenkamp, 2005).

Ekman's emotional scale is a standard reference model for categorizing emotions (Ekman, 1992), a well-established categorical framework that posits the existence of a limited number of fundamental and discernible emotions. This model delineates seven fundamental emotions suitable for classifying facial expressions: Joy, Anger, Fear, Surprise, Sadness, Disgust, and Contempt (Timme & Brand, 2020).

The assessment of emotions predominantly revolves around comprehending the seven fundamental emotions (Otamendi & Sutil Martín, 2020). Given that customer satisfaction is intricately entwined with emotional requisites, it is implicitly understood that a holistic elucidation or depiction of the satisfaction construct necessitates the incorporation of the influence of consumer emotions (Andreu et al., 2015; Phillips & Baumgartner, 2002). However, emotions frequently reside within the unconscious realm, elucidating the challenge consumers encounter when endeavoring to articulate their sentiments (Harris et al., 2018; Richins, 1997). More specifically, individuals remain oblivious to these emotions when explicitly prompted for their expression, which tends to accentuate the role of emotions in elucidating the effectiveness of marketing strategies.

2.3 | Neurophysiological tools for evaluating advertising impact on consumers

Consumer neurosciences have the potential to identify the emotions evoked during advertisements and to better understand how consumers experience, analyze, and evaluate advertisements, (Alvino et al., 2020; Golnar-Nik et al., 2019; Kaklauskas et al., 2019). Neurophysiological tools can provide insights into consumers' reactions to ads that might otherwise remain inaccessible (Pozharliev et al., 2022).

Neurophysiological tools are typically categorized based on the type of measurements they provide. Firstly, neuroimaging tools can directly detect brain activity (Eijlers et al., 2020; McInnes et al., 2023; Panteli et al., 2024). Despite their usage in communication research (for a review, see Casado-Aranda et al., 2023), they are invasive procedures with high costs and challenging setups (Alvino et al., 2020; Meyerding & Mehlhose, 2020). Alternatively, neurophysiological measurements monitor the autonomous nervous system, including voluntary and involuntary body reflexes (Ramsøy et al., 2018).

For consumer neuroscience purposes, some of the most commonly employed monitoring tools include eye-tracking, EDA, and heart rate (Alvino et al., 2020). Furthermore, FEA are valuable and precise indicators of emotions, and they can be monitored using sensors like electromyography (EMG) or image processing to capture changes in facial expressions through cameras (Kalaganis et al., 2021). EDA and FEA are both cost-effective, easy to use, and have the capacity to offer real-time assessment of neurophysiological activity. This type of activity is often beyond an individual's conscious awareness and control (Balconi & Sansone, 2021). An increasing number of studies employ multiple neuroscientific tools for two main reasons. First, in alignment with neuroscience practices, human signals are collected from various sources to improve diagnostic accuracy. Second, synchronized platforms, such as iMotions, enable the comprehensive collection of diverse consumer neurophysiological data within an accurate time span. While eye tracking and EEG dominate the integrations with other tools, the exclusive use of autonomous nervous system tools is uncommon. Specifically, using tools such as EDA and emotions detected via facial expressions offers a cost-effective alternative for analyzing real-time responses to advertising stimuli. However, their combined analysis remains insufficiently explored in clinical research (Zheng et al., 2024). As posited earlier in this paper, these tools seem helpful as complementary tools in marketing (Baldo et al., 2022) and analysis of food preferences (Pedersen et al., 2021).

2.3.1 | EDA

EDA measures skin conductance or electric resistance, which changes in response to sweat gland activity. Changes in sweat secretion are a standard physical marker for sympathetic activation and have been linked to Attention, arousal, cognition, and emotional responses (Rawnaque et al., 2020). The high sensitivity of the electrodermal system to detect even slight variations in skin conductance explains why EDA is a valuable tool for assessing consumers' emotional arousal (Kalaganis et al., 2021; Li et al., 2022). Its significance lies in the fact that EDA is only affected by the sympathetic branch of the autonomous nervous system and is not affected by the peripheral parasympathetic system, unlike many other physiological tools (Boucsein, 2012). On the other hand, positive and negative emotions can increase arousal levels, so heightened skin conductance levels reflect the intensity of the stimuli rather than their emotional type. EDA measurement enables predicting whether a product or brand will attract consumers' Attention because emotional arousal is a key indication of product and brand choice (Garczarek-Bąk et al., 2021; Reimann et al., 2012). EDA is a simple and cost-effective tool, which is not a direct predictor of valence (positive or negative), indicating why it is seldom used in studies as the exclusive physiological tool and is typically used in conjunction with other neurophysiological techniques (Rawnaque et al., 2020). By measuring fluctuations in arousal levels, EDA provides insights into consumer's comfort or discomfort when viewing an advertisement, thus helping to gauge advertising effectiveness (Rawnaque et al., 2020) (Barquero-Pérez et al., 2020; Simonetti et al., 2024).

2.3.2 | FEA

A facial expression refers to the movement and muscle placement of the face. Decoding facial expressions is particularly important in various fields, including consumer neurosciences, as it can reveal emotions and provide insights into reactions to different perceptual stimuli. The methodology for automatic decoding technology plays a fundamental role in this field, and the primary techniques used are facial EMG (fEMG) and computer-aided decoding technology (Kalaganis et al., 2021).

Computer vision-based approaches take advantage of advances in image processing algorithms and camera technology (Kalaganis et al., 2021). While image processing algorithms used in this context are much more complex than those used in fEMG research, they have yielded significant results in recognizing emotional facial expressions near real-time without requiring sensors attached to the participant. The fundamental principles of image processing algorithms involve identifying facial features and extracting and classifying these features (Canedo & Neves, 2019). There is variability in available facial expression detection systems. Still, two models are commonly used: the FACET model, based on the FACET algorithm, and the AFFDEX model, based on the AFFDEX algorithm by Affectiva Inc https://www.affectiva.com/. Both models recognize facial landmarks and classify emotions using a set of criteria based on psychological theories and statistical processes. They employ various statistical methods, facial expression databases, and landmarks for accurate emotion classification (Canedo & Neves, 2019). Validation studies have confirmed the software's reliable emotion identification (Kulke et al., 2020). The AFFDEX software not only provides the likelihood of an emotional response being present through Ekman's seven basic emotions but also employs three additional indicators of the individual's emotional involvement, namely, Attention (based on the individual's focus during the experiment as determined by the head position), Engagement (emotional responsiveness to the stimuli), and valence (emotional responsiveness to the stimuli) (iMotions, 2020). Several studies have successfully measured advertising effectiveness with FEA tools (Canedo & Neves, 2019; Hamelin et al., 2017; Otamendi & Sutil Martín, 2020).

