

UNIVERSIDAD DE MURCIA

Escuela de Doctorado

TESIS DOCTORAL

Inteligencia Artificial para Neuromarketing basado en EEG con Canales Limitados y Datos Heterogéneos

Artificial Intelligence for EEG-Based Neuromarketing with Limited Channels and Heterogeneous Data

AUTOR/A Mario Quiles Pérez

DIRECTOR/ES Lorenzo Fernández Maimó
Alberto Huertas Celdrán

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Contents

Acknowledgements **iii**

Agradecimientos **v**

Abstract **vii**
I Introduction and motivation vii
II Objectives ix
III Methodology x
IV Results xii
V Conclusions and future work xiv

Resumen **xvii**
I Introducción y motivación xvii
II Objetivos xx
III Metodología xx
IV Resultados xxiii
V Conclusiones y trabajo futuro xxv

Bibliography **xxix**

Publications composing the PhD Thesis

1 Survey on AI and Biosensors **3**

2 EEG Channel Reconstruction in Limited BCIs **31**

3 EEG Dataset Quality Assessment **49**

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Abstract

I Introduction and motivation

Neuromarketing combines neuroscience, psychology, and marketing to examine how consumers respond to commercial stimuli such as advertisements, products, brands, or digital experiences [1, 2]. In this context, physiological and neural signals can complement traditional methods such as questionnaires, interviews, and self-reported feedback. This allows researchers to study dimensions such as attention, memory, emotional impact, liking, or preference using physiological and neural information [3, 4].

To study these dimensions, the literature has used different biosignals, including Electroencephalography (EEG), eye-tracking, electrodermal activity, electrocardiography, facial response, and electromyography [5]. Among them, EEG has gained a central role due to its non-invasive nature, lower cost compared to other neuroimaging techniques, portability, and high temporal resolution [6, 7]. These characteristics make EEG suitable for studying cognitive and emotional processes in applied scenarios, where the temporal evolution of neural responses must be captured and the use of expensive or bulky medical equipment is not always feasible [8, 9]. In this context, Brain-Computer Interfaces (BCIs) provide a way to use EEG signals outside traditional clinical settings. BCIs are systems that establish a communication pathway between brain activity and external devices by acquiring neural signals, processing them, and translating the resulting patterns into commands, indicators, or information that can support interaction and monitoring tasks [10]. Together with wearable EEG systems, these technologies make EEG acquisition more accessible and facilitate its use in applied scenarios such as affective computing, entertainment, user monitoring, and marketing research [11].

These advances have increased the use of EEG in neuromarketing tasks. EEG has been applied to the study of emotional responses to advertisements, attention to specific design elements, sensory product evaluation, and purchase-related decisions [5]. These tasks are directly connected to the main objectives of neuromarketing studies, such as studying the impact of commercial stimuli, comparing different advertisements or products, and identifying modifications that can improve their effectiveness. Therefore, EEG is not only an acquisition technology, but also a signal that can be linked to dimensions of consumer behaviour used in marketing analysis.

The expansion of EEG-based neuromarketing has also increased the amount of data that can be captured in these scenarios. As a result, Artificial Intelligence (AI) supports automatic and scalable EEG analysis, especially because EEG signals are high-dimensional,

noisy, and temporally dynamic. Traditionally, AI-based EEG analysis has mainly relied on classical Machine Learning (ML) methods, which use handcrafted features to classify mental, cognitive, and affective states [12]. More recently, Deep Learning (DL) methods have gained attention because they can learn representations from raw or minimally processed EEG data and identify patterns that are not straightforward to define manually [2, 13]. Therefore, AI-based EEG analysis should not be understood only as a classification problem. It can also support other tasks related to the use of EEG data, including signal reconstruction, representation learning, and the analysis of data characteristics that affect model training and evaluation [13, 14].

However, although AI extends the scope of EEG analysis beyond classification, its application to neuromarketing still presents methodological, practical, and data-related limitations. First, the field is methodologically heterogeneous. Studies may differ in the objective pursued, the type of stimulus employed, the biosensors used during experimentation, the preprocessing pipeline, the feature extraction techniques, and the tools used to validate the study hypothesis [5]. As a result, the literature remains fragmented, which limits the construction of a unified view of the complete life cycle of neuromarketing studies based on biosignals. This fragmentation also complicates the interpretation of the current state of the art and the identification of open challenges in the field. This problem motivates the first research question of this thesis, which asks which stages, datasets, research trends, and open challenges define the current state of the art in biosignal-based neuromarketing.

A second limitation concerns the practical conditions of EEG acquisition. High-density EEG systems provide richer spatial information and allow a more detailed interpretation of neural activity. However, practical scenarios tend to favor devices that are more affordable, portable, easier to deploy, and more comfortable for end users [7, 8, 9]. In this direction, the field is moving toward wearable BCI devices that can be used by subjects themselves, without requiring continuous assistance from an operator during each experiment. This can facilitate data collection and increase the amount of EEG data available for analysis [15]. At the same time, the growing interest in practical EEG acquisition has promoted the use of low-cost BCIs with a limited number of electrodes and, in many cases, fixed channel configurations. These devices facilitate wider adoption, but they can also reduce the spatial information available for analysis [6, 11]. Therefore, the reduced number of channels in practical BCIs represents a constraint for EEG analysis in neuromarketing. This problem motivates the second research question of this thesis, which examines the trade-off between reconstruction performance, channel availability, and practical deployment constraints when using AI-based EEG channel reconstruction in limited-channel BCIs for neuromarketing.

A third limitation concerns the datasets used to train and evaluate AI models. Although wearable BCIs may increase the amount of data collected in future experiments, current EEG datasets remain highly heterogeneous. They often differ in acquisition protocols, hardware characteristics, preprocessing decisions, annotation criteria, and experimental paradigms [14, 13]. As a result, datasets designed for similar tasks may still differ considerably in the number of subjects, the number and duration of sessions, the balance between classes, the quality of event timing, or the overall signal quality. These differences affect benchmarking and limit the interpretation of downstream model performance [14]. In this context, designing predictive models is not enough. It is also necessary to characterize the quality of the data used to train and evaluate them. This problem motivates the third research question of this thesis, which examines which EEG dataset quality dimensions are most informative for benchmarking AI-based analysis in neuromarketing and how these

dimensions are related to downstream model performance.

Taken together, these three problems show that the use of AI for EEG in neuromarketing is not only a modeling problem. It also requires a structured understanding of the domain, methods to address practical EEG acquisition constraints, and objective approaches to analyze the quality of the data used during training and evaluation. Therefore, this thesis defines a methodological path that connects domain understanding, practical EEG acquisition constraints, and data quality assessment as necessary steps for applying AI to EEG-based neuromarketing.

Based on the previous considerations, this PhD Thesis studies the use of AI for the analysis of EEG signals in neuromarketing scenarios from three complementary perspectives. First, it reviews the current state of the art of neuromarketing based on biosignals by identifying the role of EEG, the main stages of current studies, available datasets, trends, and open challenges [5]. Second, it addresses a practical limitation of EEG acquisition in realistic scenarios, namely, the reduced number of channels available in low-cost and user-friendly BCI devices, by proposing a lightweight CNN for EEG channel reconstruction [16]. Finally, this thesis examines the quality and comparability of EEG datasets used in AI-based analysis pipelines, proposing a multidimensional framework that integrates several quality indicators into a normalized Quality Score (QS) [17].

This organization reflects the progression of the research conducted in this thesis: understanding the domain, addressing practical acquisition constraints, and assessing the quality of the data used to train and evaluate AI-based solutions. In this direction, three main Research Questions (RQs) arise and guide the research process of this PhD Thesis:

- RQ1: What are the main stages, datasets, research trends, and open challenges that define the state of the art in biosignal-based neuromarketing?
- RQ2: What trade-off between reconstruction performance, channel availability, and practical deployment constraints can be achieved by AI-based EEG channel reconstruction in limited-channel BCIs for neuromarketing?
- RQ3: Which EEG dataset quality dimensions are most informative for benchmarking AI-based analysis in neuromarketing, and how can they be related to downstream model performance?

II Objectives

The main goal of this PhD Thesis is to investigate the use of AI for the analysis of EEG signals in neuromarketing scenarios. In particular, this work addresses this goal from three complementary perspectives. First, it analyzes biosignal-based neuromarketing research by identifying its main objectives, stages, datasets, trends, and open challenges. Second, it studies the practical limitations of EEG acquisition in low-cost and wearable BCI devices, with particular attention to the trade-off between channel availability, reconstruction performance, and deployment constraints. Third, it examines which EEG dataset quality dimensions are most informative before training and evaluating AI-based solutions, and how these dimensions are related to downstream model performance. To this end, it proposes a multidimensional framework that considers acquisition, annotation, signal quality, class distribution, feature relevance, and class separability. From this main goal, the following specific objectives are defined, indicating the research questions related to each one:

1. Analyze the current state of the art of neuromarketing based on biosignals, with particular attention to the role of EEG, the main stages followed in current studies, the datasets available in the literature, and the main trends and open challenges of the field (RQ1).

2. Identify the main methodological gaps derived from the analysis of the literature, especially those related to experimental heterogeneity, practical acquisition conditions, and study comparability (RQ1).

3. Study the limitations imposed by low-cost and user-friendly BCI devices, particularly the reduced number of available channels, and analyze how these restrictions affect the use of EEG in practical neuromarketing scenarios (RQ2).

4. Propose and experimentally evaluate a lightweight DL-based solution for EEG channel reconstruction in limited-channel BCIs, analyzing its reconstruction performance, comparison with baseline methods, channel-configuration trade-offs, and suitability for practical deployment in neuromarketing scenarios (RQ2).

5. Analyze the main factors affecting the quality of EEG datasets used in AI pipelines, including acquisition protocols, preprocessing decisions, annotation criteria, class balance, and signal quality (RQ3).

6. Propose a framework for the multidimensional assessment of EEG datasets to characterize their quality before model training and evaluation, supporting dataset comparison under a common protocol (RQ3).

III Methodology

This PhD Thesis follows a scientific approach based on the comprehensive study of the state of the art and the analysis of the results obtained during the different stages of the research. This progressive research process resulted in a thesis structured as a set of three papers published in high-impact journals indexed in the Journal Citation Reports (JCR). The methodology follows the research questions and objectives defined in this thesis, so that each stage of the research contributes to a specific part of the overall problem.

In relation to RQ1 and Objectives 1 and 2, the first stage of the research focuses on reviewing the state of the art of neuromarketing based on biosignals, with particular attention to the role of EEG. For this purpose, this stage analyzes the main objectives pursued in neuromarketing studies and the types of stimuli employed. It also reviews the biosensors used during experimentation, the preprocessing techniques applied to the acquired signals, the feature extraction methods, and the methods used to validate the study hypotheses. In addition, this stage examines publicly available datasets and analyzes the main trends and open challenges of the field. Figure 1 summarizes this methodological view by representing the main stages involved in biosignal-based neuromarketing studies, from the definition of the commercial stimulus and the acquisition of physiological signals to signal processing, feature extraction, analysis, and hypothesis validation. This study makes it possible to identify the methodological fragmentation of neuromarketing research and the lack of a unified view of its main stages. All these considerations resulted in the first publication of this PhD Thesis, presented in Chapter 1.

After identifying the main methodological characteristics and open challenges of the field, the research focuses on a relevant acquisition problem affecting the use of EEG in neuromarketing scenarios. This stage relates to RQ2 and Objectives 3 and 4, since it studies



Figure 1: Neuromarketing cycle and main methodological stages considered in biosignal-based neuromarketing studies.

the practical limitations imposed by low-cost and wearable BCI devices and the trade-off between channel availability, reconstruction performance, and deployment constraints. One of the limitations identified in this context is the trade-off between signal richness and practical deployment. High-density EEG systems provide richer spatial information, but they usually require more controlled acquisition conditions and greater operator supervision. In contrast, wearable and low-cost BCI devices can facilitate experimentation and increase the amount of data collected in realistic scenarios. However, these devices usually provide a reduced number of channels, which limits the spatial information captured during acquisition. Based on this limitation, the second stage of the research explores how AI, and particularly DL, can contribute to the reduced-channel problem through EEG channel reconstruction. In addition, this stage analyzes different reduced-channel configurations to identify which electrode locations are better suited to specific neuromarketing use cases, such as emotional, sensory, attention-related, and decision-related scenarios.

To study this problem, the second stage proposes a lightweight Convolutional Neural Network (CNN) for EEG channel reconstruction from limited-channel configurations. The model is designed around the constraints of practical EEG devices, including the availability of fewer electrodes and the need for computationally efficient solutions. CNNs are selected because they can capture local temporal patterns in EEG signals while keeping the architecture suitable for practical deployment. Figure 2 summarizes the proposed EEG channel reconstruction pipeline, showing how real electrodes acquired from a limited-channel device are processed to estimate additional EEG channels.

The model aims to increase the amount of information available from channel-limited acquisitions. In addition, this stage defines a custom loss function that combines reconstruction accuracy with temporal similarity between the original and reconstructed signals. The model is then evaluated using public EEG datasets and compared against baseline reconstruction methods. Furthermore, a broad analysis of channel configurations is carried out to identify which compact electrode combinations are better suited for practical scenarios. These considerations resulted in the second publication of this PhD Thesis, presented in Chapter 2.

Once the practical problem of limited-channel acquisition has been studied, the research focuses on another methodological problem, namely, the quality of the datasets used to train and evaluate AI-based solutions. This stage relates to RQ3 and Objectives 5

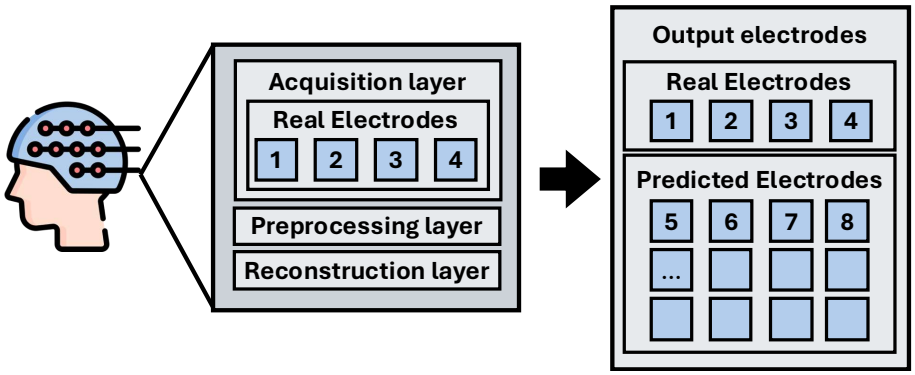


Figure 2: EEG channel reconstruction pipeline from limited-channel acquisition to predicted EEG channels.

and 6, since it examines how EEG dataset quality can be characterized through a multidimensional framework and experimentally evaluated under a common protocol. Although current acquisition technologies can facilitate larger-scale experimentation, EEG datasets still differ considerably in their protocols, preprocessing decisions, annotation criteria, and signal quality. This heterogeneity directly affects benchmarking and makes model performance more difficult to interpret. Based on this problem, the third stage of the research defines an objective framework for the multidimensional assessment of EEG dataset quality.

For this purpose, the framework defines a set of quality dimensions to characterize EEG datasets before model training and evaluation. These dimensions include session completeness, consistency of session length, class balance, and annotation timing. They also include signal-to-noise ratio, outlier prevalence, feature information content, and class separability. After defining these indicators, the framework proposes a normalized Quality Score to summarize the overall quality of a dataset while keeping the individual scores available for interpretation. The framework is then applied to several public EEG datasets in order to compare their quality under a common protocol and to study the relationship between dataset quality and downstream performance. These considerations resulted in the third publication of this PhD Thesis, presented in Chapter 3.

In summary, the methodology follows the progression of the research and its connection with the research questions and objectives. First, it reviews the state of the art of biosignal-based neuromarketing and identifies its main stages, datasets, research trends, open challenges, and methodological gaps in relation to RQ1 and Objectives 1 and 2. After that, it studies a practical acquisition problem affecting the use of EEG in realistic scenarios in relation to RQ2 and Objectives 3 and 4. Finally, it proposes and evaluates a framework to characterize the quality of the datasets that support AI-based analysis in relation to RQ3 and Objectives 5 and 6. This methodology makes it possible to respond to the research questions defined in this thesis and to connect the three publications under a single research line.

IV Results

In the first publication of the PhD Thesis, presented in Chapter 1, the state of the art of neuromarketing based on biosignals was reviewed, and several methodological gaps affecting the organization, interpretation, and comparison of existing studies were identified. This contribution is related to RQ1 and Objectives 1 and 2, since it identifies the main stages, datasets, research trends, open challenges, and methodological gaps derived from

the literature. The first gap was the lack of a commonly accepted neuromarketing cycle, which makes it difficult to describe the different stages of these studies under a unified structure. The second gap was that most previous surveys addressed only part of the problem, usually focusing on a specific biosignal or on isolated methodological stages. The third gap was the absence of a common organization of the datasets available for these scenarios, which made comparative analysis across studies more difficult. Based on these limitations, the publication organized the field according to its main objectives, biosignals, processing techniques, datasets, trends, and open challenges.

This publication also provided several concrete findings about the current state of the field. Advertisement comparison was identified as the most common neuromarketing objective, accounting for almost 45% of the reviewed works, followed by studies focused on advertisement impact and advertisement improvement, with 30.4% and 24.8%, respectively. Audiovisual stimuli were the most common stimulus type and were used in more than 50% of the works across the three objectives. In addition, EEG and ET were identified as the most widespread biosignals, with EEG appearing in almost 50% of the reviewed works. The analysis also showed that public datasets are still scarce and are usually not designed specifically for neuromarketing objectives. Overall, these findings enabled the identification of the main research trends in the field, highlighted its methodological fragmentation, and revealed several open challenges for future research. These findings respond to RQ1 and contribute to Objectives 1 and 2 by identifying the main stages, datasets, research trends, open challenges, and methodological gaps that define biosignal-based neuromarketing research.

The second publication of the PhD Thesis, presented in Chapter 2, studied a practical limitation affecting EEG acquisition in neuromarketing scenarios, that is, the reduced number of channels available in low-cost and wearable BCI devices. This contribution is related to RQ2 and Objectives 3 and 4, since it analyzes the limitations imposed by reduced-channel acquisition devices and proposes an experimentally evaluated DL-based solution for EEG channel reconstruction. For this purpose, a lightweight CNN was proposed to reconstruct EEG channels from reduced-channel configurations. In addition, a custom loss function combining Mean Squared Error (MSE) and Pearson's correlation coefficient was defined to preserve both reconstruction accuracy and the temporal dynamics of EEG signals. The work also included a systematic evaluation of more than 1,820 channel configurations in order to identify those subsets that are better suited to practical neuromarketing scenarios.

The results of this work showed that the proposed model achieved consistent reconstruction performance and outperformed the baseline methods in most evaluated scenarios. In particular, the proposed CNN obtained an NMSE of 0.042 ± 0.009, compared with 0.064 ± 0.011 for Spherical Spline Interpolation (SSI), 0.071 ± 0.013 for Partial Least Squares Regression (PLSR), and 0.055 ± 0.010 for a shallow autoencoder baseline. In addition, the evaluation of more than 1,820 channel configurations revealed that some commercial devices were better suited than others depending on the use case, particularly in emotional, sensory, attention-related, and decision-related scenarios. The resource evaluation also supported the suitability of the model for practical deployment in commercial BCIs. Overall, these results showed that the proposed model can mitigate part of the limitations imposed by limited-channel EEG devices and support their use in practical neuromarketing scenarios. These findings respond to RQ2 and contribute to Objectives 3 and 4 by analyzing the trade-off between reconstruction performance, channel availability, and practical deployment constraints in limited-channel BCI devices.

The third publication of the PhD Thesis, presented in Chapter 3, focused on the quality

and comparability of EEG datasets used to train and evaluate AI-based solutions. This contribution is related to RQ3 and Objectives 5 and 6, since it analyzes the main factors affecting EEG dataset quality and proposes an experimentally evaluated framework for multidimensional dataset assessment. The framework computes a set of indicators related to session completeness, session-length consistency, class balance, annotation timing, signal-to-noise ratio, outlier prevalence, feature information content, and class separability. These indicators are then combined into a normalized Quality Score (QS) ranging from 0 to 100. An important aspect of the framework is that the aggregation preserves the contribution of the different indicators and uses subject-wise summarization, which reduces the dependence of the final score on isolated subjects or sessions.

The evaluation of this framework was carried out on six public EEG datasets from affect recognition, event-related paradigms, and motor imagery, all processed under identical protocols. The downstream classification performance was reported using Balanced Accuracy and Area Under the ROC Curve. The results showed that the proposed QS captured differences in data integrity, temporal consistency, and class separability, and remained interpretable across heterogeneous collections. In addition, the correlation analyses indicated positive associations between separability-oriented indicators and downstream performance, and negative associations with a higher prevalence of outliers. The work also showed that targeted training adjustments guided by these indicators improved performance. These findings respond to RQ3 and contribute to Objectives 5 and 6 by identifying informative EEG dataset quality dimensions, validating their use under a common protocol, and analyzing their relationship with downstream model performance.

In summary, the results of this PhD Thesis follow the progression of the research and are directly aligned with the research questions and objectives. First, the survey identified the main stages, datasets, research trends, open challenges, and methodological gaps of biosignal-based neuromarketing, responding to RQ1 and Objectives 1 and 2. Subsequently, the second publication studied a practical limitation of EEG acquisition in realistic scenarios, namely the reduced number of channels available in low-cost BCIs, and proposed a lightweight signal reconstruction model. This contribution directly responded to RQ2 and contributed to Objectives 3 and 4. Finally, the third publication studied the quality of the datasets used in AI pipelines and proposed a framework to compare EEG datasets under a common methodology, responding to RQ3 and Objectives 5 and 6. Collectively, these contributions responded to the research questions of the thesis and integrated the three publications into a coherent and unified research line.

V Conclusions and future work

In recent years, the use of AI for the analysis of EEG signals has gained relevance in neuromarketing. This trend is motivated by the need to better understand consumer responses from physiological and neural information, moving beyond traditional approaches based only on questionnaires or interviews. In this context, EEG has become one of the most relevant biosignals due to its non-invasive nature, portability, reduced cost, and high temporal resolution. However, the practical application of EEG in neuromarketing still presents important limitations related to the methodological fragmentation of the field, the constraints of limited-channel acquisition devices, and the heterogeneity of the datasets used to train and evaluate AI-based solutions.

Considering these limitations, the first stage of this work analyzed the state of the art of neuromarketing based on biosignals. In particular, it identified that the literature still lacks a commonly accepted neuromarketing cycle and that most previous surveys address only

part of the problem. Moreover, the reviewed works show a high degree of heterogeneity in their objectives, stimuli, biosignals, preprocessing techniques, feature extraction methods, and validation approaches. In this direction, the first contribution provided a structured view of the field by organizing its principal objectives, biosignals, processing techniques, datasets, trends, and open challenges. This contribution responded to RQ1 by identifying the main stages, datasets, research trends, open challenges, and methodological gaps that motivated the subsequent stages of the research.

After that, the work addressed one of the main practical limitations affecting EEG acquisition in neuromarketing scenarios, namely, the reduced number of channels available in low-cost and wearable Brain-Computer Interface (BCI) devices. Although these devices facilitate experimentation in practical scenarios, they also reduce the spatial information available for analysis. To address this problem, the second contribution proposed a lightweight CNN for EEG channel reconstruction from limited-channel configurations. The results obtained showed that the model was able to reconstruct EEG channels with competitive performance, outperform baseline methods in most evaluated scenarios, and support practical deployment due to its computational efficiency. Furthermore, the analysis of more than 1,820 channel configurations made it possible to identify configurations better suited to different neuromarketing use cases. These results responded to RQ2 by analyzing the trade-off between reconstruction performance, channel availability, and practical deployment constraints in reduced-channel EEG devices.

Finally, the research addressed a broader methodological issue related to the quality and comparability of EEG datasets. Although acquisition technologies are evolving and can facilitate larger-scale experimentation, EEG datasets still differ considerably in acquisition protocols, preprocessing decisions, annotation criteria, and signal quality. These differences directly affect benchmarking and make downstream model performance more difficult to interpret. To address this problem, the third contribution proposed a framework for the multidimensional assessment of EEG dataset quality. The framework computes a set of indicators related to completeness, temporal consistency, class balance, annotation timing, signal-to-noise ratio, outlier prevalence, feature information content, and class separability, combining them into a normalized Quality Score. The evaluation on six public EEG datasets showed that this framework can characterize dataset quality in an interpretable way and relate it to subsequent AI-based analysis. These results responded to RQ3 by identifying informative EEG dataset quality dimensions, relating them to downstream model performance, and providing a basis for more objective dataset comparison in this field.

In summary, this PhD Thesis has addressed the application of AI for EEG analysis in neuromarketing from three complementary perspectives. First, it structured the current state of the art of the field. Subsequently, it proposed a practical solution to one of the main limitations of EEG acquisition in realistic scenarios. Finally, it introduced a methodological framework to assess the quality of the datasets that support AI-based analysis. Taken together, these contributions connect the three publications under a single research line and provide a more solid basis for future work on EEG-based neuromarketing. Therefore, the overall contribution is not limited to a specific AI model, but also includes the definition of a broader methodological path for applying AI to EEG-based neuromarketing.

As future work, it is necessary to continue advancing the methodological maturity of neuromarketing research. In particular, new datasets explicitly oriented to neuromarketing objectives should be designed, including more realistic stimuli, more consistent experimental protocols, and clearer annotation criteria. In the same direction, there is also an opportunity to explore scenarios that better resemble real consumer environments, such

as experiments involving real products, store layouts, or multimodal interactions closer to everyday decision-making processes. These directions would help reduce the gap between controlled laboratory studies and practical neuromarketing applications.

With respect to EEG channel reconstruction, future work should focus on improving the generalization and applicability of the proposed model. In particular, there is room to improve cross-hemisphere predictions, reduce the dependence on channel density, and evaluate the model on a wider variety of datasets and devices. It would also be useful to study more advanced architectures and improved strategies for preserving signal polarity and spatial dependencies. In addition, a relevant next step would be the integration of these models into practical BCI platforms, which could help translate the current results into real neuromarketing tools.

Regarding dataset quality assessment, future research should aim to extend and validate the proposed framework across a wider range of experimental paradigms, datasets, and acquisition conditions, thereby enhancing its generalizability and applicability. It would be useful to further analyze the relationship between specific quality indicators and downstream model performance, and to study how these indicators can guide preprocessing, training, and benchmarking decisions in a more systematic way. Likewise, the extension of this type of framework to multimodal datasets could be especially relevant in neuromarketing, where EEG is frequently combined with other biosignals such as eye tracking, electrodermal activity, or electrocardiography.

Overall, this thesis demonstrates that the use of AI in EEG-based neuromarketing should not be understood only as the design of predictive models. It also requires a structured understanding of the domain, practical solutions for realistic acquisition constraints, and objective methods to evaluate the quality of the data used during training and evaluation. Continued progress in these three directions will be essential for strengthening the methodological foundations of EEG-based neuromarketing and enhancing its robustness, comparability, and practical applicability in real-world scenarios.

Resumen

I Introducción y motivación

El neuromarketing combina neurociencia, psicología y marketing para estudiar cómo reaccionan los consumidores ante estímulos comerciales como anuncios, productos, marcas o experiencias digitales [1, 2]. En este contexto, las señales fisiológicas y neurológicas pueden complementar los métodos tradicionales basados en cuestionarios, entrevistas y respuestas autoinformadas. Esto permite estudiar dimensiones como la atención, la memoria, el impacto emocional, el agrado o la preferencia a partir de información fisiológica y neural [3, 4].

Para estudiar estas dimensiones, la literatura ha utilizado diferentes bioseñales, incluyendo la Electroencefalografía (EEG), el seguimiento ocular, la actividad electrodérmica, la electrocardiografía, la respuesta facial y la electromiografía [5]. Entre ellas, la EEG ha adquirido un papel relevante debido a su naturaleza no invasiva, su menor coste en comparación con otras técnicas de neuroimagen, su portabilidad y su alta resolución temporal [6, 7]. Estas características hacen que la EEG resulte atractiva para el estudio de procesos cognitivos y emocionales en escenarios aplicados, donde la evolución temporal de la respuesta neurológica es relevante y el uso de equipamiento médico costoso o voluminoso no siempre es viable [8, 9]. En este contexto, las interfaces cerebro-máquina (Brain-Computer Interfaces, BCIs) se han convertido en una vía relevante para utilizar señales EEG fuera de entornos clínicos tradicionales. Las BCIs son sistemas que establecen una vía de comunicación entre la actividad cerebral y dispositivos externos mediante la adquisición de señales neurales, su procesamiento y la traducción de los patrones resultantes en comandos, indicadores o información que puede apoyar tareas de interacción y monitorización [10]. Junto con los sistemas EEG portátiles, estas tecnologías hacen que la adquisición de EEG sea más accesible y facilitan su uso en escenarios aplicados como la computación afectiva, el entretenimiento, la monitorización de usuarios y la investigación en marketing [11].

Gracias a estos avances, la EEG se ha utilizado cada vez más en tareas de neuromarketing. Se ha aplicado al estudio de respuestas emocionales ante anuncios, la atención a elementos concretos de diseño, la evaluación sensorial de productos y las decisiones relacionadas con la compra [5]. Esto es importante porque estas tareas están directamente conectadas con los principales objetivos de los estudios de neuromarketing, como estudiar el impacto de estímulos comerciales, comparar diferentes anuncios o productos e identificar modificaciones que puedan mejorar su eficacia. Por tanto, la EEG no es solo una tecnología útil para la adquisición de datos, sino también una señal que puede vincularse con

dimensiones relevantes del comportamiento del consumidor.

La expansión del neuromarketing basado en EEG ha incrementado la cantidad de datos que pueden capturarse en este tipo de escenarios. Como resultado, la Inteligencia Artificial (IA) se ha convertido en una herramienta importante para el análisis de EEG, ya que estas señales son difíciles de interpretar manualmente, especialmente en estudios que requieren análisis automáticos y escalables. Tradicionalmente, el análisis de EEG basado en IA se ha apoyado principalmente en métodos clásicos de aprendizaje automático (Machine Learning, ML), que utilizan características definidas manualmente para predecir o clasificar estados mentales, cognitivos y afectivos [12]. Más recientemente, los métodos de aprendizaje profundo (Deep Learning, DL) han ganado relevancia porque pueden aprender representaciones a partir de datos EEG brutos o mínimamente procesados e identificar patrones que son difíciles de definir manualmente [2, 13]. Por tanto, el análisis de EEG basado en IA no debe limitarse únicamente a la predicción de estados mentales, cognitivos o afectivos. También puede apoyar otras tareas relacionadas con el uso de datos EEG, incluyendo la reconstrucción de señales, el aprendizaje de representaciones y el análisis de características de los datos que afectan al entrenamiento y la evaluación de los modelos [13, 14].

Sin embargo, aunque la IA ofrece varias posibilidades para el análisis de EEG más allá de la clasificación, su aplicación al neuromarketing todavía presenta limitaciones metodológicas, prácticas y relacionadas con los datos. En primer lugar, el campo es metodológicamente heterogéneo. Los estudios pueden diferir en el objetivo perseguido, el tipo de estímulo empleado, los biosensores utilizados durante la experimentación, las técnicas de preprocesamiento aplicadas, los métodos de extracción de características y las herramientas empleadas para validar la hipótesis del estudio [5]. Como resultado, la literatura se encuentra fragmentada y resulta difícil obtener una visión unificada del ciclo de vida completo de los estudios de neuromarketing basados en bioseñales. Esto dificulta la interpretación del estado del arte actual y la identificación de los principales retos abiertos del campo. Este problema motiva la primera pregunta de investigación de esta tesis, centrada en identificar las principales etapas, conjuntos de datos, tendencias y retos abiertos que definen el estado del arte del neuromarketing basado en bioseñales.

Una segunda limitación está relacionada con las condiciones de adquisición de EEG. Los sistemas EEG de alta densidad proporcionan una mayor riqueza de información espacial y permiten una interpretación más detallada de la actividad neuronal. Sin embargo, los escenarios prácticos tienden a favorecer dispositivos más asequibles, portátiles, fáciles de desplegar y cómodos para los usuarios finales [7, 9]. En esta dirección, el campo avanza hacia dispositivos BCI portátiles que pueden ser utilizados por los propios sujetos, sin requerir asistencia continua de un operador durante cada experimento. Esto puede facilitar la recogida de datos e incrementar la cantidad de datos EEG disponibles para el análisis [15]. Al mismo tiempo, esta evolución ha promovido el uso de BCIs de bajo coste con un número limitado de electrodos y, en muchos casos, configuraciones de canales fijas. Estos dispositivos facilitan una adopción más amplia, pero también pueden reducir la información espacial disponible para el análisis [6, 11]. Por tanto, el número reducido de canales en sistemas BCI constituye un reto importante para el análisis de EEG en neuromarketing. Este problema motiva la segunda pregunta de investigación de esta tesis, centrada en analizar la relación entre el rendimiento de reconstrucción, la disponibilidad de canales y las restricciones de despliegue práctico al utilizar reconstrucción de canales EEG basada en IA en BCIs con un número limitado de canales para neuromarketing.

Una tercera limitación está relacionada con los conjuntos de datos utilizados para entrenar y evaluar modelos de IA. Aunque las BCIs portátiles pueden incrementar la cantidad

de datos recogidos en experimentos futuros, los conjuntos de datos EEG actuales siguen siendo altamente heterogéneos. A menudo difieren en los protocolos de adquisición, las características del hardware, las decisiones de preprocesamiento, los criterios de anotación y los paradigmas experimentales [14, 13]. Como resultado, conjuntos de datos diseñados para tareas similares pueden diferir considerablemente en el número de sujetos, el número y duración de las sesiones, el balance entre clases, la calidad de la sincronización de eventos o la calidad general de la señal. Estas diferencias afectan a la evaluación comparativa de métodos y hacen que el rendimiento posterior de los modelos sea más difícil de interpretar [14]. En este contexto, no es suficiente con diseñar modelos predictivos. También es necesario comprender la calidad de los datos utilizados para entrenarlos y evaluarlos. Este problema motiva la tercera pregunta de investigación de esta tesis, centrada en identificar qué dimensiones de calidad de los conjuntos de datos EEG son más relevantes para la evaluación comparativa del análisis basado en IA en *neuromarketing* y cómo se relacionan con el rendimiento posterior de los modelos.

En conjunto, estos tres problemas muestran que el uso de IA para EEG en neuromarketing no es únicamente un problema de modelado. También requiere una comprensión estructurada del dominio, métodos para tratar las restricciones prácticas de adquisición de EEG y enfoques objetivos para analizar la calidad de los datos utilizados durante el entrenamiento y la evaluación. Por tanto, esta tesis define un recorrido metodológico que conecta la comprensión del dominio, las restricciones prácticas de adquisición de EEG y la evaluación de la calidad de los datos como pasos necesarios para aplicar IA al neuromarketing basado en EEG.

A partir de las consideraciones anteriores, esta tesis doctoral estudia el uso de IA para el análisis de señales EEG en escenarios de neuromarketing desde tres perspectivas complementarias. En primer lugar, revisa el estado del arte actual del neuromarketing basado en bioseñales e identifica el papel de la EEG, las principales etapas de los estudios actuales, los conjuntos de datos disponibles, las tendencias y los retos abiertos [5]. En segundo lugar, trata una limitación práctica de la adquisición de EEG en escenarios realistas, concretamente el número reducido de canales disponibles en dispositivos BCI de bajo coste y fáciles de usar, mediante la propuesta de una CNN ligera para la reconstrucción de canales EEG [16]. En tercer lugar, se centra en la calidad y comparabilidad de los conjuntos de datos EEG utilizados en flujos de análisis basados en IA, proponiendo un marco multidimensional que resume varios indicadores de calidad en una puntuación de calidad normalizada (*Quality Score*, QS) [17].

Esta organización refleja la progresión de la investigación realizada en esta tesis: comprender el dominio, tratar restricciones prácticas de adquisición y evaluar la calidad de los datos utilizados para entrenar y evaluar soluciones basadas en IA. En esta dirección, surgen tres Preguntas de Investigación (PI) principales que guían el proceso de investigación de esta tesis doctoral:

- PI1: ¿Cuáles son las principales etapas, conjuntos de datos, tendencias y retos abiertos que definen el estado del arte del neuromarketing basado en bioseñales?
- PI2: ¿Qué relación existe entre el rendimiento de reconstrucción, la disponibilidad de canales y las restricciones de despliegue práctico al utilizar reconstrucción de canales EEG basada en IA en BCIs con un número limitado de canales para neuromarketing?
- PI3: ¿Qué dimensiones de calidad de los conjuntos de datos EEG son más relevantes para la evaluación comparativa del análisis basado en IA en neuromarketing, y cómo se relacionan con el rendimiento posterior de los modelos?

II Objetivos

El objetivo principal de esta tesis doctoral es investigar el uso de la IA para el análisis de señales EEG en escenarios de neuromarketing. Para ello, el trabajo se articula en torno a tres perspectivas complementarias. En primer lugar, se estudia el neuromarketing basado en bioseñales mediante la identificación de sus principales objetivos, etapas, conjuntos de datos, tendencias y retos abiertos. En segundo lugar, se analizan las limitaciones prácticas asociadas a la adquisición de EEG mediante dispositivos BCI portátiles y de bajo coste, prestando especial atención a la relación entre el número y la localización de los canales disponibles, el rendimiento de reconstrucción y las restricciones propias de un despliegue práctico. En tercer lugar, se estudia cómo evaluar la calidad de los conjuntos de datos EEG antes de utilizarlos en el entrenamiento y evaluación de soluciones basadas en IA. Para ello, se propone un marco multidimensional que considera aspectos relacionados con la adquisición, la anotación, la calidad de la señal, la distribución de clases, la relevancia de las características y la separabilidad entre clases. A partir de este objetivo principal, se definen los siguientes objetivos específicos, indicando las preguntas de investigación relacionadas con cada uno de ellos:

1. Analizar el estado del arte del neuromarketing basado en bioseñales, con especial atención al papel de la EEG, las principales etapas seguidas en los estudios actuales, los conjuntos de datos disponibles en la literatura y las principales tendencias y retos abiertos del campo (PI1).

2. Identificar las principales brechas metodológicas derivadas del análisis de la literatura, especialmente aquellas relacionadas con la heterogeneidad experimental, las condiciones prácticas de adquisición y la comparabilidad entre estudios (PI1).

3. Estudiar las limitaciones impuestas por los dispositivos BCI portátiles y de bajo coste, especialmente la disponibilidad de un número reducido de canales, y analizar cómo estas restricciones afectan al uso de EEG en escenarios prácticos de neuromarketing (PI2).

4. Proponer y evaluar experimentalmente una solución ligera basada en DL para la reconstrucción de canales EEG en dispositivos BCI con un número limitado de canales, analizando su rendimiento, su comparación con métodos de referencia, la influencia del número y la localización de los canales, y su adecuación para un despliegue práctico en escenarios de neuromarketing (PI2).