Since FEA does not evaluate critical cognitive functions, namely memory and sensory perception, its use in consumer neuroscience research is restricted and needs to be complemented with complementary tools (Alvino et al., 2020). EDA equipment is portable and straightforward to assemble, which makes it convenient for field work where it may be used to measure emotional arousal. Nevertheless, the temporal resolution of EDA is limited. In reality, varying skin types might lead to subject heterogeneity in reactions, complicating data aggregation. Furthermore, EDA is highly susceptible to artifacts, which can be eliminated during data analysis by using post-processing technologies. The main limitation of EDA is its inability to ascertain the valence of emotional valence (Alvino et al., 2020). Therefore, EDA has been used in consumer neurosciences studies and other neurophysiological tools (Rawnaque et al., 2020). In summary, to the best of our knowledge, no studies used EDA and FEA to determine consumer preferences through emotions evaluation. Most studies use EDA and FEA in combination with eye-tracking (Ausin-Azofra et al., 2021; Goncalves et al., 2022). According to Venkatraman et al. (2015), eye-tracking can be used as a direct measure of Attention and Engagement and an accurate indicator of Attention (Karmarkar & Plassmann, 2019). Nevertheless, in this case, both Attention and Engagement were measured as indirect measures of FEA (Table 1). Finally, to the best of our knowledge, no studies have considered using ML techniques to predict consumer preferences or select the most relevant metrics based on EDA and FEA.

2.3.3 | Features from EDA and FEA

Considering EDA and FEA as the two approaches adopted in this work, Table 1 presents the definitions of the most relevant features considered to be considered. From the FEA monitoring, the seven emotions (Joy, Surprise, Contempt, Anger, Fear, Sadness, and Disgust) suggested by Ekman (1992), together with two indirect measures of the individual's emotional involvement (Attention and Engagement), while emotional arousal is evaluated based on the EDA monitoring.

TABLE 1 Features considered for FEA, EDA, and indirect measures—attention and engagement.

Detection	Definition	Data collection equipment
Joy	Emotion characteristically results from a sense of connection or pleasurable physical or emotional experience (Gu et al., 2019).	FEA
Anger	Emotion occurs when people are prevented from achieving their goals or are treated unfairly (Gu et al., 2019).	FEA
Fear	Emotion is raised when there is a real or imagined threat to the physical or emotional well-being, and individuals believe they have little control over the situation (Lerner & Keltner, 2000).	FEA
Surprise	Emotion that informs the individual of any deviations from the expectations (Gu et al., 2019). It is considered intrinsically unvalenced (Ortony, 2022).	FEA
Sadness	Emotion is associated with helplessness, loss, failure to obtain desired items, or punishment for getting hurtful items (Gu et al., 2019).	FEA
Disgust	Emotion is illustrated by a strong desire to throw away disagreeable stimuli (Gu et al., 2019).	FEA
Contempt	Emotion is related to the sense of moral superiority over another person or a specific target (Roseman et al., 2020).	FEA
Attention	The amount of conscious 'thinking' happens when an advertisement is being processed (Heath, 2007).	Indirect Measure from FEA
Engagement	The amount of 'feeling' happens when an advertisement is being processed (Heath, 2007).	Indirect Measure from FEA
Emotional Arousal	The signal to the eccrine sweat glands is sent through the sympathetic branch of the autonomic nervous system to activate them when a stimulus is interpreted as personally significant and sets off an emotional reaction (Caruelle et al., 2019).	EDA

Abbreviations: EDA, electrodermal activity; FEA, Facial Expression Analysis.

3 | MATERIALS AND METHODS

It is essential to understand the modeling of the proposed solution as presented in Figure 1. The proposed approach for ad prediction is based on two physiological monitoring tools (EDA and FEA), considering emotional arousal, emotions, attention and engagement. The reporting module is the reference for the AI system to be trained. For the prediction task, three ML techniques are evaluated: Random Forest (RF), SVM and K-Nearest Neighbors (KNN). In addition, the most relevant features are determined considering an inferential analysis, linear correlation and feature importance (FI). The solid lines indicate the flow of the proposed approach. The dashed line (1) indicates that the reporting answers are the labels used by the AI system, and (2), indicates that the variables and labels from the AI system as used for the XAI implementation.

3.1 | Research design

In the scope of the present research, the experimental design is centered on cosmetics advertising tailored to the Chinese female consumer demographic. This focus is attributed to the cosmetics industry's prominence as one of the world's largest sectors, with beauty product consumption attaining global peaks. Notably, China played a pivotal role in this landscape, accounting for approximately 50% of the Asia-Pacific cosmetics market and over one-fifth of the global cosmetics market in 2021 (Statista, 2022). Despite substantial marketing investments, scant attention has been directed toward applying consumer neuroscience tools in cosmetics, with existing research primarily confined to product evaluation studies (Kawabata Duncan et al., 2019; Kikuchi et al., 2021).

An inter-subject experiment was adopted, aiming to fulfill the two proposed research goals. First, to measure and evaluate the fundamental emotions and engagement elicited by a series of advertising stimuli. Secondly, the study aimed to predict the ad preferences of a selected group of Asian and non-Asian cosmetics. This involved the selection of cosmetics brands from South Korea, France, and Brazil (see Table 2). France is the world's largest cosmetics exporter, closely followed by South Korea (Statista, 2023b). Brazil was chosen because it represents the largest cosmetics market in Latin America and has been actively pursuing a globalization strategy, namely towards China (Statista, 2023b). Such a selection encompasses the county of origin effect from the local country under study, the most reputed in cosmetics (i.e., France), and a third country that serves as a control group (i.e., Brazil). Also, we use both rational and emotional advertisement types from each country.

The experiment utilized two monitoring technologies to assess participants' Engagement and emotional response: EDA and FEA. The participants were instructed to observe each advertisement, and during this process, real-time measurements of FEA and EDA responses were recorded. Changes in facial expressions and skin conductance were recorded every 0.016 s for the duration of each ad.