5. Analizar los principales factores que afectan a la calidad de los conjuntos de datos EEG utilizados en flujos de análisis basados en IA, incluyendo los protocolos de adquisición, las decisiones de preprocesamiento, los criterios de anotación, la distribución de clases y la calidad de la señal (PI3).

6. Proponer, implementar y validar experimentalmente un marco de evaluación multidimensional de conjuntos de datos EEG que permita caracterizar su calidad antes del entrenamiento y evaluación de modelos, facilitando la comparación de conjuntos de datos bajo un protocolo común (PI3).

III Metodología

Esta tesis doctoral sigue un enfoque científico basado en el estudio del estado del arte y en el análisis de los resultados obtenidos durante las distintas etapas de la investigación. Este

proceso progresivo dio lugar a una tesis estructurada como un compendio de tres artículos publicados en revistas de alto impacto indexadas en el *Journal Citation Reports* (JCR). La metodología se organiza de acuerdo con las preguntas de investigación y los objetivos definidos en la tesis, de forma que cada etapa contribuye a una parte concreta del problema general.

En relación con la PI1 y los Objetivos 1 y 2, la primera etapa de la investigación se centra en revisar el estado del arte del neuromarketing basado en bioseñales, con especial atención al papel de la EEG. Para ello, se analizan los principales objetivos perseguidos en los estudios de neuromarketing y los tipos de estímulos empleados. También se revisan los biosensores utilizados durante la experimentación, las técnicas de preprocesamiento aplicadas a las señales adquiridas, los métodos de extracción de características y las herramientas utilizadas para validar las hipótesis de los estudios. Además, se examinan los conjuntos de datos públicos disponibles y se analizan las principales tendencias y retos abiertos del campo. La Figura 1.1 resume esta visión metodológica al representar las principales etapas de los estudios de neuromarketing basados en bioseñales, desde la definición del objetivo del estudio y de las hipótesis hasta la selección de estímulos, la adquisición mediante dispositivos y bioseñales, el preprocesamiento, la extracción de características y la validación de hipótesis.



Figura 1.1: Ciclo de neuromarketing y principales etapas metodológicas consideradas en estudios de neuromarketing basados en bioseñales.

Este estudio permite identificar la fragmentación metodológica de la investigación en neuromarketing y la falta de una visión unificada de sus principales etapas. Todas estas consideraciones dieron lugar a la primera publicación de esta tesis doctoral, presentada en el Capítulo 1.

Tras identificar las principales características metodológicas y los retos abiertos del campo, la investigación se centra en un problema relevante de adquisición que afecta al uso de EEG en escenarios de neuromarketing. Esta etapa se relaciona con la PI2 y los Objetivos 3 y 4, ya que estudia las limitaciones prácticas impuestas por los dispositivos BCI portátiles y de bajo coste, así como la relación entre la disponibilidad de canales, el rendimiento de reconstrucción y las restricciones de despliegue práctico. Una de las principales limitaciones identificadas en este contexto es la relación entre la riqueza de información espacial y la viabilidad práctica de la adquisición. Los sistemas EEG de alta densidad proporcionan una mayor cantidad de información espacial, pero suelen requerir condiciones de adquisición

más controladas y una mayor supervisión por parte de un operador. En cambio, los dispositivos BCI portátiles y de bajo coste facilitan la experimentación y pueden aumentar la cantidad de datos recogidos en escenarios realistas. Sin embargo, estos dispositivos suelen disponer de un número reducido de canales, lo que limita la información espacial capturada durante la adquisición. A partir de esta limitación, la segunda etapa de la investigación explora cómo la IA, y en particular el DL, puede contribuir al estudio del problema de los canales reducidos mediante la reconstrucción de canales EEG. Además, esta etapa analiza diferentes configuraciones de canales reducidos para identificar qué localizaciones de electrodos resultan más adecuadas para casos de uso específicos de neuromarketing, como escenarios emocionales, sensoriales, atencionales o relacionados con la toma de decisiones.

Para estudiar este problema, la segunda etapa propone una red neuronal convolucional ligera (Convolutional Neural Network, CNN) para la reconstrucción de canales EEG a partir de configuraciones con un número limitado de canales. El modelo se diseña teniendo en cuenta las restricciones de los dispositivos EEG prácticos, incluyendo el número reducido de canales y la necesidad de soluciones computacionalmente eficientes. Las CNN se seleccionan porque permiten capturar patrones temporales locales en las señales EEG, manteniendo al mismo tiempo un modelo suficientemente ligero para su despliegue práctico. La Figura 1.2 resume el flujo de reconstrucción de canales EEG propuesto, mostrando cómo los electrodos reales adquiridos mediante un dispositivo con canales limitados se procesan para estimar canales EEG adicionales.

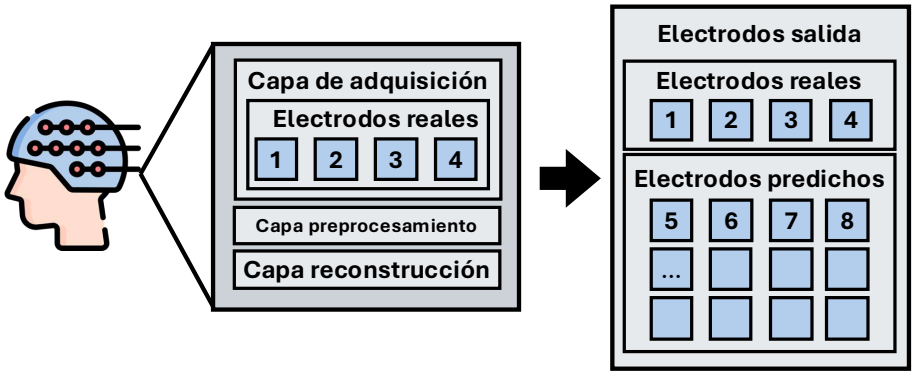


Figura 1.2: Flujo de reconstrucción de canales EEG desde la adquisición con canales limitados hasta la estimación de canales EEG adicionales.

El objetivo del modelo es aumentar la cantidad de información disponible a partir de adquisiciones con canales reducidos. Además, esta etapa define una función de pérdida personalizada que combina la precisión de reconstrucción con la similitud temporal entre las señales originales y reconstruidas. Posteriormente, el modelo se evalúa utilizando conjuntos de datos EEG públicos y se compara con métodos de referencia. Además, se realiza un análisis amplio de configuraciones de canales para identificar qué combinaciones compactas de electrodos resultan más adecuadas para escenarios prácticos. Todas estas consideraciones dieron lugar a la segunda publicación de esta tesis doctoral, presentada en el Capítulo 2.

Una vez estudiado el problema de la adquisición con canales reducidos, la investigación se centra en otro problema metodológico: la calidad de los conjuntos de datos utilizados para entrenar y evaluar soluciones basadas en IA. Esta etapa se relaciona con la PI3 y los Objetivos 5 y 6, ya que examina cómo puede caracterizarse la calidad de los conjuntos de datos EEG mediante un marco multidimensional y cómo puede evaluarse experimentalmente bajo un protocolo común. Aunque las tecnologías actuales de adquisición pueden facilitar experimentos a mayor escala, los conjuntos de datos EEG siguen presentando diferencias

considerables en sus protocolos, decisiones de preprocesamiento, criterios de anotación y calidad de señal. Esta heterogeneidad afecta directamente al benchmarking y dificulta la interpretación del rendimiento de los modelos. A partir de este problema, la tercera etapa de la investigación define un marco objetivo para la evaluación multidimensional de la calidad de conjuntos de datos EEG.

Para ello, el marco define un conjunto de dimensiones de calidad que permiten caracterizar los conjuntos de datos EEG antes del entrenamiento y la evaluación de modelos. Estas dimensiones incluyen la completitud de las sesiones, la consistencia en la duración de las sesiones, el balance de clases y la sincronización de las anotaciones. También incluyen la relación señal-ruido, la presencia de valores atípicos, el contenido informativo de las características y la separabilidad entre clases. Tras definir estos indicadores, el marco propone una puntuación de calidad normalizada que resume la calidad global de un conjunto de datos, manteniendo al mismo tiempo las puntuaciones individuales disponibles para su interpretación. Posteriormente, el marco se aplica a varios conjuntos de datos EEG públicos con el fin de comparar su calidad bajo un protocolo común y estudiar la relación entre la calidad del conjunto de datos y el rendimiento posterior de los modelos. Estas consideraciones dieron lugar a la tercera publicación de esta tesis doctoral, presentada en el Capítulo 3.

En resumen, la metodología sigue la progresión de la investigación y mantiene una conexión directa con las preguntas de investigación y los objetivos definidos. En primer lugar, revisa el estado del arte del neuromarketing basado en bioseñales e identifica sus principales etapas, conjuntos de datos, tendencias, retos abiertos y brechas metodológicas en relación con la PI1 y los Objetivos 1 y 2. A continuación, estudia un problema práctico de adquisición que afecta al uso de EEG en escenarios realistas, en relación con la PI2 y los Objetivos 3 y 4. Finalmente, propone y evalúa un marco para caracterizar la calidad de los conjuntos de datos que sustentan el análisis basado en IA, en relación con la PI3 y los Objetivos 5 y 6. Esta metodología permite responder a las preguntas de investigación planteadas en la tesis y conectar las tres publicaciones bajo una misma línea de investigación.

IV Resultados

En la primera publicación de esta tesis doctoral, presentada en el Capítulo 1, se revisó el estado del arte del neuromarketing basado en bioseñales y se identificaron varias brechas metodológicas que afectan a la organización, interpretación y comparación de los estudios existentes. Esta contribución está relacionada con la PI1 y los Objetivos 1 y 2, ya que identifica las principales etapas, conjuntos de datos, tendencias, retos abiertos y brechas metodológicas derivadas de la literatura. La primera brecha fue la ausencia de un ciclo de neuromarketing comúnmente aceptado, lo que dificulta describir las distintas etapas de estos estudios bajo una estructura unificada. La segunda brecha fue que la mayoría de revisiones previas estudiaban solo una parte del problema, normalmente centrándose en una bioseñal concreta o en etapas metodológicas aisladas. La tercera brecha fue la falta de una organización común de los conjuntos de datos disponibles para estos escenarios, lo que dificultaba el análisis comparativo entre estudios. A partir de estas limitaciones, la publicación organizó el campo de acuerdo con sus principales objetivos, bioseñales, técnicas de procesamiento, conjuntos de datos, tendencias y retos abiertos.

Esta publicación también proporcionó varios resultados concretos sobre el estado actual del campo. La comparación de anuncios se identificó como el objetivo de neuromarketing más frecuente, representando casi el 45 % de los trabajos revisados, seguida de los estudios centrados en el impacto de los anuncios y en la mejora de anuncios, con un 30.4 %

y un 24.8 %, respectivamente. Los estímulos audiovisuales fueron el tipo de estímulo más utilizado y aparecieron en más del 50 % de los trabajos en los tres objetivos analizados. Además, la EEG y el seguimiento ocular fueron identificados como las bioseñales más extendidas, con la EEG presente en casi el 50 % de los trabajos revisados. El análisis también mostró que los conjuntos de datos públicos siguen siendo escasos y que, generalmente, no están diseñados específicamente para objetivos de neuromarketing. En conjunto, estos resultados permitieron identificar las principales tendencias del campo, su fragmentación metodológica y varios retos abiertos para investigaciones futuras. Estos hallazgos contribuyen a responder la PI1 y a cumplir los Objetivos 1 y 2, al identificar las principales etapas, conjuntos de datos, tendencias, retos abiertos y brechas metodológicas que definen la investigación en neuromarketing basada en bioseñales.

La segunda publicación de esta tesis doctoral, presentada en el Capítulo 2, estudió una limitación práctica que afecta a la adquisición de EEG en escenarios de neuromarketing: el número reducido de canales disponibles en dispositivos BCI portátiles y de bajo coste. Esta contribución está relacionada con la PI2 y los Objetivos 3 y 4, ya que analiza las limitaciones impuestas por los dispositivos con canales reducidos y propone una solución basada en DL, evaluada experimentalmente, para la reconstrucción de canales EEG. Para ello, se propuso una CNN ligera capaz de reconstruir canales EEG a partir de configuraciones reducidas. Además, se definió una función de pérdida personalizada que combina el error cuadrático medio (*Mean Squared Error*, MSE) y el coeficiente de correlación de Pearson, con el objetivo de preservar tanto la precisión de reconstrucción como la dinámica temporal de las señales EEG. El trabajo también incluyó una evaluación sistemática de más de 1,820 configuraciones de canales, con el fin de identificar qué subconjuntos resultan más adecuados para escenarios prácticos de neuromarketing.

Los resultados de este trabajo mostraron que el modelo propuesto alcanzó un rendimiento de reconstrucción consistente y superó a los métodos de referencia en la mayoría de escenarios evaluados. En particular, la CNN propuesta obtuvo un NMSE de $0{,}042 \pm 0{,}009$, frente a $0{,}064 \pm 0{,}011$ para *Spherical Spline Interpolation* (SSI), $0{,}071 \pm 0{,}013$ para *Partial Least Squares Regression* (PLSR) y $0{,}055 \pm 0{,}010$ para un *autoencoder* superficial de referencia. Además, la evaluación de más de 1,820 configuraciones de canales mostró que algunos dispositivos comerciales resultan más favorables que otros dependiendo del caso de uso, especialmente en escenarios emocionales, sensoriales, atencionales y relacionados con la toma de decisiones. La evaluación de recursos también apoyó la adecuación del modelo para su despliegue práctico en BCIs comerciales. En conjunto, estos resultados mostraron que el modelo propuesto puede mitigar parte de las limitaciones impuestas por los dispositivos EEG con un número limitado de canales y apoyar su uso en escenarios prácticos de neuromarketing. Estos hallazgos contribuyen a responder la PI2 y a cumplir los Objetivos 3 y 4, al analizar la relación entre el rendimiento de reconstrucción, la disponibilidad de canales y las restricciones de despliegue práctico en dispositivos BCI con un número limitado de canales.

La tercera publicación de esta tesis doctoral, presentada en el Capítulo 3, se centró en la calidad y comparabilidad de los conjuntos de datos EEG utilizados para entrenar y evaluar soluciones basadas en IA. Esta contribución está relacionada con la PI3 y los Objetivos 5 y 6, ya que analiza los principales factores que afectan a la calidad de los conjuntos de datos EEG y propone un marco evaluado experimentalmente para su evaluación multidimensional. El marco propone calcular un conjunto de indicadores relacionados con la completitud de las sesiones, la consistencia en la duración de las sesiones, el balance de clases, la sincronización de las anotaciones, la relación señal-ruido, la presencia de valores atípicos, el contenido informativo de las características y la separabilidad entre clases.

Estos indicadores se combinan posteriormente en una puntuación de calidad normalizada (Quality Score, QS) con un rango de 0 a 100. Un aspecto importante del marco es que la agregación conserva la contribución de los distintos indicadores y utiliza un resumen por sujeto, lo que reduce la dependencia de la puntuación final respecto a sujetos o sesiones aisladas.

La evaluación de este marco se llevó a cabo sobre seis conjuntos de datos EEG públicos procedentes de reconocimiento afectivo, paradigmas relacionados con eventos e imaginación motora, todos ellos procesados bajo protocolos idénticos. El rendimiento de clasificación posterior se evaluó mediante *Balanced Accuracy* y A*rea Under the ROC Curve*. Los resultados mostraron que el QS propuesto capturó diferencias en la integridad de los datos, la consistencia temporal y la separabilidad entre clases, manteniéndose interpretable en colecciones heterogéneas. Además, los análisis de correlación indicaron asociaciones positivas entre los indicadores orientados a la separabilidad y el rendimiento posterior de los modelos, así como asociaciones negativas con una mayor presencia de valores atípicos. El trabajo también mostró que los ajustes de entrenamiento guiados por estos indicadores mejoraron el rendimiento. Estos hallazgos contribuyen a responder la PI3 y a cumplir los Objetivos 5 y 6, al identificar dimensiones informativas de calidad de conjuntos de datos EEG, validar su uso bajo un protocolo común y analizar su relación con el rendimiento posterior de los modelos.

En resumen, los resultados de esta tesis doctoral siguen la progresión de la investigación y mantienen una conexión directa con las preguntas de investigación y los objetivos definidos. En primer lugar, la revisión estructuró el estado del arte del neuromarketing basado en bioseñales e identificó las principales brechas metodológicas del campo, contribuyendo a la PI1 y a los Objetivos 1 y 2. A continuación, la segunda publicación estudió una limitación práctica de la adquisición de EEG en escenarios realistas, concretamente el número reducido de canales en BCIs de bajo coste, y propuso un modelo ligero de reconstrucción, contribuyendo a la PI2 y a los Objetivos 3 y 4. Finalmente, la tercera publicación estudió la calidad de los conjuntos de datos utilizados en flujos de análisis basados en IA y propuso un marco para comparar conjuntos de datos EEG bajo una metodología común, contribuyendo a la PI3 y a los Objetivos 5 y 6. En conjunto, estos resultados permitieron responder a las preguntas de investigación de la tesis y conectar las tres publicaciones bajo una misma línea de investigación.

V Conclusiones y trabajo futuro

En los últimos años, el uso de la IA para el análisis de señales EEG ha ganado relevancia en neuromarketing. Esta tendencia está motivada por la necesidad de comprender mejor las respuestas de los consumidores a partir de información fisiológica y neural, superando los enfoques tradicionales basados únicamente en cuestionarios o entrevistas. En este contexto, la EEG se ha convertido en una de las bioseñales más relevantes debido a su naturaleza no invasiva, portabilidad, bajo coste y alta resolución temporal. Sin embargo, la aplicación práctica de EEG en neuromarketing todavía presenta limitaciones importantes relacionadas con la fragmentación metodológica del campo, las restricciones de los dispositivos de adquisición con un número limitado de canales y la heterogeneidad de los conjuntos de datos utilizados para entrenar y evaluar soluciones basadas en IA.

Considerando estas limitaciones, la primera etapa de este trabajo analizó el estado del arte del neuromarketing basado en bioseñales. En particular, se identificó que la literatura todavía carece de un ciclo de neuromarketing comúnmente aceptado y que la mayoría de revisiones previas tratan solo una parte del problema. Además, los trabajos revisados

muestran un alto grado de heterogeneidad en sus objetivos, estímulos, bioseñales, técnicas de preprocesamiento, métodos de extracción de características y enfoques de validación. En esta dirección, la primera contribución proporcionó una visión estructurada del campo, organizando sus principales objetivos, bioseñales, técnicas de procesamiento, conjuntos de datos, tendencias y retos abiertos. Esta contribución permitió responder a la PI1 al identificar las principales etapas, conjuntos de datos, tendencias, retos abiertos y brechas metodológicas que motivaron las siguientes etapas de la investigación.

A continuación, el trabajo estudió una de las principales limitaciones prácticas que afectan a la adquisición de EEG en escenarios de neuromarketing: el número reducido de canales disponibles en dispositivos BCI portátiles y de bajo coste. Aunque estos dispositivos facilitan la experimentación en escenarios prácticos, también reducen la información espacial disponible para el análisis. Para tratar este problema, la segunda contribución propuso una CNN ligera para la reconstrucción de canales EEG a partir de configuraciones con un número limitado de canales. Los resultados obtenidos mostraron que el modelo fue capaz de reconstruir canales EEG con un rendimiento competitivo, superar a los métodos de referencia en la mayoría de los escenarios evaluados y favorecer su despliegue práctico gracias a su eficiencia computacional. Además, el análisis de más de 1,820 configuraciones de canales permitió identificar configuraciones más adecuadas para diferentes casos de uso en neuromarketing. Estos resultados contribuyeron a responder a la PI2 al analizar la relación entre el rendimiento de reconstrucción, la disponibilidad de canales y las restricciones de despliegue práctico en dispositivos EEG con un número limitado de canales.