The designed methodology consists of participants watching six cosmetics advertisements, as presented in Table 2, while real-time FEA and EDA were recorded. Two advertisements were from different Brazilian brands, two from a French cosmetic brand, and the last two from a South Korean brand. The participants were not questioned about previous exposure or introduced to the brands before watching the ads. The average duration of the ads is 64.5 s, the shortest ad is 30 s, and the longest is 93 s. After watching the six cosmetics advertisements, which were presented in a fixed sequence,

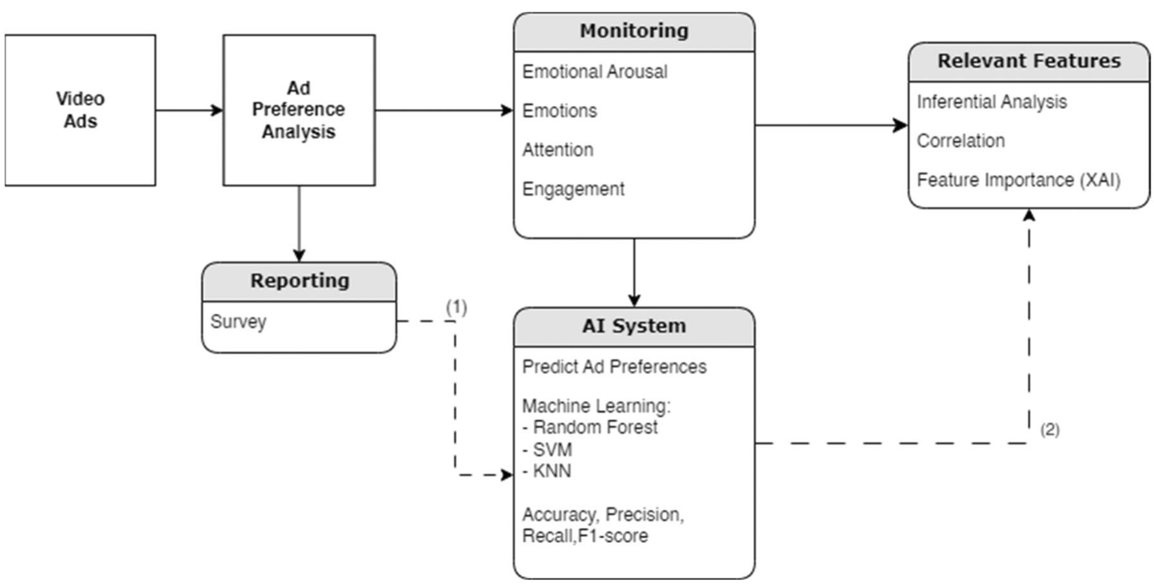

FIGURE 1 General model of the proposed approach for ad preference prediction based on physiological monitoring tools. AI, artificial intelligence.

TABLE 2 Experiment design with the sequence of six cosmetic product advertisements, their duration, tone, and origin.

Steps	Product	Brand	Tone of Ad	Link	Country	Advertisment
1	Skin Ritual | Face Serum (duration: 55 s)	Costa Brazil	Emotional	https://www.youtube.com/watch?v=oQmEHXpnfrQ (Accessed on February 4, 2023)	Brazil	
2	Bum Bum Body Scrub (duration: 93 s)	Sol de Janeiro	Rational	https://www.youtube.com/watch?v=yv9s9VBSB0Y (Accessed on February 4, 2023)	Brazil	
3	Orchidée Impériale High Regeneration Cream (duration: 47 s)	Guerlain	Rational	https://www.youtube.com/watch?v=uEGvl31ewjg (Accessed on February 4, 2023)	France	
4	Orchidée Impériale High Regeneration Cream (duration: 79 s)	Guerlain	Emotional	https://www.youtube.com/watch?v=0IGXRfWeXuM (Accessed on February 4, 2023)	France	
5	Concentrated Ginseng Renewing Serum (duration: 30 s)	Sulwhasoo	Rational	https://www.youtube.com/watch?v=jh7rx14c5P4 (Accessed on February 4, 2023)	Korea	
6	Timetreasure Renovating EX (duration: 83 s)	Sulwhasoo	Emotional	https://www.youtube.com/watch?v=erUdWktpncg (Accessed on February 4, 2023)	Korea	
7	Survey—Participant's Ad Preferences					

the participants were asked to answer a survey identifying the product of their preference.

The six cosmetic product advertisements conveyed distinct messages and incorporated various elements, including images and background music, to evoke emotions and convey messages, as outlined in Table 2. A panel of 10 marketing and business specialists, invited following a convenience sampling, classified each advertisement's "Tone of Ad" as "Emotional" or "Rational" using voting and consensus agreement.

3.2 | Sampling strategy

In behavioral studies, a sample size of 30 to 50 participants is typically considered relevant. (Shaw & Bagozzi, 2018). This study involves a group of 37 potential consumers and products within the cosmetics industry to validate the proposed predictive intelligent system for consumer neuroscience applications. In addition, since socioeconomic status, age, and culture influence various aspects of interest in marketing research, specific demographic criteria need to be established to mitigate potential group-level differences.

Thirty-seven female Chinese individuals aged between 19 and 45 years old (mean age = 28 years, SD = 5.0) have participated in this study. As such, the inclusion criteria for this study was basically to recruit Chinese female aged between 18 and 45 years. A non-probability convenience sampling strategy was adopted to select participants recruited from different sources, such as various companies in Macau SAR, China. This approach is widely used in research, allowing researchers to enroll participants based on availability and accessibility (Mills & Birks, 2014).

The cosmetics industry stands as one of the largest global sectors. In 2022, the cosmetics market witnessed substantial growth, with 93.1 billion U.S. dollars, signifying a remarkable increase of over 16% compared to the previous year. Forecasts project a continuous growth rate of 20.8% between 2023 and 2027 (Statista, 2023b), with China playing a pivotal role in the market in Asia and globally. The beauty market is projected to grow annually by 6.67% (Statista, 2023a). To stand out in a competitive and saturated market, beauty companies are increasingly adopting customer-centric strategies, emphasizing the importance of understanding consumer behavior and providing meaningful experiences (Wu & Lee, 2016). While multinational cosmetics companies offer brief historical insights, there is a need for more substantial evidence on how these companies develop and implement their marketing strategies (Geuens et al., 2011; Statista, 2023b). Recent data indicates that advertisement expenditures in the cosmetics industry surpassed four billion US dollars in 2021 (Statista, 2023b).

Despite substantial investments in marketing, research on consumer neuroscience tools in the cosmetics sector is primarily focused on product evaluation, with limited expansion (Kawabata Duncan et al., 2019; Kikuchi et al., 2021). Companies utilize various physiological and neurophysiological metrics along with traditional marketing assessments to improve consumer behavior evaluation. However, a common issue is the reluctance of companies to share their data, algorithms, and analysis methods, which hampers progress in this field. Confidentiality agreements between consulting firms and advertisers have reduced collaboration with academia, leading to a lack of transparency in commercial study methodologies (Hakim et al., 2021; Núñez-Cansado et al., 2020).

3.3 | Data collection and analytics platform

For the data collection, the iMotions software version 8.2 is used. The experiment used a laptop computer with a 12-in. display, an i7 processor, 16 GB RAM, GPU, and Microsoft Windows 10 operating system. iMotions is an integrated analytic platform designed to assess customer behavior and track various elements of human reactions to marketing stimuli. It can integrate up to six consumer neuroscience instruments, including eye-tracking, FEA, and EDA. iMotions offers external integration through an Application Programming Interface and Lab Streaming Layer (iMotions, 2020). This platform has been used in several studies (Ausin-Azofra et al., 2021; Simonetti et al., 2024). Additionally, it provides a survey creation tool for data collection from participants, which can be triangulated with neurophysiological responses. One of its primary features and advantages is the ability to tailor iMotions to the specific requirements of each study (Alvino et al., 2020). In Figure 1, the data collection is represented in the block called "Experiment Data."

For the data analytics part, the development platform employed was Python, with multiple libraries such as Scikit-learn, Pandas, SciPy, and Numpy (Pedregosa et al., 2011), suitable for the ML data analysis. Also, in Figure 2, the data analytics is represented in the blocks identified as "Statistical Module" and "Artificial Intelligence Module."

3.4 | Data analysis methods

The proposed methodology for the data analysis is outlined in Figure 2 and is divided into two parts. It begins with the inferential and exploratory data analysis, referred to as the Statistical Module. In parallel, the AI module is implemented and is responsible for predicting the participant's preference using ML classifiers. This module is accompanied by another component that explains the most relevant features that contributed to the prediction task: the XAI Module.

As shown in Figure 2, data analysis has been conducted through two modalities: (1) a statistical module using inferent analysis that led to Pearson correlation analysis between positive emotions, Engagement, and Attention, and (2) an AI Module that allowed the classification of the data using ML classifiers to predict consumer preference. An extra step was performed through an XAI module, which allowed us to determine the most relevant features for the system prediction.

Inferential Analysis Analysis of variance (ANOVA) is a statistical method traditionally used in neuroscience research and consumer psychology (Wedel & Dong, 2020; Yu et al., 2022). The two-way ANOVA inferential test is employed in this study to determine whether there are significant statistical differences among more than two subgroups and more than one independent variable, considering all the FEA and EDA features. A two-way ANOVA was performed to evaluate statistical differences in emotions, Attention and Engagement by advertisement and participant. The null hypothesis posits that there are no significant differences between participants or among ads. If the event that the inferential test rejects the null hypothesis, a Tukey post hoc test is conducted to provide a detailed differentiation between subgroups (Pereira et al., 2015).

Finally, the Person correlation is calculated to evaluate if there is a correlation between emotions, Engagement, and Attention, which assigns a value (r) between 0 and 1, with 0 indicating no connection, -1 representing total negative correlation, and 1 indicating total positive correlation. A correlation value of 0.5 or higher between two variables indicates a significant correlation (Nettleton, 2014). A robust statistical correlation is typically considered when a correlation value of 0.7 or higher is observed (Nettleton, 2014).

3.5 | AI

ML techniques, such as predictive algorithms, have been widely used to provide comprehensive analysis when applied to physiological monitoring (Al Machot et al., 2019; Hussain et al., 2021). This work proposes the use of three ML algorithms, based on different classification approaches, to identify the best predictor for consumer ad preferences using EDA and FEA, which are briefly defined as follows (Pedregosa et al., 2011): (i) KNN is an instance-based classifier with no training model in its formulation. The instances are stored during the training phase, and predictions are made through majority voting of neighbors' distance; (ii) SVM: The SVM classifier relies on extracted information from the training data, known as support vectors, used for class separation. This classifier works well with large databases due to its high computational complexity; (iii) Random Forrest (RF): It adopts *decision trees* as the classification approach and is an *ensemble bagging* method, where the predictions are generated from the combination of multiple decision-tree classifiers.

The widespread use of AI techniques for various classification tasks across multiple domains has gained immense popularity. However, due to the complexity and opacity of AI algorithms, there is a growing demand for tools that can explain how these algorithms arrive at their results. In response to this demand, XAI has emerged as an area of study with multiple possible definitions, owing to the various approaches taken to analyze AI techniques (Barredo Arrieta et al., 2020). The goal is to develop a suite of ML techniques that can generate explanations about the models under scrutiny without compromising their performance. This empowers humans to comprehend and trust the tasks performed by AI systems (Barredo Arrieta et al., 2020).