Finalmente, la investigación estudió un problema metodológico más amplio relacionado con la calidad y comparabilidad de los conjuntos de datos EEG. Aunque las tecnologías de adquisición están evolucionando y pueden facilitar experimentos a mayor escala, los conjuntos de datos EEG siguen presentando diferencias considerables en sus protocolos de adquisición, decisiones de preprocesamiento, criterios de anotación y calidad de la señal. Estas diferencias afectan directamente al benchmarking y dificultan la interpretación del rendimiento posterior de los modelos. Para tratar este problema, la tercera contribución propuso un marco para la evaluación multidimensional de la calidad de conjuntos de datos EEG. El marco propone calcular un conjunto de indicadores relacionados con la completitud, la consistencia temporal, el balance de clases, la sincronización de anotaciones, la relación señal-ruido, la presencia de valores atípicos, el contenido informativo de las características y la separabilidad entre clases, combinándolos en una puntuación de calidad normalizada. La evaluación sobre seis conjuntos de datos EEG públicos mostró que este marco permite caracterizar la calidad de los datos de forma interpretable y relacionarla con análisis posteriores basados en IA. Estos resultados contribuyeron a responder a la PI3 al identificar dimensiones informativas de calidad de conjuntos de datos EEG, relacionarlas con el rendimiento posterior de los modelos y proporcionar una base para una comparación más objetiva de conjuntos de datos en este campo.

En resumen, esta tesis doctoral ha estudiado el uso de IA para el análisis de EEG en neuromarketing desde tres perspectivas complementarias. En primer lugar, ha estructurado el estado del arte del campo. A continuación, ha propuesto una solución práctica para una de las principales limitaciones de la adquisición de EEG en escenarios realistas. Finalmente, ha introducido un marco metodológico para evaluar la calidad de los conjuntos de datos que sustentan el análisis basado en IA. En conjunto, estas contribuciones conectan las tres publicaciones bajo una misma línea de investigación y proporcionan una base más sólida para futuros trabajos sobre neuromarketing basado en EEG. Por tanto, la contribución global de esta tesis no se limita a un modelo concreto de IA, sino que también incluye la definición de un recorrido metodológico más amplio para aplicar IA al neuromarketing

basado en EEG.

Como trabajo futuro, es necesario seguir avanzando en la madurez metodológica de la investigación en neuromarketing. En particular, sería conveniente diseñar nuevos conjuntos de datos orientados explícitamente a objetivos de neuromarketing, que incluyan estímulos más realistas, protocolos experimentales más consistentes y criterios de anotación más claros. En esta misma dirección, también existe la oportunidad de explorar escenarios que se aproximen mejor a entornos reales de consumo, como experimentos con productos reales, distribución de espacios comerciales o interacciones multimodales más cercanas a los procesos cotidianos de toma de decisiones. Estas líneas ayudarían a reducir la distancia entre los estudios controlados de laboratorio y las aplicaciones prácticas del neuromarketing.

Con respecto a la reconstrucción de canales EEG, los trabajos futuros deberían centrarse en mejorar la generalización y aplicabilidad del modelo propuesto. En particular, existe margen para mejorar las predicciones entre hemisferios, reducir la dependencia de la densidad de canales y evaluar el modelo en una mayor variedad de conjuntos de datos y dispositivos. También sería útil estudiar arquitecturas más avanzadas y estrategias mejoradas para preservar la polaridad de la señal y las dependencias espaciales. Además, un paso relevante sería la integración de estos modelos en plataformas BCI prácticas, lo que podría contribuir a trasladar los resultados actuales hacia herramientas reales de neuromarketing.

En relación con la evaluación de la calidad de conjuntos de datos, los trabajos futuros deberían centrarse en extender el marco propuesto a paradigmas, conjuntos de datos y condiciones experimentales adicionales. También sería útil profundizar en la relación entre indicadores específicos de calidad y el rendimiento posterior de los modelos, así como estudiar cómo estos indicadores pueden guiar de forma más sistemática las decisiones de preprocesamiento, entrenamiento y benchmarking. Asimismo, la extensión de este tipo de marcos a conjuntos de datos multimodales podría ser especialmente relevante en neuromarketing, donde la EEG se combina frecuentemente con otras bioseñales como el seguimiento ocular, la actividad electrodérmica o la electrocardiografía.

En conjunto, esta tesis muestra que el uso de IA en neuromarketing basado en EEG no debe entenderse únicamente como el diseño de modelos predictivos. También requiere una comprensión estructurada del dominio, soluciones prácticas para restricciones realistas de adquisición y métodos objetivos para evaluar la calidad de los datos utilizados durante el entrenamiento y la evaluación. Avanzar en estas tres direcciones será esencial para hacer que el neuromarketing basado en EEG sea más robusto, más comparable y más aplicable en escenarios reales.

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Publications composing

the PhD Thesis

1

Survey on AI and Biosensors



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Abstract

The primary goal of any company is to increase its profits by improving both the quality of its products and how they are advertised. In this context, neuromarketing seeks to enhance the promotion of products and generate a greater acceptance on potential buyers. Traditionally, neuromarketing studies have relied on a single biosignal to obtain feedback from presented stimuli. However, thanks to new devices and technological advances studying this area of knowledge, recent trends indicate a shift towards the fusion of diverse biosignals. An example is the usage of electroencephalography for understanding the impact of an advertisement at the neural level and visual tracking to identify the stimuli that induce such impacts. This emerging pattern determines which biosignals to employ for achieving specific neuromarketing objectives. Furthermore, the fusion of data from multiple sources demands advanced processing methodologies. Despite these complexities, there is a lack of literature that adequately collates and organizes the various data sources and the applied processing techniques for the research objectives pursued. To address these challenges, the current paper conducts a comprehensive analysis of the objectives, biosignals, and data processing techniques employed in neuromarketing research. This study provides both the

technical definition and a graphical distribution of the elements under revision. Additionally, it presents a categorization based on research objectives and provides an overview of the combinatory methodologies employed. After this, the paper examines primary public datasets designed for neuromarketing research together with others whose main purpose is not neuromarketing, but can be used for this matter. Ultimately, this work provides a historical perspective on the evolution of techniques across various phases over recent years and enumerates key lessons learned.

Keywords

Data fusion · Neuromarketing · Biosignals · Life cycle · Brain–computer interfaces · Biosensors

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Full length article

Data fusion in neuromarketing: Multimodal analysis of biosignals, lifecycle stages, current advances, datasets, trends, and challenges

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Biosensors

ABSTRACT

The primary goal of any company is to increase its profits by improving both the quality of its products and how they are advertised. In this context, neuromarketing seeks to enhance the promotion of products and generate a greater acceptance on potential buyers. Traditionally, neuromarketing studies have relied on a single biosignal to obtain feedback from presented stimuli. However, thanks to new devices and technological advances studying this area of knowledge, recent trends indicate a shift towards the fusion of diverse biosignals. An example is the usage of electroencephalography for understanding the impact of an advertisement at the neural level and visual tracking to identify the stimuli that induce such impacts. This emerging pattern determines which biosignals to employ for achieving specific neuromarketing objectives. Furthermore, the fusion of data from multiple sources demands advanced processing methodologies. Despite these complexities, there is a lack of literature that adequately collates and organizes the various data sources and the applied processing techniques for the research objectives pursued. To address these challenges, the current paper conducts a comprehensive analysis of the objectives, biosignals, and data processing techniques employed in neuromarketing research. This study provides both the technical definition and a graphical distribution of the elements under revision. Additionally, it presents a categorization based on research objectives and provides an overview of the combinatory methodologies employed. After this, the paper examines primary public datasets designed for neuromarketing research together with others whose main purpose is not neuromarketing, but can be used for this matter. Ultimately, this work provides a historical perspective on the evolution of techniques across various phases over recent years and enumerates key lessons learned.

1. Introduction

Neuromarketing is the discipline that applies neuropsychology to marketing research with the aim of studying and predicting the human behaviors generated by marketing practices. Historically, this area has been of interest to companies because it improves advertising campaigns and increases profits. Some of the first companies to apply these techniques were Paypal [1] and Google [2]. Specifically, PayPal used neuromarketing techniques to study how to encourage more e-shoppers to use their online payment service. Through their research, PayPal found that commercials focusing on Unique Selling Points (USPs), such as speed and convenience, triggered a more significant brain response than promoting features like safety and security. This insight led them to emphasize the speed and ease of their payment system in their marketing efforts to attract more users. For a similar study, Google used the Eye-Tracking (ET) technique to identify how users behaved when reading searches. The results showed that users tended to read them in order, from top to bottom, so thumbnails appeared in the search results, trying to draw users' attention directly to the results below. These techniques can also be applied to physical products, as in the case of PepsiCo [3], which used neuromarketing to redesign

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the packaging of Lays potato chip bags. The company used electroencephalography (EEG) to make them more acceptable to the female audience. This study resulted in packaging with brown tones that seem to be homemade, low-calorie, and healthy products. In the last years, the techniques employed for obtaining user feedback have evolved towards the acquisition of biosignals [4] and the automatic detection of mental states using Artificial Intelligence (AI) [5]. In this context, more affordable and portable devices have been developed to acquire diverse biosignals. Brain–Computer Interfaces (BCIs) [6], Electrodermal Activity (EDA) sensors [7], or ET glasses [8] are well-known and representative examples of new devices used in neuromarketing to capture biological signals. These devices easy to conduct experiments based on the application of stimuli such as images or videos to a group of subjects and monitor their biosignals without needing professional equipment. Moreover, they combine multimodal data to yield more comprehensive insights [9]. Once the data are obtained from the subjects participating in the experimentation, the latest works propose using AI solutions to identify specific biosignal patterns that can be related to a mental state or reaction [10]. Traditionally, experts have performed this identification by gathering statistics from the signals and visually interpreting them [11]. However, this has disadvantages, such as the subjectivity introduced when evaluating the results.

Neuromarketing studies follow a life cycle of several stages to detect mental states from diverse biosignals. This cycle begins with the definition of the study objective and ends with the validation of this objective (see Fig. 1) [12]. In the first stage of the cycle, the following three possible objectives have been identified in the literature: improving the impact of an advertisement, comparing similar advertisements, and studying the impact of an advertisement [13,14]. Once the objective is selected, the second stage defines the hypothesis together with the metrics used to measure the impact of the stimulus, namely, the emotional state evoked or product preference. This impact will be measured by the data obtained from the biosignals, so the relationship with phase four is very close. The third phase of the cycle decides the stimuli used to perform the study [15], such as audiovisual (e.g., a video), or cognitive inputs, like browsing a web page. Next, during the fourth stage, the process determines which set of devices is the most appropriate to capture the biosignals of interest, for example a BCI, or an ET system. This device will provide a data flow of measurements. The fifth and sixth phases preprocess this data flow to clean the signal and extract relevant information. The algorithms applied in these two phases are key to a correct subsequent data fusion. The concluding phase involves data classification, which traditionally has been performed manually to yield statistics. However, the recent introduction of Machine Learning (ML) and Deep Learning (DL) algorithms into this field enables pattern recognition and reduces the subjectivity introduced by human judgment, further highlighting the tools used for hypothesis validation in the context of multimodal data fusion.

Each of the phases of neuromarketing studies hosts a wide range of alternatives. Therefore, the potential combinations increase exponentially, and finding the optimum combination to obtain the best performance becomes challenging and time-consuming. Moreover, no work in the literature considers all phases of the neuromarketing cycle and explores the options at each stage. To tackle this challenge, the present work compiles the most representative efforts to raise similarities and differences in this context. Specifically, Bercea [16] conducted the first literature review to highlight the advantages and disadvantages of the different biosignals used for neuromarketing objectives. Three years later, Dos et al. [17] studied the feasibility of using ET biosignals in real product selection or pricing scenarios. After that, Mileti et al. [18] presented the concept of nanomarketing from a theoretical point of view, analyzing how this concept could help current neuromarketing. Subsequently, due to the emergence of BCIs and EEG, and their application for mental state detection, the number of studies using this biosignal increased and, therefore, the number of surveys collecting information about them. Furthermore, Hakim et al. [15] and Bazzani et al. [12] performed a compilation of works on the EEG signal applied to neuromarketing scenarios. During the year 2021, two more papers were published. The first one, by Kalaganis et al. [19] presented, from a theoretical point of view, the different biosensors used for neuromarketing and in which scenarios they are used. In contrast, Khurana et al. [20] studied those technical aspects necessary for the experiments, such as preprocessing, feature extraction, and data classification.

Table 1 summarizes the previous works, showing the number of biosignals studied, as well as each of the phases of the neuromarketing cycle, and whether they are detailed or not. As conclusion of the works described above, some challenges are still open. First, the literature does not define a homogeneous neuromarketing cycle [24]. Due to this, most works exclude certain phases of the cycle, a crucial gap we address in this survey. While various studies recognize the multifaceted nature of neuromarketing, they often do not provide an inclusive review that integrates both the applied objectives and technical aspects, such as data preprocessing, feature extraction, or data classification. Conversely, those surveys that detail the technical part of the work only consider a biosignal, usually the EEG signal. The present survey extends beyond this limited scope by analyzing the different biosignals used, what processing techniques are needed, what information can be obtained from them, and the combination with other biosignals that have been proposed. Another point not addressed in the literature is the available datasets for this scenario. This work has identified this as a critical area for research and provides a comprehensive list of datasets, facilitating benchmarking and comparative analysis across studies. Finally, the literature does not show the general trends followed in the literature in recent years or the challenges that neuromarketing research will face in the coming years. Our work traces these trends and proposes future challenges, thus setting a course for prospective research in the field. Based on these identified gaps, this paper proposes a series of research questions focused on answering and resolving each of the shortcomings mentioned above:

- Q1: *What are the most applied objectives, biosensors, and processing techniques in neuromarketing?* Specific biosensors and particular techniques are used depending on the objective of the campaign. There is a lack of works in the literature covering all these considerations.
- Q2: *What combinations of data from biosignals, stimuli, and data processing and classification techniques are suitable for each objective?* Once all the techniques that have been applied for these investigations are known, the combinations between them, depending on the objective pursued, should be studied. Since no studies have been found considering all the campaign phases and the biosensors available, these associations are not reflected in the present works.
- Q3: *What datasets are publicly available in neuromarketing, and what type of data include?* This study aims to identify existing public datasets that facilitate data fusion and are applicable to neuromarketing objectives. In this way, the problem of the dependence on the data obtained from the biosignals can be solved when comparing the methodologies proposed by the different works.
- Q4: *How has the role of data fusion in neuromarketing evolved over time, and what are the open challenges?* Current surveys do not show the evolution of the work in terms of the objectives in neuromarketing, as well as the data fusion used over the years. Likewise, they do not show the evolution of the datasets that have appeared in recent years and for which objectives they have been proposed. Finally, an overview of the published works, limitations, and opportunities for further work needs to be identified.

To answer the above research questions, the main contributions of this paper are the following:

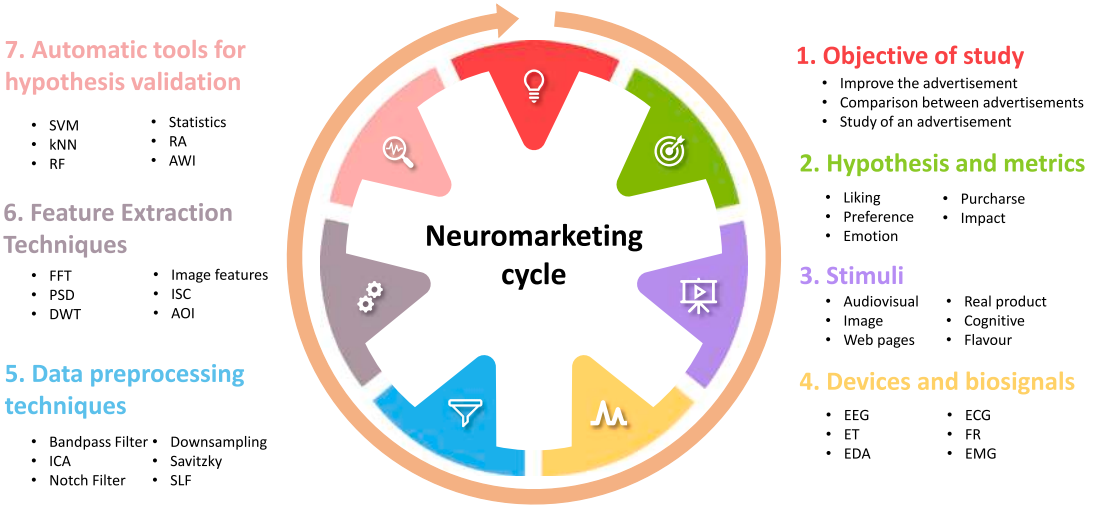


Fig. 1. Neuromarketing cycle.

Table 1
Surveys on neuromarketing and biosignals.

Ref	Year	Cites	Biosignal	Objectives	Stimuli	Preprocessing	Feature extraction	Tools	Results	Datasets	Challenges and trends
[16]	2012	130	EEG, ECG, ET, FR, EDA, EMG	✗	✗	✗	✗	✗	✗	✗	✗
[17]	2015	103	ET	✓	✓	✗	✗	✗	✗	✗	✗
[18]	2016	15	None	✗	✗	✗	✗	✗	✗	✗	✓
[15]	2018	42	EEG	✓	✓	✓	✓	✓	✗	✗	✓
[12]	2020	16	EEG	✓	✗	✓	✗	✗	✗	✗	✓
[21]	2020	86	EEG, ECG, ETEDA, EMG	✗	✓	✓	✓	✓	✓	✗	✗
[19]	2021	1	EEG, ECG, ET, FR, EDA, EMG	✓	✓	✗	✗	✗	✗	✗	✗
[20]	2021	5	EEG	✓	✓	✓	✓	✓	✗	✓	✓
[22]	2021	61	EEG, ECG, ETEDA, EMG	✗	✗	✗	✗	✗	✗	✗	✓
[23]	2022	12	EEG	✗	✗	✓	✓	✗	✓	✗	✓
This work	2023	0	EEG, ECG, ETC, FR, EDA, EMG	✓	✓	✓	✓	✓	✓	✓	✓

- A complete analysis of the objectives, biosensors, and processing data techniques employed in neuromarketing. This study presents the technical definition and a graphical distribution of the use of the elements in question. This contribution responds to question *Q1* in Section 2.
- A literature analysis based on neuromarketing, obtaining the main characteristics of each work applied in the neuromarketing cycle and grouped by objectives. In this sense, this paper presents in Section 3 the combinations of techniques used in each of the works, as well as the results obtained, answering *Q2*.
- An analysis of the primary public datasets explicitly designed for research work related to neuromarketing. This review answers question *Q3*, detailing in Section 4 those datasets focused on neuromarketing, together with others whose main purpose is not neuromarketing, but can be used for this purpose.
- An overview of how the techniques of the different phases have evolved over the last few years and a list of lessons learned, aiming to respond to question *Q4* in Section 5.

The previous questions are interrelated and provide a comprehensive overview of the current state of the data and techniques used in neuromarketing. *Q1* focus on stu/dying the objectives, biosensors, and techniques currently used in this type of research. In contrast, *Q2* and *Q3* show the combinations of data used in current literature and the existing datasets for prospecting work. These aspects represent the most critical sections of this paper. Finally, *Q4* highlights the trends followed in recent years and the consequences of these trends. As a summary, Fig. 2 shows which sections of this paper answer the research questions presented.