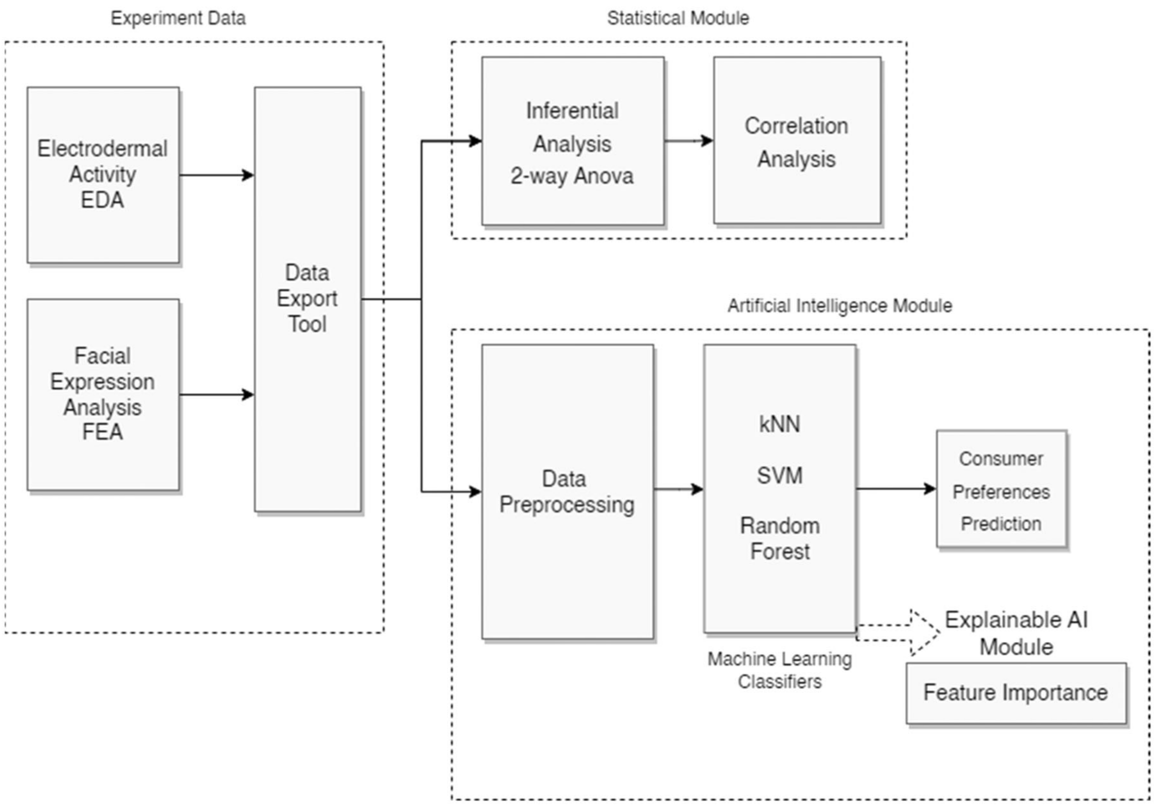

FIGURE 2 Proposed methodology for data analysis.

One crucial aspect of explaining AI systems is determining the most relevant features contributing to successful classification or prediction. This is accomplished through the FI index, which assigns scores to each feature under analysis. The Mean Decrease in Impurity (MDI) technique, also known as the Gini Importance and based on the RF algorithm, is commonly used for this purpose (Han et al., 2016). This approach also offers the potential for reducing unnecessary features in collected data to achieve dimensionality reduction, simplifying future prediction tasks.

The MDI is calculated through an exhaustive testing process with the RF technique, using the provided data to measure how much accuracy is lost when each variable is removed from the model. The greater the decrease in accuracy, the more significant the variable becomes for the success of the classification. The mean reduction in the Gini index measures how each variable contributes to the uniformity of the nodes and leaves in the resulting RF. A higher mean decrease parameter signifies the variable's greater importance in the model (Nembrini et al., 2018).

3.6 | Model validation and performance evaluation

Given the sample size and the research design, the model validation considers the Leave-one-out cross-validation (LOOCV), which uses k-fold cross-validation (Cauley, 2006). The LOOCV is used as an approach of k-fold cross-validation with the maximum computational cost, requiring one model to be created and evaluated for each example in the training data set, but suitable for small datasets, creating a robust estimate of model performance as each row of data is given an opportunity to represent the entirety of the test data set (Gronau & Wagenmakers, 2019). This approach is considered appropriate when an accurate estimate of model performance is critical (Wong, 2015).

To assess the performance of the proposed AI system, we consider four metrics presented in Equations 1 to 4, as follows:

Accuracy (Acc): Computes the percentage of correct predictions, considering all possible cases.

$$Acc = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision: Estimates the performance based on the correct positive prediction rate.

$$P = \frac{TP}{TP + FP} \tag{2}$$

Recall (R): Estimates the performance based on the correct negative prediction rate.

$$R = \frac{TP}{TP + FN} \tag{3}$$

F1-score (F1): This is the harmonic mean of the Precision and Recall metrics, giving an overall idea about both performances.

$$F1 = \frac{2 \times P \times R}{P + R} \quad (4)$$

Where

TP—Total number of true positive cases
TN—Total number of true negative cases
FP—Total number of false positive cases
FN—Total number of false negative cases.

4 | RESULTS AND DISCUSSION

The present section is structured into three main parts. The first part presents the results of the intelligent system for predicting consumer preferences based on three ML techniques: KNN, SVM, and RF. Secondly, the inferential analysis of the participant's responses focuses on each feature monitored by the EDA (emotional arousal) and FEA (emotions, Engagement, and Attention). Finally, the outcomes of the XAI module and its significance are presented.

4.1 | Computerized intelligent system for consumer ad preference prediction

Table 3 presents the results obtained by the proposed intelligent system for consumer preference prediction based on ML techniques (KNM, SVM, and RF are used from the Python sci-kit-learn library as listed in 3.5.2). Considering the LOOCV k-fold cross-validation with k = 5, the best performances were achieved by the RF technique.

Considering the accuracy, the most general performance metric, as it includes the total number of trees and false positives and negatives since it consists of the total number of true and false positives and negative cases, kNN is the algorithm with the lowest performance (Acc = 0.58), surpassed by SVM (Acc = 0.66). RF (Acc = 0.81) achieved the best performance.

For the Precision (P), the RF achieved the best performance again ($p = 0.84$), followed by the SVM ($p = 0.81$) and kNN ($p = 0.59$). It is important to note that the precision of the SVM technique was substantially higher. Still, the Recall ($R = 0.61$) was similar to the kNN ($R = 0.62$), which indicates that the method's sensitivity is low for this problem. RF also achieved the best performance for Recall ($R = 0.79$). Since the F1-score is the harmonic mean between P and R, the results follow the same trend with kNN (F1 = 0.60) with the poorest performance, SVM (F1 = 0.69) as the second best, and RF (F1 = 0.81) as the best performance.

TABLE 3 Four performance metrics obtained for the three different ML techniques.

Technique	Accuracy (Acc)	Precision (*P*)	Recall (*R*)	F1-score (F1)
k-Nearest Neighbors (kNN)	0.58	0.59	0.62	0.60
Support Vector Machine (SVM)	0.66	0.81	0.61	0.69
Random Forest (RF)	**0.81**	**0.84**	**0.79**	**0.81**

Note: Numbers in bold indicate the highest value.
Abbreviation: ML, machine learning.

4.2 | Inferential system for consumer ad preference prediction

An inferential classification system is implemented to determine statistically significant differences between product advertisement preferences exclusively based on the analysis of FEA and its features.

As previously explained, our research employed FEA to evaluate the participants' emotions while observing the selected stimuli. In addition to the seven basic emotions (Joy, Surprise, Contempt, Anger, Fear, Sadness, and Disgust), two additional indicators of the individual's emotional involvement were considered: Attention and Engagement. The outputs were measured by frames and included only when they exceeded or were equal to a predefined duration threshold of 30 ms. The number of frames detected over or equal to the predefined threshold was then converted into a percentage to provide a more detailed analysis of the emotions displayed for different stimuli, as presented as follows (see Figure 3).

Figure 3 has been separated into (a) and (b) to make it possible to perceive the percentage of emotions effortlessly. The figure shows that Attention and Engagement are the dominant variables across all product advertisements, with no significant variations observed between ads. This finding suggests a consistent level of participant involvement throughout the experiment.

In Table 4, the relevant results of the inferential analysis indicate that four variables rejected the null hypothesis: Joy, Surprise, Disgust and Peaks per minute. The table is described as follows.

In the case of Joy, a two-way ANOVA analysis was conducted, revealing a statistically significant difference in the average percentage of joy among participants ($f(2) = 2.898$, $p < 0.001$) and advertisements ($f(1) = 4.372$, $p < 0.001$). The Tukey post-hoc test revealed significant pairwise differences between the following comparisons:

1. Skin Ritual versus 4. Orchidee Imperiale (mean difference = 3.768),
2. Skin Ritual versus 5. Ginseng Serum (mean difference = 4.259),
3. Skin Ritual versus 6. Timestreasure EX (mean difference = 4.239).

In the case of Surprise, a two-way ANOVA analysis was performed, revealing a statistically significant difference in the average percentage of surprise among participants ($f(2) = 1.504$, $p < 0.044$) and advertisements ($f(1) = 99.48$, $p < 0.0001$). A Tukey post hoc test indicated significant pairwise differences, as follows:

1. 1. Bum Bum Body Scrub versus 1. Skin Ritual (mean difference = 29.44),

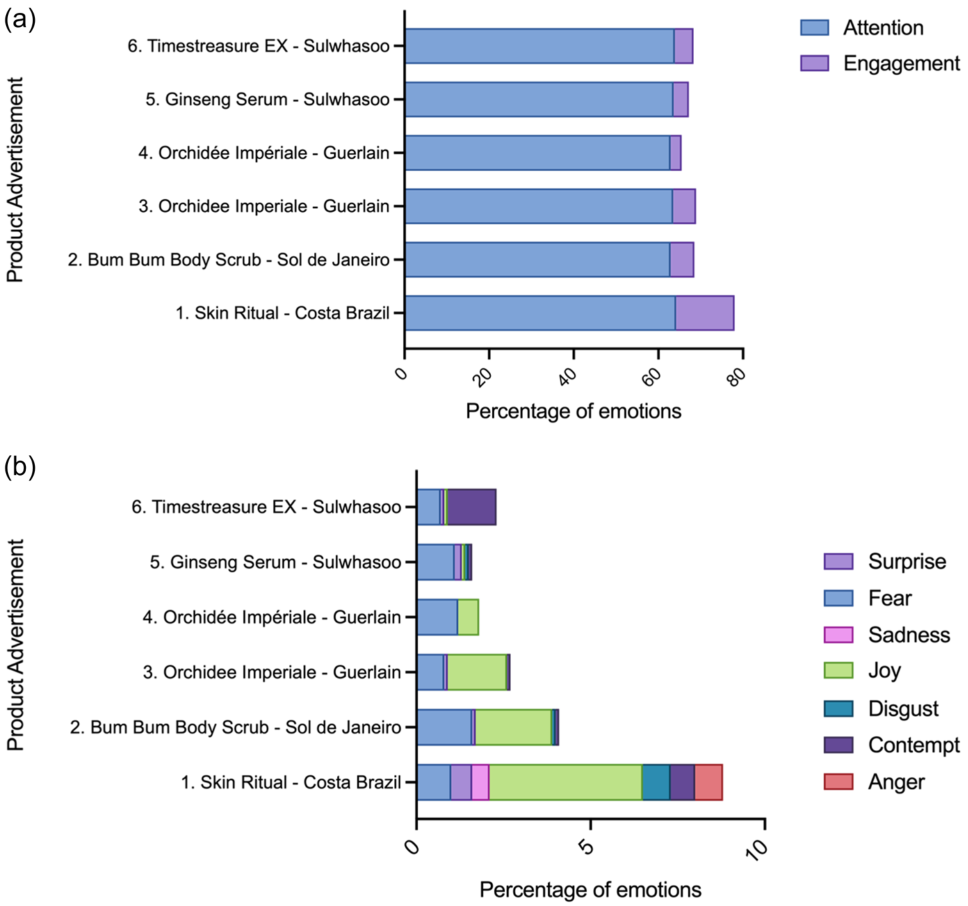

FIGURE 3 Facial Expression Analysis variables per Product Advertisement. (a) Attention and Engagement (b) Emotions according to Ekman's emotional scale.

2. 2. Bum Bum Body Scrub versus 3. Orchidee Imperiale (mean difference = 29.95),
3. 3. Bum Bum Body Scrub versus 4. Orchidee Imperiale (mean difference = 29.96),
4. 4. Bum Bum Body Scrub versus 5. Ginseng Serum (mean difference = 29.83)
5. 5. Bum Bum Body Scrub versus 6. Timestreasure EX (mean difference = 29.91).

The third variable is Disgust. A two-way ANOVA analysis was conducted indicated a statistically significant difference in the average percentage of disgust observed by advertisement ($f(1) = 2.660$, $p = 0.0240$) although no significant difference was found by participant ($f(2) = 1.287$, $p = 0.1451$). A Tukey post hoc test revealed significant pairwise differences, as follows:

1. Skin Ritual vs. 3. Orchidee Imperiale (mean difference = 0.8016)
2. Skin Ritual versus 4. Orchidee Imperiale (mean difference = 0.8195).

Finally, for the variable "Peaks per minute," a two-way ANOVA analysis was performed for the peaks per minute data. This analysis revealed a statistically significant difference in the average percentage of emotional arousal by both participants ($f(2) = 6.733$, $p < 0.0001$) and advertisement ($f(1) = 5.902$, $p < 0.0001$). A Tukey post hoc test revealed significant pairwise differences between the following product advertisements:

1. Skin Ritual versus 4. Orchidee Imperiale (mean difference = 2.121),
2. Skin Ritual versus 5. Ginseng Serum (mean difference = 2.468),
3. Skin Ritual versus 6. Timestreasure EX (mean difference = 1.971).