The remainder of this article is organized as follows. Section 2 analyzes biosensor types, objectives, and techniques used in neuromarketing. After that, Section 3 describes and compares the leading solutions found in the state of the art. Moreover, Section 4 examines the primary public datasets containing biosignals. Then, Section 5 draws a set of lessons learned, current trends, and future challenges in the research area. Finally, Section 6 provides an insight into the conclusions extracted from the present work.

2. What are the most applied objectives, biosensors and processing techniques in neuromarketing?

This section answers the first research question by following a search methodology composed of the next steps.

- Definition of the subsequent search terms: Given the traditional association of neuromarketing with neuroimaging and the contemporary expansion of the field, the search strategy was broadened to encompass a more diverse terminological range [25]. Search terms were not only limited to Neuromarketing but also included Marketing, alongside various biosignal methodologies such as Electroencephalography (EEG), EDA, Galvanic Skin Response (GSR), Electromyography (EMG), Electrocardiography

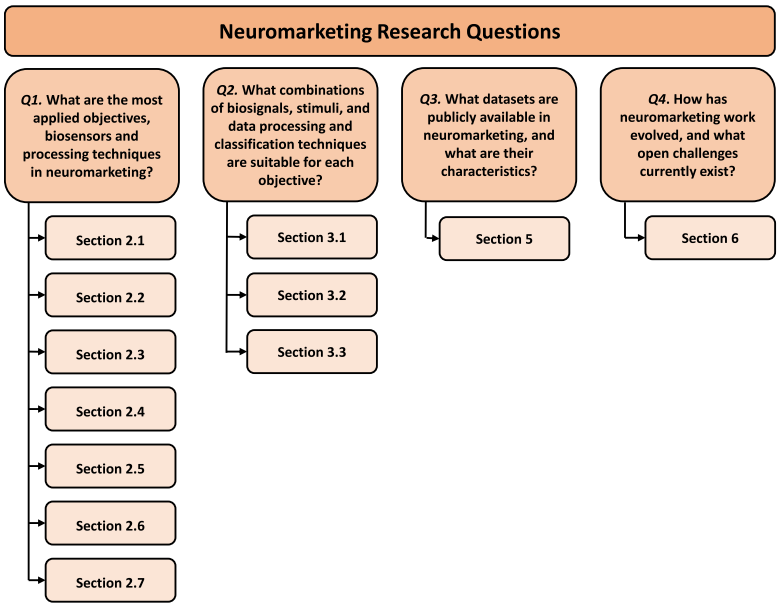


Fig. 2. Discussed questions per article section.

(ECG), Eye Tracking (ET), Facial Recognition (FR), and Biosignal, coupled with Survey, and Review. These terms were utilized in combinations of two or more to reflect the multidisciplinary aspect of current neuromarketing research.
- Selection of the scientific databases where the search for articles is performed: The search was conducted using reputable academic databases, including Google Scholar and Scopus, to ensure the credibility of the literature included in this study.
- Initial screening of publications: Abstracts and introductions of the retrieved publications were meticulously examined to verify their relevance to the neuromarketing scope explored in this work, emphasizing the synergy between traditional marketing efforts and an expanded array of biosignal analyses.

The study of title, abstract, and keywords has already been used as a search methodology in other studies [26]. In the case of this work, this methodology has been used only for the first selection of related works. Once these works have been selected, a more in-depth study of the technical and experimental parts is carried out, collecting the joint parts (see Fig. 3):

1. **Objective of study**: The first phase defines the objective of the study designed. Three objectives have been identified, (i) study the impact of an advertisement, (ii) modify the advertisement to improve its impact, and (iii) compare an advertisement with other similar ones.
2. **Hypothesis and metrics**: The second phase focuses on the hypothesis posed to solve the objective and the metrics used to obtain a conclusion.
3. **Stimuli**: The third phase focuses on the stimuli applied to subjects during the experimental period.
4. **Devices and biosignals**: The fourth phase involves selecting both the biosignals used in the study and the biosensors needed to capture them.
5. **Data processing techniques**: In order to eliminate possible noises introduced during acquisition, the analyzed works apply a data preprocessing phase.
6. **Feature extraction techniques**: To extract the relevant information from the data, a feature extraction phase is applied.
7. **Automatic tools for hypothesis validation**: Once the necessary information is available, the last phase is the classification stage. This phase studies the information coming from previous steps, and decides to which label it corresponds.

The details of each phase are shown in Sections 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, and 2.7. Moreover, Fig. 3 shows the distribution charts between for the different stages. The graphs show the number of publications using each of the defined techniques and approaches.

2.1. Objective of study

The objective of a marketing campaign is fundamental when designing a campaign study. The literature mainly proposes three different objectives [13,14].

- The first objective studies the impact of a given advertisement on the subject. Data is collected from the different biosensors to measure this impact, applying specific preprocessing and feature extraction techniques to obtain the relevant information. Once this information is available, classification algorithms can be used to measure the impact generated by the stimulus [27].
- The second objective focuses on improving the impact of the advertisement presented to users. In this approach, the same advertisement is usually presented with slight modifications while collecting the biosignal data to study how the modifications affect the stimuli and, thus, conclude whether the impact is improved [28].
- The third objective compares different advertisements, usually from the same market niche. This objective is the most common since it directly compares advertisements from different brands, obtaining which advertisements generate a more significant impact or a higher purchase probability [29].

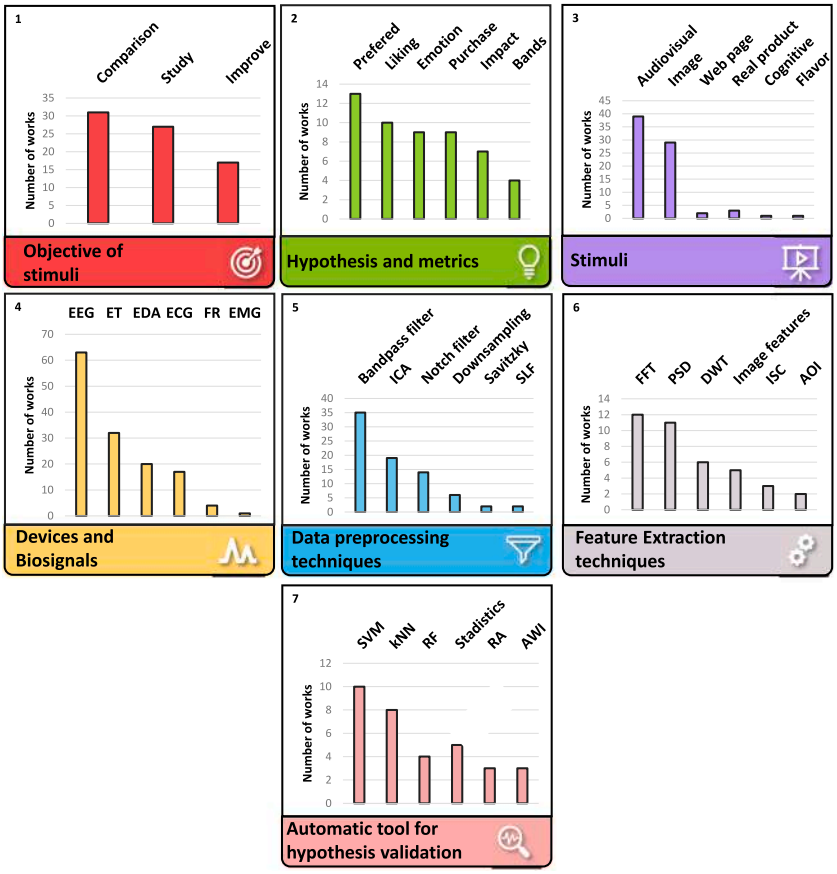


Fig. 3. Number of works using the main techniques in each phase of the neuromarketing cycle.

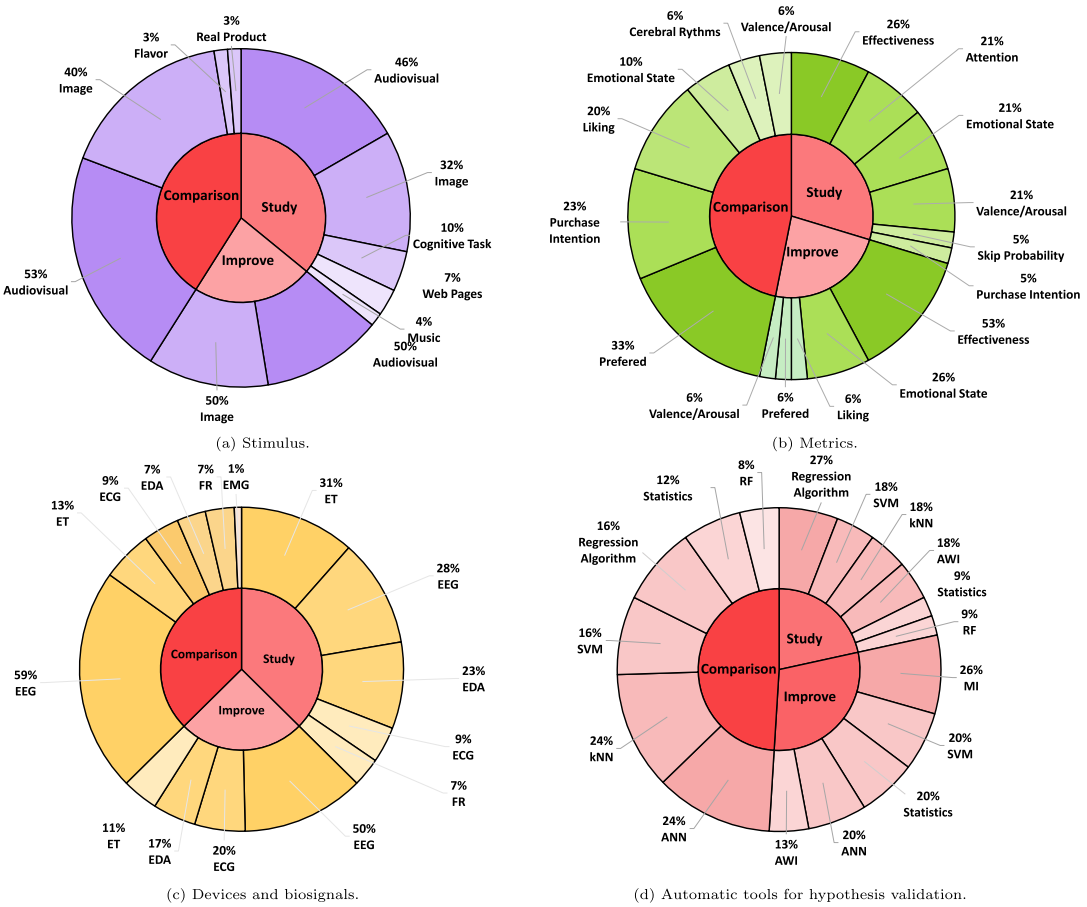
Fig. 3 shows the distribution of the most used techniques in the different phases of the neuromarketing cycle. Specifically, for the distribution of the objectives shown in the first box, this figure highlights that the most proposed objective is the comparison between different advertisements. After this, the objectives focused on improving stimuli and assessing if their impact are distributed homogeneously.

2.2. Hypothesis and metrics

After presenting the objective of the study, it is necessary to define the hypothesis and metrics to measure whether or not the objective has been met. Each study hypothesizes how advertisements influence purchase intention, emotional response, and attention levels. To quantitatively measure these aspects, they employ metrics. The metrics across these studies vary, including advertisement impact, purchase intention, and emotional reactions. These metrics provide a standardized way to assess and compare the effectiveness of advertising strategies in influencing consumer behavior and decision-making. One of these metrics is the impact a given advertisement has on the subject, quantifying it as low, medium, or high [30]. The impact is one of the main objectives since a direct result can be obtained from the designed stimulus. Another objective is the purchase intention or preference for a product [31,32]. These metrics are directly related to the sample objective of multiple similar products. In this way, the literature intended to recognize which advertisements generated a higher purchase probability.

Other metrics are based on non-quantifiable human reactions, such as the emotional state they evoke or liking [33,34]. The objective of detecting these states is to study emotional neuromarketing, which seeks to represent past situations to increase the probability of purchase [35]. Usually, these states are measured by valence and arousal values. For this reason, some studies attempt to predict these values to relate them to a particular mental state [36,37]. In this way, if a specific state of mind can be detected, it is possible to check whether the target has been designed correctly to achieve the proposed objective. Another point of interest studied in the literature is whether the subject intends to skip an advertisement (e.g., a web page) and the attention that the subject is paying to a given advertisement [38].

As shown in the second box in Fig. 3, the most studied metrics are the impact generated by an advertisement and the intention to purchase a product. This is mainly because these are the most interesting parameters for promoter companies. Other targets, such as liking or emotional state (directly related to brain bands), are of some interest in designing a stimulus. However, the main metrics differ depending on the objective for which they are proposed (see Fig. 4(b)). As can be seen, for the study and improvement objectives, the main metric is to measure the effectiveness of a given advertisement, while for



(a) Stimulus.

(b) Metrics.

(c) Devices and biosignals.

(d) Automatic tools for hypothesis validation.

Fig. 4. Distribution of techniques and approaches for each objective.

comparison, predicting which product is the favorite in a larger group is critical. Other elements of interest, such as attention generated, emotional state, or purchase intent, appear in the second position.

2.3. Stimuli

The stimuli used in the related work is another crucial factor when designing a neuromarketing study. Because of this, this section reviews the different inputs used in the literature [39,40]. The first category corresponds to visual stimuli, which is based on continuously displaying a series of images to the user during a specific period [41]. These images are usually commercial products to generate a reaction in the user that can be captured. The main advantage of this type of inputs is that the exposure time should not be very high, being also the most abundant type of stimuli in society, from billboards to social networks. However, the disadvantage of visual inputs is that they only provoke stimulation in the sense of sight so they may have less impact than others involving more senses. The second type of stimuli is audiovisual [42]. In particular, different sounds are added to the previously mentioned visual stimuli, which stimulate the sense of hearing, used commonly in TV. Thus, it can significantly impact the subject's attention since the load required to analyze the different inputs coming from various dimensions is more remarkable than if only one of them were involved. The disadvantage, however, is that the exposure time must be prolonged, which increases the probability of a loss of interest from the user.

In another direction, several works seek to stimulate senses other than the classic ones mentioned above, where some of these works use flavors to obtain a reaction from the user [43]. This type of stimulus is an excellent indicator to obtain consumers' reactions against food products, although it only applies to some real use cases. In another type of work, subjects interact with the product being publicized and, thus, get a response more aligned to reality [44].

Finally, due to the increase in online shopping in recent years, the literature has moved towards obtaining information about the design of a web page [45]. Only visual stimuli can be used in these environments, so the colors, shapes, and distribution of the elements that compose it must be varied. Similarly to this trend, and thanks to the development of social networks, many companies have chosen to promote their products through online sites, doing it through "influencers". Influencers are people with the ability to influence potential buyers of a product or service by promoting or recommending the items on social media. Due to this, some studies seek to predict the impact of these promotional images or videos to advertise products [46].

As seen in Fig. 3, the most used stimuli in the literature are visual and audiovisual. This usage is mainly because traditional advertising has been transmitted through television commercials or posters. Since most advertising has been done through the Internet recently, studies related to these techniques have gained popularity in recent years. Fig. 4(a) relates the first phase of objectives, with the second phase of stimuli, showing relevant information on usability when selecting the best techniques.

2.4. Devices and biosignals

Next, this work analyzes the devices and biosignals used in the studied literature [16]. In particular, the authors employ diverse biosensors, such as BCIs, electrodermal sensors, cardiac event monitors, ET glasses, facial recognition cameras, and needle electrodes.

- BCI is a bidirectional system that allows direct communication between the brain and external devices. It interprets brain signals to control devices like computers or prosthetic limbs and can send signals back to the brain, enabling brain stimulation for medical and rehabilitation purposes [47]. Concerning monitoring, the EEG signal [48] is collected based on the electrical exchanges produced by the neurons [6].
- Electrodermal sensors detect the changes in electrical (ionic) activity resulting from changes in sweat gland activity. The electrodes must be sensitive to these changes and able to transmit that information to the recording device. Specifically, this signal is known as EDA [49].
- Devices for measuring cardiac events have traditionally been used in the medical sector for measuring cardiovascular problems. It is possible to measure the heartbeat through heart rate measurement devices or obtain an electrocardiogram (ECG) [50].
- ET, meanwhile, uses the reflection of the eyes in near-infrared light beams, thus detecting the presence, attention, and focus, as well as the position of a person's eye and the pupil size [17].
- Cameras for Facial Recognition (FR) allow recognition of a user's facial expressions in response to a stimulus [51].
- Electromyography (EMG) uses electrodes to measure facial gestures. This signal acquires the electrical activity generated by the muscles [52].

Each of these biosignals can be associated with neuromarketing objectives due to the benefits they provide. Specifically, the EEG signal is related to various mental states such as emotions, attention, or stress [53]. This association allows for understanding the impact of an advertisement, offering insights crucial for neuromarketing. One significant advantage of the EEG signal is that users cannot intentionally manipulate it, ensuring a more genuine reflection of their mental states. Nevertheless, the EEG signal presents two primary challenges: firstly, its spatial resolution is limited, especially when compared to imaging techniques like fMRI, which, although impractical for many neuromarketing applications, offer superior spatial details. This limitation often causes difficulties in pinpointing the exact source of brain activity. Specifically, each electrode covers a broad area of neurons, which becomes especially problematic when activity arises from adjacent yet distinct regions. Moreover, EEG cannot capture the electrical activity from deeper brain regions that are not surface-level, which might be significant in specific neuromarketing contexts. Secondly, the SNR or signal-to-noise ratio of EEG is low. Given its low amplitude nature after traversing through tissues, bones, and the scalp, it is susceptible to artifact contamination, emphasizing the importance of rigorous preprocessing steps.

The EDA signal, often used in neuromarketing, gauges the stress level of a user through skin sweating, a reaction to stress, or varying emotional states [54]. One advantage is that users cannot consciously alter their reactions, and the devices are generally portable. Yet, a significant drawback for neuromarketing applications is EDA's inability to discern emotional valence, leaving ambiguity if the emotion is positive or negative. For marketers, this means relying solely on EDA might not provide a complete emotional profile of a consumer's response to a product or advertisement. Thus, it is beneficial to pair it with other techniques, like EEG or ECG. The ECG signal, valuable in neuromarketing contexts, predicts stress or excitement scenarios by tracking alertness levels and heart pumping rates. Its direct correlation with stressful situations and portability are primary strengths. However, in the realm of neuromarketing, its inability to delineate specific emotions often necessitates its combination with other techniques.

In contrast, the ET signal can be related to states of interest through the time of fixation on an object. Examples of these states could be attention, measured by the number of blinks; or emotional interest, measured by pupil dilation. Since these aspects are essential in neuromarketing studies, this signal is widely used in this area of knowledge [55]. One of the main advantages of this signal is that it is adaptable to multiple environments. ET can also be used in passive tasks, such as viewing a television spot, and active tasks like assessing product placement while walking through the supermarket. Moreover, it can be combined with other devices since it is a sight-centered system and does not compete in space with EEG, EDA, or ECG. The main disadvantage of this signal is the need to combine it with other neuromarketing techniques to get a comprehensive insight into a consumer's response, as ET does not offer information on emotional valence and has some ambiguity in pinpointing specific cognitive processes.