Finally, the Pearson correlation is also presented in Table 4 and the results indicate a positive correlation between joy and engagement for the following products:

1. Skin Ritual ($r = 0.75$),
2. Bum Bum Body Scrub ($r = 0.86$),
3. Orchidée Impériale ($r = 0.58$),
4. Orchidée Impériale ($r = 0.58$),
5. Timestreasure EX ($r = 0.59$).

There is no correlation between joy and engagement for "5. Ginseng Serum."

TABLE 4 Analysis of variance (ANOVA) for participants and adversisements, followed by the Tuckey post hoc test, a brief interpretation of the results and the Pearson correlation between joy and engagement.

	Joy			Surprise			Disgust			EDA—peaks per min		
1. ANOVA (Participants)	F1-score		2.898	F1-score		1.504	F1-score		1.287	F1-score		6.733
	p Value		<0.001	*p* Value		0.044	*p* Value		0.1451	*p* Value		<0.0001
2. ANOVA (Advertisements)	F1-score		4.372	F1-score		99.48	F1-score		2.660	F1-score		5.902
	p Value		<0.001	*p* Value		<0.0001	*p* Value		0.0240	*p* Value		0.0001
3. Tuckey post-hoc Mean Differences	1. Skin Ritual	versus	4. Orchidee Imperiale	1. Bum Bum Body Scrub	versus	1. Skin Ritual	1. Skin Ritual	versus	3. Orchidee Imperiale	1. Skin Ritual	versus	4. Orchidee Imperiale
	3.768			29.44			0.8016			2.121		
	2. Skin Ritual	versus	5. Ginseng Serum	2. Bum Bum Body Scrub	versus	3. Orchidee Imperiale	2. Skin Ritual	versus	4. Orchidee Imperiale	2. Skin Ritual	versus	5. Ginseng Serum
	4.259			29.95			0.8195			2.468		
	3. Skin Ritual	versus	6. Timestreasure EX	3. Bum Bum Body Scrub	versus	4. Orchidee Imperiale				3. Skin Ritual	versus	6. Timestreasure EX
	4.239			29.96						1.971		
				4. Bum Bum Body Scrub	versus	5. Ginseng Serum						
				29.83								
				5. Bum Bum Body Scrub	versus	6. Timestreasure						
				29.91								
4. Interpretation	Statistically significant difference between participants and advertisements.			Statistically significant difference between participants and advertisements.			Statistically significant differences were observed by advertisement but not by the participant.			Statistically significant difference between participants and advertisements.		
5. Pearson correlation	Results indicate a positive Pearson correlation between JOY and ENGAGEMENT for the following products: 1. Skin Ritual (r = 0.75), 2. Bum Bum Body Scrub (r = 0.86), 3. Orchidée Impériale (r = 0.58), 4. Orchidée Impériale (r = 0.58), 5. Timestreasure EX (r = 0.59).No correlation between Joy and Engagement for 5. Ginseng Serum.											

4.3 | Determining the most relevant features for automatic prediction

Using multiple physiological monitoring tools inevitably leads to a large number of features to be analyzed in parallel. This increases the complexity of the analysis process and the computational system due to multidimensionality, generating additional difficulty for marketing managers in understanding predictions. The results obtained by the three ML techniques have led to the identification of the RF as the best predictor of consumer preferences for the advertisements selected. However, it could remain unclear which emotions or features are the most relevant for that prediction. Consequently, it should be explored whether an emotion of greater significance exists in consumer selection. This inquiry might not find a resolution by comparing performance metrics such as Acc and F1 but by contemplating the development of a module based on XAI. This approach is aligned with the results obtained, where the importance of the feature is illustrated in Figure 4.

Therefore, as shown in Figure 4, the XAI module indicates that this study's four most relevant FEA-monitored features are Attention, Engagement, Disgust, and Joy as a result of the FI using MDI. Based on the earlier findings, the positive correlation between Joy and Engagement was established, further emphasizing the significance of these two metrics for predicting consumer preferences.

5 | DISCUSSION

As previously stated, to our knowledge, no prior research has exclusively explored the combination of EDA and FEA with ML techniques to predict consumer ad preferences, nor has it assessed the most suitable metrics for these neurophysiological tools. This study also pioneers the application of XAI techniques to demystify the outcomes produced by AI and ML classifiers or predictors, a crucial step towards enhancing transparency, trust, and manageability in AI systems.

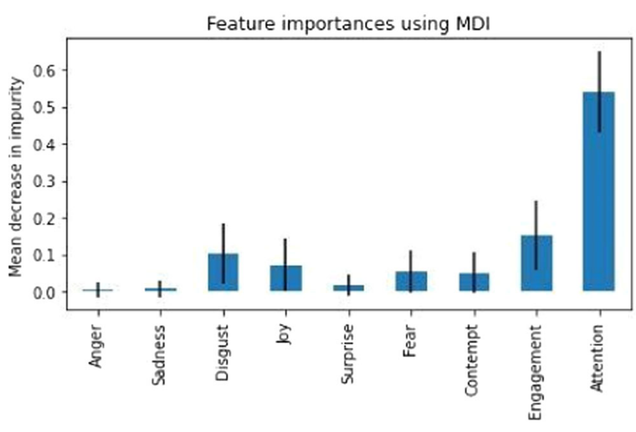

FIGURE 4 Facial expression analysis variables per product advertisement using MDI. MDI, Mean Decrease in Impurity.

Our findings underscore the potential of ML techniques to significantly support marketing strategies by accurately predicting ad preferences based on data from EDA and FEA tools. Using these two neurophysiological monitoring tools intends to create a simple setup that is easily replicated, avoiding possible data collection bias and apparatus influence on the experiment participants and simplifying the data analysis process. By leveraging these physiological monitoring techniques, we can obtain detailed insights into consumer emotional responses, which are critical to creating effective marketing campaigns. The data-driven approach not only enhances the precision of the prediction but also provides actionable insights for marketers while simplifying the complexity of neuroscience datasets and avoiding the need for multidimensional analysis that is not possible using traditional statistical methods.

Moreover, this study identifies and validates the most relevant emotional and arousal features for consumer ad preference prediction. By pinpointing key physiological indicators and emotional states, marketers can tailor their strategies to better align with consumer needs and preferences, ultimately enhancing the effectiveness of their campaigns. Our results highlight specific emotions and arousal metrics that will potentially support the predictive power of predicting consumer ad preferences, offering a nuanced understanding of the emotional drivers behind consumer behavior.