Finally, Facial Recognition (FR) is especially potent in detecting emotional valence — determining if the emotion is positive or negative. While the versatility of FR spans fields like politics to studying speech listener responses, its significance in neuromarketing is paramount. This technique is prominent due to its advantages: rapid real-time emotional feedback and non-intrusiveness, negating the need for any device wear. It is also adept at gauging emotional valence, ascertaining if stimuli trigger positive or negative emotions. However, its weaknesses include not being ideal for determining emotion intensity or arousal and its sensitivity to user movements. To counter some of these challenges, the EMG signal can be employed in certain contexts. EMG excels at capturing immediate stimulus reactions, shedding light on intricate emotional nuances [56]. It can further discern between voluntary and involuntary muscle actions, illuminating masked emotions. Nonetheless, its adoption in neuromarketing is limited due to its noise susceptibility and the invasive nature of the electrodes.

Following the detailed discussion on the characteristics and applications of various bio-signal technologies in the context of neuromarketing, Table 2 provides a brief comparison of their advantages and disadvantages. This table serves as a handy reference, facilitating a clearer understanding of the strengths and limitations of each method, thereby aiding in the selection of the most appropriate technique for specific neuromarketing studies.

Fig. 3 shows, in yellow, the usage distribution of each biosignal described above. It can be seen that EEG is the most widely used since the study of the signal has become popularized in recent years and is gaining momentum. Furthermore, the relationship of the different biosignals for each previously defined objective is shown in Fig. 4(c). In the case of biosignals, a homogeneous distribution is observed, where the most used signal for all objectives is EEG. The second signal in popularity is the ET signal, except for the objective consisting in improving an advertisement, where the ECG signal is found.

2.5. Data preprocessing techniques

Once data sources are identified and biosignals are monitored using the previously explained sensors, it is crucial to process these data. This processing is essential to filter out noise signals caused by users' actions, such as flickering or involuntary movements, as well as noise from external sources like the electrical network. The Bandpass filter [57], predominantly used in EEG signals, is also applicable for ECG and

Table 2
Advantages and disadvantages of biosignal technologies in neuromarketing context.

Biosignal technology	Advantages	Disadvantages
EEG	– Direct measurement of brain activity. – High temporal resolution. – Non-invasive.	– Limited spatial resolution. – Sensitive to noise and artifacts. – Requires proper electrode placement.
fMRI	– High spatial resolution. – Direct measurement of brain activity. – Able to visualize deep brain structures.	– Expensive. – Low temporal resolution. – Requires a controlled environment.
ET	– Provides insight into visual attention. – Non-invasive. – Can be combined with other bio-signal technologies.	– Can be sensitive to lighting conditions. – Requires calibration to obtain data. – Limited insight into cognitive processes.
GSR	– Measures arousal and emotional states. – Non-invasive. – Easy to use and relatively affordable.	– Influenced by external factors like temperature. – Cannot specify the type of emotion being experienced.
FR	– Non-invasive. – Can detect basic emotions through facial expressions. – Can be used in real-world settings.	– Sensitive to lighting and orientation. – May not detect subtle or complex emotions. – Requires high-quality imaging technology.
EMG	– Direct measurement of muscle activity. – Can indicate emotional states through facial muscle activity. – High temporal resolution.	– Invasive (if needle electrodes are used). – Requires proper electrode placement. – Limited to measuring muscle activity.
ECG	– Measures heart rate and heart rate variability. – Can infer levels of stress and emotional states. – Non-invasive.	– Does not provide direct insight into brain activity. – Can be affected by physical movement and other artifacts. – Requires proper electrode placement.

GSR [58]. This filter defines a specific frequency range and attenuates frequencies outside this range. It can focus on target bands frequently used to extract different brain rhythms. This filter can be specialized as the Lowpass filter [59], which attenuates higher frequencies, or the Highpass filter [60], which attenuates lower frequencies. Another filter commonly mentioned in the literature is the Notch filter, designed to eliminate a specific frequency range [61], often used to filter out interference from the electrical grid. Other types of filters more specifically tailored for EEG include the Savitzky-Golay filter, which is used as a smoothing filter in the time domain, or Surface Laplacian filter [62,63]. Using these filters helps in obtaining a smoothed signal by calculating new data points.

In some instances, specific EEG channels might produce erroneous measurements, for which different algorithms and techniques can be applied. EEG channel interpolation is essential when data from a channel is of low quality or missing [64]. Algorithms like Artifact Subspace Reconstruction (ASR) aim to clean those channels providing erroneous data [65]. To handle the high data density in EEG signals, downsampling techniques are applied, producing a subset of less frequent but representative data, facilitating more efficient analysis and thus enhancing real-time processing efficiency [66]. The Common Average Reference (CAR) technique, contrary to improving execution time, aims to improve the signal-to-noise ratio by averaging the reference for all electrodes. This is a computationally simple technique suitable for on-chip and real-time applications, predominantly used in EEG, especially when identifying small signal sources in noisy recordings [67].

Other preprocessing techniques like ICA are employed to identify individual components [68]. It is possible to filter out interfering components, such as flicker, and select the components for subsequent classification stages. ASR, similar to ICA in some respects, facilitates online and real-time evaluation, serving as a component-based method adept at removing transient or high-amplitude artifacts [69].

Box five of Fig. 3 showcases the distribution of these techniques among the researched papers. Generally, the Bandpass and Notch filters are most common due to their fundamental applicability across various biosignals. Meanwhile, ICA, ASR, or Downsampling techniques are more EEG-centric. Given the vast number of studies employing EEG signals, these techniques witness widespread usage.

2.6. Features extraction techniques

Once the data have been processed, the relevant information is extracted depending on the objective of the study. This information may be based on signal power, frequency, temporality, or a combination thereof. For the analysis of biosignals like ECG, EDA, and EEG, techniques based on signal frequencies are commonly employed.

For example, the Fast-Fourier Transform (FFT) [70] is an efficient algorithm that computes the Discrete Fourier Transform (DFT) and its inverse, offering a frequency domain representation of a time-domain signal. The Power Spectral Density (PSD) [71], while not an algorithm in itself, represents how the power of a signal is distributed across different frequencies. The Discrete Wavelet Transform (DWT) [72] decomposes a signal into different sets, with each set being a time series of coefficients that capture the time evolution of the signal within a specific frequency band. For time-domain analysis, Detrended Fluctuation Analysis (DFA) is employed to determine the statistical self-affinity of a signal [73], especially useful for time series that exhibit long-range correlations.

Other techniques focus on extracting specific features from the EEG signal. For instance, hemispheric symmetry [74] computes the Frontal Band Powers (FBP) [75] for the five principal frequency bands (Delta, Theta, Alpha, Beta, and Gamma) using voltage differences between front-lateral electrodes. Global Field Power (GFP) calculates the spatial standard deviation, quantifying the magnitude of activity at each time point in the potential field. By considering data from all recording electrodes simultaneously, GFP provides a reference-independent description of the potential field [76]. The Individual Alpha Frequency (IAF) stands as a significant electrophysiological marker of inter-individual cognitive differences, associating with trait-like differences in information processing and general intelligence and offering an empirical foundation for the definition of personalized frequency bands [77]. Methods like mutual information analysis help detect shifts in information flow linked to sleep stage transitions and unveil the influence of age on interdependence values. For other sensors, notably (fMRI), Inter-subject Correlations (ISC) [78] present a model-free technique to assess intricate data gathered in natural, context-sensitive scenarios, like during movie watching.

For signals such as ET, understanding the inherent characteristics of eye movement and gaze patterns is paramount. Dwell time, representing when the eye remains relatively stationary within a region, suggests areas of the stimulus that hold sustained attention [79]. The number of fixations indicates how frequently eyes pause on a part of the visual scene, hinting at regions of heightened interest or potential ambiguity [80]. Similarly, the number of revisits to an Area of Interest

(AOI) might allude to the importance or complexity of that section, with users revisiting critical or intricate content [81]. The Time to First Fixation (TTFF), measuring the interval from when viewing starts until the gaze zeroes in on a specified AOI, can shed light on the immediate draw or prominence of that spot [82]. One of the foundational metrics in this domain is AOI, which delineates regions on a visual stimulus for focused data extraction [83]. Heat maps, in contrast, visually pinpoint areas of user attention, revealing engagement concentrations [84].

For simple signals such as EDA or ECG, algorithms are usually used to extract information from the amplitude and frequency of these signals. In the case of EDA, the most commonly used features are Skin Conductance Level (SCL) and Skin Conductance Response (SCR) [85]. High SCL values are related to greater receptivity on the part of the subjects. In contrast, the SCR feature is very sparse and occurs when a relevant stimulus has been elicited. For the ECG signal, it is common to obtain features such as the heart rate, which represents the number of beats per second, as well as its variability [86].

Block six of Fig. 3 shows the distribution of the use of these techniques for the extraction of characteristics, the most used being those related to power and frequency. This is mainly because they are common to most sensors, so their use is higher. Since ET is another of the most widespread sensors, techniques based on images and the position of the user's view are among the most common. Finally, valence estimation from user interaction features is the least used, as they can be very susceptible to the user's subjectivity.

2.7. Automatic tools for hypothesis validation

Once the relevant data information is available, it is necessary to classify them to define to which state they are associated. The works on neuromarketing follow two different trends for data classification: extracting statistics from the data to be studied by experts and applying ML/DL algorithms. First, researchers obtain statistical values and represent the data graphically, allowing the identification of the different mental states visually. This situation has been widely studied in scenarios with ECG, GSR, and EEG biosignals where specific statistical values such as mean, standard deviation, or median, among others, can be directly related to an intention or state. Another of these values can be the Memorization Index (MI) [87], which is obtained by calculating the mean of the values of the theta band, which can be directly translated into this index. In the same way, the Approach-Withdrawal Index (AWI) [88] defines the asymmetry of Pre-Frontal Cortex Activity that is closely linked to the feeling of pleasantness experienced by the subject during sensorial stimulation.

In the second case, where the authors apply ML algorithms, the most common are Support Vector Machines (SVM) [89], k-Nearest Neighbors (kNN) [90], and Random Forest (RF) [91]. These algorithms perform relatively well in most scenarios, with low computational consumption, also achieving high accuracy values with biological data types such as EEG [92].

Another AI-based approach corresponds to DL algorithms. These algorithms based on neural networks have become more relevant in recent years, especially in neuromarketing studies. The surge in their application in neuromarketing contexts is attributed to advancements in portable biosensors. Furthermore, the time factor for evaluation and the elimination of feature extraction make these AI algorithms preferable in scenarios striving for rapid analysis without the tedious feature extraction phase. Because of these advantages, they prove invaluable in contexts receiving vast amounts of data where evaluation times need curtailment. Examples include Convolutional Neural Networks (CNNs), Probabilistic Neural Network (PNN), and Artificial Neural Networks (ANNs).

As illustrated in block seven of Fig. 3, the predominant algorithms in the literature are SVM, kNN, and RF, followed by statistics studies and Regression Algorithms (RA). However, while DL-based algorithms have gained relevance, their broader application, particularly outside neuromarketing, remains limited due to their substantial data requirements. This often becomes a bottleneck, considering the intricate nature of biosignal data acquisition and preprocessing. The distribution of these algorithms per objective is depicted in another figure. ANN, for instance, is widely employed for advertisement matching, succeeded by traditional ML algorithms like kNN and SVM. In contrast, techniques focusing on advertisement enhancement often revolve around Memorization Index (MI) and visual statistics studies. Regression algorithms stand out for study objectives as they predict specific numerical advertisement values, such as a rating scale. Broadly, kNN and SVM, both traditional ranking algorithms, emerge as favorites.

3. What combinations of data from biosignals, stimuli, and processing and classification techniques are suitable for each objective?

In data fusion, integrating heterogeneous signal sources, particularly biosignals, is a notable challenge [93]. Techniques such as ensemble methods [94], multi-level data fusion [95], and canonical correlation analysis (CCA) [96] intend to address this complexity, combining diverse data types for more robust and comprehensive insights. More specifically, ensemble methods integrate multiple learning models, improving interpretability and prediction accuracy. Multi-level data fusion allows for data integration at different levels, providing a comprehensive view that considers the variations in data types and sources. Finally, canonical correlation analysis is a statistical method used to understand the relationship between two sets of variables, often used in EEG-fMRI data fusion.

However, the practical implementation of these methods encounters specific barriers, including data incongruence, scalability issues, and computational demands [124]. The fusion of biosignals, especially those of varying nature (like EEG, fMRI, or GSR), requires methods that handle large volumes of data and interpret them in a biologically relevant context. Addressing these challenges is crucial for advancing practical applications in neuromarketing, necessitating a continued focus and innovation in developing more sophisticated fusion methodologies.

Building on the discussion of data fusion methodologies, this section goes further into a comparative analysis of the articles collected, categorized by the neuromarketing objectives they were designed to address. As delineated in Section 2.1, neuromarketing research primarily orbits around three objectives: (i) analyzing the impact of an advertisement, (ii) enhancing the efficacy of an advertisement, and (iii) comparing various advertisements. This classification facilitates a thematic study of the works, enabling a comparative assessment of the methodologies employed and the consequent findings through common end goals.

3.1. Study of the impact of an advertisement

This objective is based on collecting different biosignals representing the user's mental states and thus relating it to a lower or higher impact. Table 3 shows the works collected, grouped by the stimuli used, also highlighting aspects of the papers taken into account, such as the number of subjects participating in the experimentation, the type of stimulus used, the preprocessing techniques, feature extraction, and classification techniques. Finally, the number of states recognized in the classification and the results gathered by each study are considered.

Some researchers employ audiovisual stimuli to simulate the most common stimuli encountered in real life. The work performed by Dimpfel et al. [97] aimed to determine whether EEG biosignals and ET are effective methods for neuromarketing studies. The FFT algorithm was applied for the EEG signal and heat map in the case of ET. The researchers did the classification visually, obtaining statistics from them and concluding that these algorithms suit this purpose. Later, Cartocci et al. [100] carried out a study combining EEG with ECG and EDA sensors, using IAF and GFP characteristics to obtain values

Table 3
Works that seek to study the impact of an advertisement.

Ref	Year	Biosignal	Subjects	Stimuli	Preprocessing	Feature extraction	Classification	Predicted states	Results
[97]	2015	EEG ET	10	Audiovisual	Not specified	FFT Heat map	Value display	Not specified	Neurocode-tracking with ET can be successfully used in advertisement research and gives valid information
[98]	2016	EEG	7	Audiovisual	Notch filter ICA	IAF GFP	AWI	Effective Ineffective	Increased deactivation in the right dorsa land increased left frontal gyrus activation
[11]	2016	ET	62	Audiovisual	Not specified	AOI	Statistics	Focus of attention in screen	Position of objects in the center of the screen obtains the greatest impact
[99]	2017	ECG EDA	36	Audiovisual	Bandpass	No specified	Recall	Emotional state	Advertisements that evoke sadness have greater impact
[100]	2017	EEG ECG EDA	22	Audiovisual	Bandpass filter Notch filter ICA	IAF GFP	AWI	Awarded Effective Ineffective	Fear-based campaigns with complex narrative stories reported worse results than those with a narrative o experiential communication style.
[101]	2017	FR	60	Audiovisual	Not specified	High valence Low valence	Statistics	Attitude score	Advertisements designed to evoke emotions have greater impact
[36]	2017	EDA	DEAP MAHNOB-HCI	Audiovisual	Bandpass filter Notch filter ICA	Image characteristics	Regression algorithm	High attention High arousal	Value of EDA
[37]	2018	EEG	30	Audiovisual	Bandpass filter	FFT	LR kNN SVM SVR	Valence	72.40% of accuracy
[33]	2018	EEG	16	Audiovisual	Bandpass filter	FFT	Statistics	Emotional State	During the video watching dominated the neutral feelings, while the results of the electrical brain activity measurements indicated prevailing negative emotions
[38]	2019	EEG	4	Audiovisual	Bandpass filter Downsampling	Entropy Power-based CV2	RF kNN SVM	Skip No skip	75.8% of accuracy
[102]	2019	EEG ET	30	Audiovisual	Not specified	Cognitive load	Not specified	Arousal	Differences in ET and EEG signals depending on the tourist destination presented
[103]	2019	EEG EDA ECG ET	142	Audiovisual	Bandpass filter Notch filter	FFT	Statistics	Purchase intention	High arousal when seeing non-luxury brand stores
[104]	2020	ET	Not specified	Audiovisual	Not specified	Fixation duration	Not specified	Recognition of influencer marketing	Offers recommendations to policy makers to develop sponsorship disclosures
[105]	2013	EEG EDA ET	44	Image	Not specified	Relevance	Not specified	Reaction	The honey packaging generates a positive reaction but it needs a long time to do that
[106]	2018	EDA ET FR	5	Image	Not specified	Heat map Total time spent Peaks of EDA Facial expressions	Visual study	Colors that generate the greatest impact	Yellow is the color that generates the greatest impact
[10]	2018	EEG	26	Image	Highpass filter Lowpass filter ASR	DWT	RF regression	Rating	Product liking value

(*continued on next page*)

Table 3 (*continued*).

[107]	2018	EEG	32	Image	Bandpass filter Automatic artifacts removal	Valence Arousal	Statistics	Study of reactions to images after having been previously influenced positively and negatively	Subjects positively influenced in a previous way generate ERPs
[108]	2019	EEG ET	40	Image	Not specified	Alpha-band Oscillation AOI	Not specified	Correlation between attention levels and preferences	Consumers' eye movements could not be employed as a parameter to predict packaging preferences
[30]	2020	EEG EDA ECG ET	52	Image	Bandpass filter ICA	PSD AWI	Not specified	Impact of logo	Color improves user response to advertisements
[109]	2021	FR EDA ET	40	Image	Not specified	Heat map TTFF	Not specified	Preference Purchasing intention	Strong correlation between bio-signals and respondent preference and purchasing intention. Most respondents did not focus on the price of products.
[110]	2022	EEG	49	Image	High-pass filter Notch filter	Skewness, Kurtosis, Hjorth parameters	SVM, KNN, Neural Networks	Preference	Accuracy 75.7%
[111]	2022	EEG	15	Image	Bandpass filter Notch filter ICA	Time domain Frequency domain Time-frequency domain	SVM	Positive affective attitude Negative affective attitude	98% of accuracy
[112]	2022	EEG	45	Image	Bandpass filter ICA	PSD, Coherence, LRTC	Clustering (KNN)	Preference for electric cars	Increased PSD and specific brain coherences for electric car preference
[113]	2022	ET	67	Image	Not Specified	Heat maps AOI	Not specified	Visual attention	Cues for identifying influencer marketing on instagram
[114]	2016	EEG ET	N.E	Web pages	Not specified	PSD STFT AOI	Visual study	Study of webpage	Higher brain activity only during decision making processes
[45]	2017	EDA ET	10	Web pages	Not specified	Heat map Pupil size	Not specified	AOI Time spent	Human emotions and visual attention are highly correlated with practical marketing applications
[115]	2017	EEG ET	21	Web pages	Not specified	Heat map Frequency bands	DWT	Saliency	71.09% accuracy
[116]	2022	EEG	36	Static and dynamic Content	Bandpass filter Riemannian alignment	Sample covariance matrices (SCMs)	SVM ensemble	Preference	Improved accuracy in preference prediction
[117]	2018	EDA ET FR	19	Music	Not specified	Heat map AOI	Not specified	Enjoy Engagement	Music improves the impact
[118]	2020	ET	72	Music	Not specified	Fixation time Fixation count	Not specified	Food choice	Taste-congruent soundtracks guide visual attention and influence food choice
[119]	2020	EEG EDA	26	Cognitive task	Highpass filter Lowpass filter ASR	PSD	Statistics	Valence	Preference for machines containing market-leader brands
[120]	2020	ET	30	Real world Image	Not specified	Fixation duration Number of fixations	Not specified	Consumer choice	Brand and product are leading criteria driving attention and choice
[121]	2023	EEG	42	Image	Sample covariance Riemannian alignment	Brain activation patterns	SPDNet	Buy-NoBuy	Superiority of DL-decoder in neuromarketing
[122]	2022	EEG EDA ECG	Not specified	Real world	Not specified	Biosignal feedback Feature extraction	Not specified	Beverage preferences	Methodology framework for neuromarketing evaluation

(*continued on next page*)

Table 3 (*continued*).

[123]	2021	ET	46	Virtual retail environment	Not specified	TFC TDT APD	Statistical analysis	Visual attention Emotional arousal	Different responses to spatial arrangements; Gender differences in responses

related to the frequencies in the data. The values produced by the AWI algorithm were obtained to analyze the results, describing the effectiveness or ineffectiveness of the different advertisements.

Other papers focus on using audiovisual stimuli and seek to study the impact of specific parameters on users, such as colors or the positioning of objects. The first work was performed by Cosic et al. [11], focusing on obtaining the best position for placing objects and studying the best composition of objects on the screen. For this research, an ET biosensor was applied to 62 subjects. Statistics were extracted from the data produced by AOI, concluding that the best position is the center. In the same direction, Baraybar et al. [99] and Hamelin et al. [101] focused on emotional aspects that the advertisements evoke in the subjects, using ECG, EDA, and FR since they directly relate to the different emotional states. These works used the first approach to classification based on the collection of statistics and visualization by the researchers. The results obtained by Hamelin et al. [101] show that the advertisements that evoke emotions are the ones that obtain the best results. Specifically, Baraybar et al. [99] concluded that the emotion getting the best results is sadness.

From the audiovisual stimuli, other aspects can be identified, such as the effectiveness of an advertisement or the likelihood that a given advertisement will be skipped, as previously presented in Section 2.2. Concerning effectiveness, Cartocci et al. [98] conducted a study on how audiovisual stimuli affect neural response in subjects. They used a relatively low number of seven subjects and obtained their EEG signals. This signal for each subject was treated with the Notch filter and the ICA algorithm, once the external noise has been removed, the relevant information is gathered from it using the IAF and GFP algorithms. They classified this information by using the AWI algorithm as effective or ineffective. The results show that the activation generated in each of the hemispheres can be related to the effectiveness of the advertisement on the subject. Regarding purchasing intention, Sung et al. [103] used EEG, EDA, ECG, and ET signals obtained from 142 users. For noise removal, the authors applied the Notch and Bandpass filters, after which they extracted the relevant information using the FFT algorithm from the EEG, EDA, and ECG signals. They concluded that consumers' experience of anger underlies their negative responses towards the brand when it was marketed to be luxurious. Finally, Libert et al. [38] gathered entropy and CV2 values from the EEG signal acquired from four users to use a series of ML algorithms, such as RF, SVM, and kNN. The objective was to predict the probability of skipping a given advertisement, obtaining 75.8% accuracy.

In the same way, the prediction of numerical values to assess the quality of a stimulus in neuromarketing studies from audiovisual stimuli, such as a value that represents how much a user liked the advertisement. Following this objective, Ogino et al. [37] sought to predict the valence from the EEG signal and the different bands obtained by FFT. They collected this signal from 30 subjects, obtaining a 72.40% average accuracy using LR, kNN, SVM, and SVR algorithms. Another numerical value that can be predicted is arousal, where Michael et al. [102] investigated the prediction of this value using EEG signals and ET. These data were collected from 30 participants, obtaining statistics about the cognitive load generated and visually estimating the arousal value generated. In addition, Hernandez et al. [36] aimed to predict when the arousal value was low or high employing the EDA biosignal value. This study used public datasets (DEAP) and preprocessed them with the Bandpass filter, Notch filter, and the ICA algorithm. After this, this work extracted features from the displayed images, applying a regression algorithm to predict a specific value of the EDA signal.

Another category of stimuli applicable to study objective is visual stimuli. Similar to the previously studied works, some authors have focused on studying the characteristics of images. In pursuit of this goal, Cuesta et al. [106] studied the best color for generating a positive reaction by the subject, using ET, EDA, and FR signals. Data such as heat maps, fixation points, or facial expressions were gathered from these signals. After this, the authors conducted a visual study of this information on five subjects, concluding that the color that attracted the subjects' attention the most was yellow. Similarly, Santos et al. [30] focus on analyzing a logo modification, such as the logo of the brand "Worten". They used four biosignals for this improvement: EEG, EDA, ECG, and ET. From these signals, they obtained frequency-based data from EEG, EDA, and ECG signals using the PSD algorithm. In addition, they extracted information from the EEG signal by applying the AWI algorithm and a heat map using ET. All this information was studied visually to know the impact of the logo. Furthermore, an area of interest is the analysis of subjects' reactions to images utilizing EEG, EDA, and ET, such as the one carried out by Pop et al. [105] or Bastiaansen et al. [107]. The former collected these data from a considerably large number of subjects, 44. They extracted the relevance from these data to measure the subjects' reactions. In the second paper, the researchers gathered the EEG signal from 32 subjects, extracted valence and arousal features, and classified the results visually. Focused only on information obtained from the EEG signal, Raiesdana et al. [112] explores consumer preferences for electric cars. The study aims to correlate neural measures with self-reported preferences, using images of automobiles and their specifications as stimuli. It investigates differences in brain dynamics between those who choose electric cars and others, focusing on PSD, coherence analysis, and long-range temporal correlations (LRTCs). The results show increased PSD and specific brain coherences for participants preferring electric cars, demonstrating the potential of EEG in understanding consumer behavior for electric vehicles. Maintaining only the use of the EEG signal, Georgiadis et al. [121] introduces a EEG decoding scheme in neuromarketing, utilizing Riemannian Geometry principles and a deep learning architecture, SPDNet. It differs from typical neuromarketing practices by not relying solely on signal-power related features. The research employs a multi-subject dataset focusing on product selection scenarios, comparing the performance of SPDNet with traditional EEG neuromarketing tools. The methodology involves using sample covariance for brain activation pattern estimation, followed by alignment to reduce inter-subject variability. The study demonstrates the effectiveness of this DL-decoder in neuromarketing, surpassing conventional and other Riemannian Geometry-based methods in generalizability and prediction accuracy. Based on the information obtained from multiple sources, the article by Hamelin et al. [109] explored the relationship between package design and consumer choice for over-the-counter (OTC) analgesic products. The study employed ET technology, facial expression analysis, and EDA to measure autonomic body reactions in 40 respondents. The findings suggested a strong correlation between these bio-signals and respondent preference and purchasing intention. A heat map analysis for each package revealed that most respondents did not focus on the price while evaluating the products. Other works focused on predicting how much users liked an advertisement are those done by Kumar et al. [10] and Mashrur et al. [111]. The first work uses an RF regression algorithm to predict a value between zero and five. In the second work, the authors aim to predict a positive or negative affective attitude. For this purpose, temporal and frequency characteristics of the EEG signal were used, obtaining up to 98% accuracy in identifying product preferences. Other authors, such as Ali et al. [110], have focused on studying the

differences in the reactions of the subjects depending on their gender. This study uses EEG data to classify consumer preferences in response to image advertisements. It employs a 14-channel EMOTIV EPOC+ headset for data collection, with preprocessing involving high-pass and notch filtering. The feature extraction uses statistical measures like skewness, kurtosis, and Hjorth parameters. Classification is done via SVM, KNN, and neural networks, with a focus on gender differences in responses. The study achieves a maximum accuracy of 75.7% and sensitivity of 95.8% using KNN, particularly for female subjects. It suggests that frontal region electrodes are most effective in this analysis.

Following the growing demand for online shopping in recent years, articles related to the study of web page designs have emerged. Kvasnicova et al. [114] aimed to show if EEG and ET signals were valid for this study. For this, they collected data on ten subjects and applied algorithms to study frequencies such as PSD and STFT in the case of the EEG signal. Additionally, they obtained AOI data from the ET signal. These data were analyzed visually, concluding that these techniques are helpful. In the same direction, Ungureanu et al. [45] replaced the EEG signal with the EDA signal. In this case, the ET biosignal was paid special attention by obtaining AOI and pupil size data. This work corroborates again that these methods are valid. Similarly, Slanzi et al. [115] sought to predict which areas of a webpage were most likely to receive clicks. This prediction was based on the saliency maps of web pages and the subjects' EEG signal data. The final accuracy obtained was over 70%. In the case of social networks, Boerman and Müller [113] aims to elucidate how Instagram users identify influencer marketing on the platform and what cues they use for this identification. The research comprises two parts: an ET study and an online experiment. The ET study involved 67 participants, while the online experiment included 371 participants. The significant findings from this study are threefold: While Instagram users are generally aware of influencer marketing, they sometimes make mistakes in identifying it within their Instagram feed. Users pay the most attention to brand tags in pictures and "Paid partnership" labels, while they pay the least attention to the hashtag #ad. The level of conceptual persuasion knowledge is influenced by disclosures, brand presence, and the type of influencer involved in the marketing. Similar to this one, the study created by Van Reijmersdal et al. [104] investigates the effects of disclosing influencer marketing within videos, particularly focusing on an adolescent demographic. Using ET technology, the research aims to understand how disclosure impacts the recognition of influencer marketing.

Finally, some authors have tried to explore new types of stimuli. Cuesta et al. [117] proposed a series of experiments to study subjects' reactions to music. EDA, ET, and FR were used with a heat map and AOI. The results show that music increases the impact of a product on the subjects. Using this same stimulus, Peng-Li, D et al. [118] explores the impact of taste-congruent soundtracks on consumers' visual attention and food choices. ET technology was utilized to study Chinese and Danish consumers using a cross-cultural approach. The results illustrated that tailored soundtracks could guide eye movements and influence food choices, bridging a novel understanding between sound-taste correspondences and implicit measurements. Similar to this work, Georgiadis et al. [116] conducted a study on the difference between static and dynamic stimuli. This work employs Riemannian geometry concepts to represent EEG signals as sample covariance matrices (SCMs). The study focuses on decoding consumer choices, like willingness to buy a product, by employing an ensemble classifier that operates on different frequency bands. The results demonstrate the effectiveness of the method in neuromarketing scenarios, showing improved accuracy in preference prediction compared to traditional methods. Another stimulus is based on generating a cognitive load in the subjects by performing different tasks, such as choosing a particular vending machine. Sargent et al. [119] explored the preference for a particular brand when selecting a vending machine to purchase coffee. For this purpose, EEG and EDA biosignals were used, together with PSD. Frequent-related statistics are obtained to classify the results, and a visual classification is subsequently performed. The results demonstrate that the machines whose brands are the market leaders or, more extended, obtain greater consumer acceptance. Bialkova et al. [120] conducted two ET studies to investigate consumer attention and choice in both controlled lab settings and real-world supermarket shelves. The researchers recorded fixation duration, number of fixations, and the consumer's choice, finding that the brains and product are the primary criteria. They further explored the influence of shopping goals, labels, and brand placement on observed attention and choice patterns, aiming to understand on-shelf merchandising, visual attention, and purchase intention of products positioned on the supermarket shelves. Following the tendency to study the stimuli that most closely resemble reality, Kim, N., & Lee, H. [123] delved into how consumers visually experience retail environments, specifically in virtual settings. Utilizing ET technology and virtual reality, they analyzed visual attention and emotional arousal in response to spatial and design elements in a virtual retail setting. The study revealed differing consumer responses to specific areas of interest based on spatial arrangements in sales and service areas and statistically analyzed gender differences in these responses. The study aimed to provide deeper insights into visual merchandising strategies by correlating visual attention with other factors. The study by Georgiev et al. [122] aims to develop a methodology framework for neuromarketing evaluation of drinks and tastes by collecting biosignals such as EEG, EDA, and ECG. The collected data are analyzed to understand the degree of response variation in a test group to ascertain their beverage preferences. The methodology is targeted towards obtaining statistically significant feedback for neuromarketing evaluations.

3.2. Improve the impact of an advertisement

The second objective is based on improving an advertisement. In contrast to the previous goal, where the main objective is only to study how a given advertisement affects users, in this one, different tests are performed varying these advertisements to improve the acceptance of the target audience in general. The works analyzed are grouped according to the same strategy followed in the previous section, depending on the type of stimulus used. These papers are listed in Table 4, which summarizes the main aspects of each of them.

Starting with audiovisual stimuli, some papers focus on studying the subjects' reactions, classifying these reactions as positive or negative. Among these, the work by Colomer et al. [125], used EEG, ECG, and EDA biosignals from 47 subjects, together with Global Field Power (GFP) and PSD techniques for feature extraction. After this, they applied ML algorithms obtaining up to 87.62% accuracy to describe the effectiveness of a given advertisement. Similarly, Emsawas et al. [126], conducted a study using EEG, ECG, and ET, applying only PSD and ML algorithms, where they obtained 76.4% accuracy. Similarly, it is possible to measure the impact of the advertisement based on the emotional state of the subject. Gill e al., [127] highlights the lack of research in applying machine learning methods for classifying customer preferences in neuromarketing. The study employs an LSTM-based model to analyze DEAP EEG signals for emotion recognition. The findings indicate that the LSTM model is effective in EEG-based emotion recognition, suggesting its potential for enhancing understanding of consumer behavior in marketing contexts.

Other authors seek to predict when an advertisement has generated user acceptance by measuring liking. In this way, it is possible to vary the stimuli to obtain the best combination and thus increase the impact of the advertisement. Mateusz and Kesra [133] proposed a study using EEG, ECG, and EDA sensors to test whether these techniques are applicable in this objective. They extracted information from the data using GFP and IAF algorithms, subsequently using MI, AW, and EI algorithms for classification. The authors concluded that these methods are acceptable in this research field. Complementary, Martínez et al. [130] employed EEG, ECG, EDA, and ET biosignals to study the visual fixation

Table 4
Works that seek to improve an advertisement.

Ref.	Year	Biosignal	Subjects	Stimuli	Preprocessing	Feature extraction	Classification	Predicted states	Results
[128]	2010	EEG	45	Audiovisual	ICA	FFT	Mean classifier	Potential of TV advertisements	Statistically significant difference among the three advertisements
[129]	2014	EEG	19	Audiovisual	Bandpass filter Notch filter	FFT GLM	Statistics	Study the impact of the green color	Frontal theta activations were higher among eco-friendly subjects
[125]	2016	EEG ECG EDA	47	Audiovisual	Bandpass filter ICA Adjust	GFP PSD	MCC BAG RF ASC	Positive Neutral Negative	87.62% of accuracy
[130]	2018	EEG ECG EDA ET	22	Audiovisual	Bandpass filter Notch filter ICA	GFP	MI EI	Pleasant Unpleasant	The number of fixations affects the recall of the showed products
[126]	2019	EEG ECG ET	130	Audiovisual	Not specified	PSD	LSTM MLP SVM	Positive Negative	76.4% of accuracy
[131]	2019	EEG ECG EDA	30	Audiovisual	Not specified	Not specified	AWI MI	Study the effectiveness of social advertising in the context of promoting a healthy lifestyle	Methods suitable for study
[132]	2020	EEG	20	Audiovisual	Not specified	Bayesian factor Chi-square analysis	Not specified	Change of decision	Subliminal messages did have significant influence
[133]	2020	EEG ECG EDA	20	Audiovisual	Bandpass filter ICA	GFP IAF	MI AW EI	Redesign advertisements to be shorter and have a better impact	Relevant fragments can be identified
[127]	2022	EEG	28	Audiovisual	Not specified	Emotion recognition	LSTM	Emotional states	Effective in emotion recognition for marketing
[134]	2012	EEG	12	Image	Bandpass filter ICA	GLM	Mutual information	Impact of image	Colors, patterns, or their combinations played a significant role in the selection of a product
[135]	2013	EEG	15	Image	Bandpass filter FIR1	PSD	RF kNN SVM DNN	Reaction	94% of accuracy 92% of accuracy 62% of accuracy 88% of accuracy
[136]	2014	EEG ECG EDA	20	Image	Bandpass filter ICA CAR	PSD	Statistics	Vote Dominance Trustworthiness	50% of accuracy
[137]	2016	EEG ET	40	Image	Bandpass filter	FFT	Not specified	Improving the advertisement design	Guidelines to advertisers
[138]	2016	EEG	7	Image	Bandpass filter CAR	Welch method	SVM BPTT	Red Yellow Green Blue	85.26% of accuracy 80.2% of accuracy 78.32% of accuracy 76.4% of accuracy
[139]	2016	EEG ET	15	Image	Bandpass filter Baseline correction	P300 ERP N100	Statistics	Attention level	ERP and the ET results were inconsistent at stimulus discrimination task
[140]	2019	EEG	16	Image	Bandpass filter ICA	PSD	SVM LDA	Like vs. Neutral Dislike vs. Neutral Buy vs. Neutral	87.06% of accuracy 95.95% of accuracy 93.87% of accuracy
[141]	2020	ET	72	Image	Not specified	Fixation duration Fixation count	Not specified	Visual attention Attitude Job-pursuit intention	Increased visual attention with personalized advertisements.
[142]	2023	EEG	230	Image	Bandpass filter Downsampled	Neural activity patterns	DLN	Willingness to pay	Superior prediction accuracy of WTP using DLN

points for the recall of each of the products shown. For this, they applied the GFP algorithm to obtain the information from the different biosignals and the MI and EI algorithms for the classification.

Another relevant dimension for researchers is the study of specific aspects of the advertisements, such as the colors used. Lee et al. [129] studied how the green color can improve an advertisement and how it affects consumers through the EEG biosignal. For that, they applied FFT and GLM and, after obtaining statistics, they concluded that regular consumers of green products have a greater activation when exposed to this type of product. In contrast, Ohme et al. [128] performed a study on how to improve the potential of advertisements shown on television. This experiment was performed on 45 users, obtaining the EEG signal, preprocessed using the ICA algorithm, and extracting the relevant information employing the FFT algorithm. For the classification, a mean classifier was applied, indicating that certain advertisements generate an activation peak in the frontal lobe.

In the case of image stimuli, there is a similar trend to those created with audiovisual stimuli. For example, some solutions study the visual design of products, such as colors, patterns, or combinations of these characteristics. Khushaba et al. [134] completed an experiment for color modification using the EEG signal with GLM and a Mutual Information (MI) classifier. The results showed that the different combinations of these characteristics have a tangible impact on user perception. Moreover, Matukin et al. [137] did a similar work defining the best techniques for the visual design of advertisements. For this, they used EEG and ET signals together with FFT.

Finally, Aldayel et al. [135] focused their research on predicting the subjects' reactions with EEG signals. The authors used PSD values and ML algorithms such as RF, kNN, or SVM for this. They obtained up to 94% accuracy in predicting these reactions from users. Similarly, Samsuri et al. [139] aimed to obtain the level of users' attention when viewing an advertisement using EEG and ET signals, thus studying the evoked potentials generated by these stimuli. Likewise, Golnar et al. [140] pretends to predict whether users liked or disliked an advertisement. For this, they used PSD values collected from the EEG signal. Regarding classification, they used SVM and LDA algorithms, obtaining up to 95% accuracy for predicting these states. Another experiment conducted by Pfiffelmann, Dens, and Soulez [141] corroborates that personalizing job advertisements with potential employees' first names and photographs enhances visual attention towards the advertisement. The metrics used to measure visual attention were fixation duration and fixation count. The results indicated that personalized advertisements persuade individuals to fixate on the ad more frequently and for extended durations, thereby potentially influencing their attitudes and job-pursuit intentions positively. Focused on the use of neuoronal networks with EEG, Hakim et al. [142] focuses on using deep learning networks to predict consumer willingness to pay based on EEG data. It overcomes the limitations of small datasets and high variability in EEG data by employing advanced computational modeling. The study of DLN successfully predicts WTP with higher accuracy than conventional methods, providing insights into neural mechanisms related to consumer valuation and decision-making. This research signifies the potential of DLNs in neuromarketing, particularly for EEG-based predictions.