A significant contribution of this research is the development of an interpretation module based on XAI techniques. This module aims to identify and elucidate the most relevant features in the predictive analysis of consumer preferences. By employing XAI, we enhance the transparency of ML models, making it easier for marketers to understand and trust the predictive outcomes. This interpretability is crucial for the practical application of AI systems in marketing, as it allows practitioners to gain deeper insights into the factors influencing consumer decisions, thereby fostering greater confidence in the use of AI-driven tools.

The results obtained by the three ML techniques have led to identifying the RF technique as the best approach in predicting consumer preferences for the advertisements selected compared with KNN and SVM. RF is a decision tree-based approach, and its selection as the most suitable classification tool for this task may indicate a relevant outcome for future analysis of other consumer neuroscience experiments. The system output is validated and ready to be reproduced in similar experiments. Since there is no need for computer science scientists or AI experts to operate the system, these findings have substantial implications for the future of marketing, offering a more accessible, transparent, and effective approach to consumer analysis.

Emotions detected through FEA have been established as a significant predictor of advertising effectiveness, as Hamelin et al. (2022) demonstrated, who employed eye-tracking and FEA techniques. However, their study did not incorporate EDA. Our findings regarding the role of emotions are consistent with the Affect Infusion Model (Forgas, 1995), which posits that affect can influence judgments either directly or indirectly by shaping attention, encoding, retrieval, and interpretation processes. Advertisement preference can be understood as a type of judgment elicited by ads. Further, the study found a strong link between Joy and Engagement, as observed by Pearson correlation results, further emphasizing the significance of these two metrics for predicting consumer ad preferences. Those results suggest leveraging Joy in cosmetics advertisements to significantly boost Engagement and influence consumer ad choice. This highlights their crucial role in predicting consumer preferences. In addition, it is essential to emphasize that with the popularization of AI approaches to classify and predict labeled data, such as consumer preference, different models have widely been suggested as the best classification candidate without properly explaining how the selected model achieved that specific result. Because of that, determining the most relevant features that may contribute to the classification task using an explainable module (XAI) based on the RF approach is also a key result of this work. The proposed module shows that Attention, Engagement, Disgust, and Joy are the most relevant features for predicting consumer preferences. For both Joy and Disgust, statistically significant differences were observed by the participants but not by advertisement as per the ANOVA analysis performed. The significant influence of the emotions of joy and disgust observed in our study indicates the presence of peripheral cues consistent with the ELM, which shape attitudes and serve as precursors to advertisement preferences. Joy, in particular, has been identified as the most prominent emotion associated with positive ad evaluation (Otamendi & Sutil Martín, 2020). Conversely, disgust negatively impacts consumers' appraisal of advertisements, ultimately leading to a lack of purchase intention (Shimp & Stuart, 2004).

6 | CONCLUSIONS

This work presents a computerized intelligent system for consumer ad preference prediction exclusively based on the analysis of EDA and FEA, which are neurophysiological monitoring tools that measure real-time responses. The proposed experiment analyzes the data of 37 potential consumers (participants) presented to a set of stimuli consisting of six marketing videos of three multinational cosmetic brands. Our research substantiates the critical role of attention in shaping advertising effectiveness, as evidenced by prior eye-tracking studies (Wedel & Pieters, 2006) and, more recently, through the integration of eye-tracking with machine-learning methodologies (Unger et al., 2024). Additionally, this study offers novel contributions by extending the scope of attention's influence to include advertisement preference, employing EDA and FEA as key analytical tools.

Addressing the first research question, the inferential analysis indicates statistically significant differences in monitored emotions such as Joy, Surprise, and Disgust, as well as in EDA peaks per minute. Notably, Joy and Disgust emerged as two of the most relevant features for the prediction of ad preferences, indicating that these two emotions should be highly considered and monitored when planning product advertisements. Furthermore, a positive correlation was found between Joy and Engagement for five of six ads. In addition, using AI for feature relevance identification, the proposed XAI module is validated, identifying Attention, Engagement, Joy, and Disgust as the most relevant emotions influencing consumer ad preference prediction.

Considering the second research question, an AI system is proposed and validated based on three ML classifiers. The results indicate that RF, with an overall Accuracy of 81%, is the most adequate technique for consumer preference prediction using EDA and FEA monitoring.

Regarding emotion types' influence on advertisements, our results partially agreed with Ausin-Azofra et al. (2021), who found that Joy and Surprise were the salient emotions in 360° video ads. Indeed, the novelty of the 360° advertising triggers the effect of Surprise. Therefore, Joy remains the most established influencer emotion in advertising. Both conclusions indicate that to translate emotional arousal into Engagement, marketers should focus on designing brand advertisements in cosmetics that elicit strong feelings of Joy.

The main contributions of this study can be divided into three key aspects: (i) The development of a computerized intelligent system using the RF ML technique to effectively predict consumer ad preferences by leveraging data from EDA and FEA; (ii) the implementation of an inferential classification system designed to discern statistically significant variations in brand preferences solely based on the analysis of FEA and its associated features; (iii) the development of an XAI module aimed at identifying the most salient features with respect to predictive analysis.

Based on these findings and aligned with the hierarchy of the advertising effects model, we propose a hierarchy of effects from Attention to two salient emotions, Joy and Surprise, that lead to customer Engagement as predictors of consumer ad preference. This theoretical approach would require causal testing in further studies but represents a new proposed model.

Our study affirms the applicability of the SOR framework within a neurotheological context. The organismic changes observed through EDA and FEA are reliable predictors of advertisement preference.

6.1 | Research limitations and suggestions for future research

The current investigation has limitations. To increase the capacity of generalization of the proposed approach for predicting preferences among different ads, a larger sample size should be considered. In addition, other variables can also be under strict control, such as ads duration, sounds, colors, among others.

There are several avenues for future research. Incorporating behavioral data, such as buying behavior would provide a deep understanding of consumption relationships. Future works may consider validating the performance of the proposed AI system to other industries. In addition, brand awareness as relevant in influencing consumer preferences for a product, which is consistent with the results from McClure et al. (2004), who, using fMRI, found that participants' recognition of the brand activated various brain areas, including the dorsolateral prefrontal cortex, hippocampus, and the midbrain. Finally, while FEA is a cutting-edge platform that deciphers facial expressions into the seven basic emotions, Attention, and Engagement, and its combination with EDA for assessing the valence of emotions is seen as a strengthening factor, the simultaneous use of other neurophysiological tools, such as EEG for measuring brain activity and eye-tracking, may provide additional insights and valuable interpretations.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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