3.3. Comparison between advertisements

The last objective compares different advertisements belonging to the same market niche. There is an interest in comparing them as they share the same objective or advertised product. Following the structure of the previous sections, the present section analyzes articles that use audiovisual stimuli, those that only use visuals, and the rest of the works. These studies have been collected and summarized in Table 5, where the main characteristics of each one are shown.

The main objective proposed in this objective is predicting a favorite item in a set of articles. This has been done using visual stimuli, as they can describe a product quickly and concisely. Murugappan et al. [143] intended to obtain the favorite product of each subject by using the EEG signal, along with features related to PSD, Spectral Energy (SE), and Spectral Centroid (SC). After this, they generated models based on ML as kNN; and DL, like PNN algorithms, obtaining up to 96.6% accuracy in detecting the product with the highest user preference. Following a similar objective, Oon et al. [144] employed the EEG signal and features from DFA, obtaining 67.4% accuracy with the NN algorithm. The same approach was followed by Hakim et al. [32], where they used FBP and hemispheric symmetry based feature extraction and ML algorithms such as SVM, LR, kNN, and DT, obtaining a maximum of 68.51% accuracy in a binary classification. Other authors studied whether it is possible to recognize the probability of purchasing a product through exposure to audiovisual stimuli. This recognition makes it possible to compare different campaigns employing the likelihood of buying the advertised product. Following the same objective, Dmochowski et al. [145] developed a study based on EEG where, using features related to the ISC, they were able to obtain 66% accuracy. Similarly, Gupta et al. [146] conducted a survey using STFT applied to the EEG signal and classification algorithms such as kNN and PNN. For the experimentation, advertisements for commercial soap brands such as Pears, Lux, Cinthol and Dove were shown. The results yielded by this methodology indicated that these algorithms could identify the changes caused by different stimuli.

Another objective in neuromarketing studies is predicting the interest or "Liking" that the advertisement generates in the users. The first study for this purpose was conducted by Soria et al. [147], which performed an analysis based on ANN from the raw data of the EEG signal, obtaining 68% accuracy in detecting whether a given advertisement is liked or disliked by the user. In the same year, Boksem et al. [34] extracted the EEG signal of 29 subjects and extracted information related to the frequency of the signal using the FFT algorithm. They then applied regression-based classification algorithms, concluding that these methods adequately solved this problem. Later, Guixeres et al. [148] pursued the same objective but added ECG and ET biosignals to the historically used EEG. The information extracted from the EEG signal was based on power using PSD and GFP, while they calculated the AOI for the ET signal. With this information, an ANN-based model was created to recognize those products the user liked, obtaining 82.9% accuracy. Finally, Alimardani et al. [149] conducted a similar experiment where they used EEG signals and added visual stimuli from images. Again, frequency-related features of the signal were obtained by PSD, and for classification, they used SVM, RF, LR algorithms, and a CNN network. This work gathered a maximum accuracy of 74.56% between all the algorithms used.

Some advertisements generate certain emotions in users, such as happiness or nostalgia, which increases the possibility of purchasing. For this reason, predicting when a stimulus generates a specific emotion is very interesting for companies. In 2009, Ohme et al. [150], focused on studying the emotions evoked by each advertisement. The authors relied on the EEG biosignal, and EMG and FR, two classic techniques for recognizing emotions from facial gestures. In the case of the EEG signal, FFT was applied to study the different frequency bands directly related to emotions. This data extracts statistics and corroborates that different emotional responses are obtained depending on the design of the advertisement. With a similar objective, Ural et al. [151] studied how the frequency bands behave but, in this case, added EEG, ECG, and EDA biosignals. Again, the results showed that different band responses are gathered depending on the design of the advertisement.

Other authors propose the detection of states other than classical ones. Among these, Barnett et al. [152] studied how to predict scores between zero and ten from the correlation of data from Cross-Brain Correlation (CBC) using EEG, ECG, and EDA. Later, Hakim et al. [154] conducted a study to predict a binary decision for selecting the favorite product. They used only the EEG signal and features extracted from

Table 5
Works that compare campaigns.

Ref.	Year	Biosignal	Subjects	Stimuli	Preprocessing	Feature extraction	Classification	Predicted states	Results
[150]	2009	EEG EMG FR	45	Audiovisual	Bandpass filter Notch filter ICA	FFT	Statistics	Response Emotion	Different responses between advertisements
[143]	2014	EEG	12	Audiovisual	Bandpass filter Surface Laplacian filter	PSD SE SC	kNN PNN	Preference	96.62% of accuracy
[145]	2014	EEG	12	Audiovisual	Bandpass filter	ISC	RA	Purchase intention	66% of accuracy
[147]	2015	EEG	10	Audiovisual	Not specified	Not specified	ANN	Liking	82% of accuracy
[34]	2015	EEG	29	Audiovisual	Downsampling Highpass	FFT	Mix-Models Regression	Liking	EEG allows measurement of purchase preferences
[152]	2017	EEG ECG EDA	58	Audiovisual	Not specified	CBC	Correlation	Rating 0–10	68% of accuracy
[153]	2017	EEG ET	27	Audiovisual	Downsampling Highpass filter Notch filter	Spectro-temporal domain Cognitive-congruency	R2	Variance	73% of accuracy
[148]	2017	EEG ECG ET	35	Audiovisual	Downsampling Bandpass filter ICA Interpolation	PSD GFP	ANN	Liking	82.9% of accuracy
[146]	2017	EEG	18	Audiovisual	Bandpass filter Notch filter Surface Laplacian filter	STFT	kNN PNN	Purchase intention	Dove brand advertisements generate a greater impact on subjects
[144]	2018	EEG	10	Audiovisual	Notch filter Bandpass filter	DFA	NN kNN	Preference	67.44% of accuracy
[154]	2018	EEG	33	Audiovisual	Highpass filter Notch filter ICA	STFT FBP Hemispheric asymmetry ISC	SVM RGT kNN KDL	Binary choice	68.50% of accuracy
[151]	2019	EEG ECG EDA	30	Audiovisual	CWT	Wavelet coherence Phase difference	Statistics	Alpha Beta Gamma Delta Theta	Coherence in bands
[155]	2020	EEG	23	Audiovisual	Not specified	FFT	Not specified	Variations of each band	Increase in EEG activity
[32]	2021	EEG	13	Audiovisual	Notch filter ICA	FBP Hemispheric symmetry	SVM Logistic regression kNN DT	Preference	68.51% of accuracy
[149]	2021	EEG	25 35	Image Audiovisual	Bandpass filter	PSD	SVM RF Logistic regression CNN	Liking	74.57% of accuracy
[156]	2012	EEG	18	Image	Bandpass filter PCA	FFT	MI	Purchase intention	Significant change in spectral activities for subject preferences
[157]	2013	EEG ET	18	Image	ICA	DWT	Mutual information	Preference	Changes in EEG for preference
[158]	2014	EEG	15	Image	Bandpass filter Remove eye blink manually	PSD	Logistic regression	Liking	Male and female behavior for this set of stimulant images were similar
[159]	2015	EEG	15	Image	Notch filter ICA	N200 Theta band power	Neural random utility model	Purchase intention	60% of accuracy
[160]	2015	EEG	40	Image	Preference index	Not specified	1D linear classifier	Preference	80% of accuracy

(*continued on next page*)

Table 5 (*continued*).

[75]	2017	EEG	25	Image	Savitzky-Golay	DWT	HMM	Preference	95.33% of accuracy
[161]	2018	EEG ECG EDA ET	21	Image	Notch filter Bandpass filter	Not specified	WALD	Purchase intention	65.8% of accuracy
[162]	2018	EEG ET	16	Image	Downsampling Bandpass filter	DWT	Not specified	Purchase intention	Methods suitable for study
[31]	2019	EEG FR ET	119	Image	Bandpass filter Downsampling	FFT	LASSO	Purchase intention	60% of accuracy
[163]	2020	EEG	25	Image	CAR	DWT	DT	Preference	93%
[164]	2019	EEG	5	Image	Not specified	FFT	Not specified	Decision making	Right hemisphere is the most activated
[165]	2021	EEG	25	Image	Downsampling Bandpass filter ICA Savitzky-Golay	DWT Welch method	DNN SVM kNN RF	Liking	87% of accuracy
[166]	2016	EEG FR	22	Flavor	Not specified	Facial expression	Statistics	Positive Negative	Neuromarketing can be a useful tool that will help manufacturers and sellers to offer products that truly, and not only in appearance, satisfy customers
[44]	2020	EEG ECG EDA	21	Real product	Not specified	Attention index Pleasant index	Correlation	Subjects are exposed to both utilitarian and hedonic products	Functional and hedonic products generate emotional responses in consumers

STFT, FBP, hemispheric asymmetry, and ISC. After that, they applied both ML and DL algorithms, obtaining a maximum accuracy of 68.51%.

The next category of stimulus used is visual, which leaves aside the auditory dimension. Similar to the work done with audiovisuals, predicting the purchase preference between a set of advertisements is of great interest. Some of the first authors who followed this objective with visual stimuli were Baldo et al. [160], which conducted a research where they performed a series of experiments from the EEG signal, training a 1D linear classifier algorithm, achieving an 80% accuracy. In this sense, Yadava et al. [75] studied this same problem, but with the difference of applying DWT to extract relevant information from the EEG signal and using the HMM algorithm to classify the purchase preference. With this algorithm selection, they increased the classification accuracy to 95.33%. Furthermore, Amin et al. [163] changed the classification algorithm to DT, reaching up to 93% accuracy. Similar to the objective of determining the preference when purchasing a product, obtaining a probability for user purchase is also of great interest. For this, Khusaba et al. [156] employed the EEG signal along with features obtained from FFT and the MI algorithm, obtaining as a result that their proposed framework can recognize purchase intentions. Similarly, Telpaz et al. [159] obtained different evoked potentials such as N200 from the EEG signal along with neural random utility model algorithms, reaching 60% accuracy. Later, Garczarek [161,162] and Huseynov et al. [31] increased the number of biosensors, from EEG only, up to four biosignals such as EEG, ECG, EDA, and ET. These signals were collected from 21 subjects, obtaining at most 65.8% accuracy.

As with audiovisual stimuli, obtaining how much a user has liked an image is an essential point of interest. To obtain this liking, Yilmaz et al. [158] considered the EEG signal and the PSD technique to extract the information from the image. Finally, they applied a linear regression algorithm, obtaining a model that recognizes when a user likes an image. Years later, Alday et al. [165] performed a similar experiment, varying the algorithms for extracting characteristics. In this case, they use DWT and Welch method, increasing the number of algorithms to four: DNN, SVM, RF, and kNN. The maximum accuracy obtained in this case is 87%.

Finally, new stimuli are proposed in addition to those mentioned above. One of these stimuli was used by Horska et al. [166], which employed the taste of different products to compare them. As biosignals, it used EEG and FR, obtaining statistics to predict whether it is a positive or negative stimulus. From the biosignal of FR, the authors extracted the facial expression from the user, which is related to emotion. The results show that these biosignals can detect the subjects' reactions, possibly predicting them. Bettiga et al. [44] employed authentic products to study the subjects' reactions. The biosignals used were EEG, ECG, and EDA, obtaining the attention and pleasure indices from these biosignals. Correlation algorithms were then applied for classification, whose results show that it is possible to predict these reactions.

4. What datasets are publicly available in neuromarketing, and what type of data include?

This section reviews public datasets currently available for neuromarketing objectives. However, these datasets have yet to be designed with the specific purpose of being used for neuromarketing. Consequently, the datasets most commonly used in the literature are those aimed at detecting different states of the person. Many of these datasets are previously labeled with aspects of subjects' states, such as cognitive load or emotional states. For all these reasons, multiple works focused on neuromarketing have opted to use these datasets to avoid data dependency.

Table 6 shows the collected datasets used in neuromarketing works, as well as others that can be used in neuromarketing domains. For each of the datasets, this section takes into consideration the following characteristics: (i) the year of publication, (ii) the types of biosignals they incorporate, (iii) the number of subjects studied, (iv) the size of the dataset, (v) the stimuli used and (vi) the labels employed. The datasets collected in this work are public and can be requested from the respective authors.

The first public dataset about mental states was created in 2009, named "Imagined Emotion" [167]. This data/set contains EEG and ECG signals, where 31 subjects were asked to remember a specific past situation to evoke an emotion. At the end of the experiment, each subject completed a questionnaire to assess the intensity of the emotion sought to be evoked. The data is labeled with the valence value, which can be translated to a specific mental state. In total, it contains 34 GB of data from EEG and ECG signals.

Table 6
Public datasets available.

Ref.	Name	Year	Biosignals	Subjects	Size	Stimuli used	Labels used
[167]	Imagined emotion	2009	EEG, ECG	31	34 GB	Recollection of past emotional situations	Valence
[168]	DEAP	2012	EEG, EMG, EDA, ET, BVP, Temperature	32	2.9 GB	Music videos	SAM
[169]	MAHNOB HCI	2012	EEG, ECG, EDA, ET, FR, Temperature	30	2.5 GB	Video images	SAM
[170]	DECAF	2015	EMG, MEG, ECG, ET, FR	30	300 GB	Movie clips	SAM
[171]	SEED	2015	EEG, ET	15	6.95 GB	Movie clips	Positive Neutral Negative
[172]	ASCERTAIN	2016	EEG, ECG, EDA, FR	58	56 MB	Video	SAM
[75]	Analysis of EEG signal in neuromarketing	2017	EEG	25	86 MB	Images	Like Dislike
[173]	SEED IV	2017	EEG, ET	15	10 GB	Movie clips	Happy Sad Fear Neutral
[174]	Google facial expression comparison dataset	2018	FR	156 000	200 MB	N.A	Happiness Anger Surprise Content
[175]	DREAMER	2018	EEG, ECG	23	500 MB	Audiovisual	SAM
[176]	CASE	2018	ECG, ET, EMG, EDA, Respiration, Temperature	30	5 GB	Audiovisual	SAM
[177]	DEAR-MULSEMEDIA	2020	EEG, EDA, ET	18	1 GB	Multiple senses	SAM
[178]	K-EmoCon	2020	EEG, ECG, EDA, Temperature acceleration	32	100 MB	People-to-people discussions	Labeled from three sources
[179]	An EEG dataset recorded during affective music listening	2020	EEG	31	100 MB	Auditory	SAM
[180]	MAUS	2021	ECG, PPG, EDA	22	77 MB	N-Back task	Cognitive load
[32]	Machines learn neuromarketing	2021	EEG	33	18 GB	Video	Preferred product
[181]	NeuMa	2023	EEG, ET	42	35 MB	Supermarket brochures	Questionnaire

Three years later, the DEAP dataset [168] was created and became one of the most used in emotional recognition. This dataset comprises EEG, EMG, EDA, and ET biosignals obtained from 32 subjects, having a total size of 2.9 GB. The authors used music videos to stimulate the subjects and label the data. After presenting these stimuli, the subjects had to perform the self-assessment questionnaire known as Self-Assessment Manikin (SAM). SAM is a questionnaire based on valence and arousal, which can directly translate into different emotional states. Moreover, the dataset also provides liking and dominance values for data labeling, which can be very useful in studies related to neuromarketing. Similarly, the MAHNOB HCI dataset [169] uses a very similar technique maintaining all previous biosignals and adding, in this case, FR as a biosignal. In addition, it also modifies the stimuli presented, using videos and images instead of music videos. The number of subjects and dataset size are also very similar, with 30 subjects participating in the experiment and 2.5 GB in total size.

Later, in 2015, the DECAF [170] and SEED [171] datasets were created. The DECAF dataset is similar to those presented above, although varying the stimulus used, in this case, pieces of movies. DECAF is one of the most extensive datasets, weighing about 300 GB, and includes 30 participants. Meanwhile, the SEED dataset modifies the labeling of the data concerning the DECAF dataset, assigning a specific state to each movie clip, thus eliminating each person's factor. The SEED dataset has certain drawbacks since the selected clip may not cause the states for which it was designed. One year later, the ASCERTAIN dataset [172] was constructed, where the number of subjects studied was increased to 58, maintaining the EEG, ECG, EDA, and FR biosensors. This dataset uses visual stimuli, and the data labeling was again performed using the SAM system, reaching a size of 56 MB.

Yadava et al. [75] created in 2017 the first dataset designed specifically for neuromarketing work. The stimuli used in this dataset are a series of images of commercial products, labeled as "like" or "dislike". The objective of the dataset is to decide whether the subject liked them. These images were shown to 25 subjects, obtaining the EEG signal of each one of them. In addition, the second version of the SEED dataset appeared the same year, known as SEED-IV [173]. It follows the same methodology as its previous version, although the labels assigned to the data vary. The labels included in this dataset are *Fear*, *Sadness*, *Happiness*, and *Neutral*.

Then, in 2018, Google created a massive dataset with people's faces to identify a particular emotional state from facial expressions [174]. The most remarkable feature of this dataset is that it is composed of more than 156,000 faces labeled as *Happiness*, *Anger*, *Surprise*, and *Contempt*. Despite a large number of images, the size of the dataset is reduced to 200 MB. The same year, the DREAM/ER [175], and CASE [176] datasets appeared. Both datasets are similar in terms of the type of stimulus selected and the stimuli they use in their work. The difference between them is the type of biosignals used. The DREAMER

dataset uses the EEG and ECG signals, while the CASE dataset suppresses the EEG signal and adds the ECG, ET, EMG, EDA, Respiration, and Temperature signals.

In 2020, the DEAR-MULSEMEDIA dataset focused on stimulating all human senses, thus employing odors, tastes, texture, sounds, and videos [177] . At the same time, they were capturing EEG, EDA, and ET biosignals, labeling these data using the SAM questionnaire. In the same year, the dataset called K-EmoCon [178] appeared, whose peculiarity is that the stimulus used is based on personal contact, simulating a debate between two people. The data were labeled from multiple sources, including the interviewee, the interviewer, and a series of observers who decided based on the whole context. 32 subjects were selected for this experiment, capturing EEG, ECG, EDA, Temperature, and Acceleration signals. The present work considers this dataset because one of the main challenges in neuromarketing is the use of new stimuli leaving aside the classic ones, and this work takes it into account. One of these stimuli is how other people influence the purchase of a product, so the K-EmoCon dataset helps study this task. Finally, in 2020, Daly et al. [179] created a dataset to study how auditory stimuli affected a person's state. For this, the EEG signal of 31 participants was captured, labeling the data utilizing the SAM questionnaire and stimulating these subjects with different sounds.

The MAUS dataset, was released in 2021 [180]. It measures the cognitive load generated by a stimulus to a subject using the ECG, ET, and EDA signals. The stimuli used in this study is the N-Back task, which involves counting the number of digits that appear on the screen, following a series of patterns. For the creation of this dataset, 22 subjects participated, obtaining 77 MB of data. The design of this dataset could help study how the arrangement of the objects and the patterns they follow affect their impact on the subjects.

Another dataset was created by Hakim et al. [32] in 2021, where the emphasis was on utilizing multiple EEG measures and machine learning to enhance preference prediction from self-reports. Here, participants engaged with video commercials for six food products, while their EEG activity was recorded. Their subsequent questionnaire responses acted as a self-report reference. By weaving in EEG measures, notably frontal powers in the alpha band and hemispheric asymmetry in the beta band, prediction accuracy for product preference skyrocketed.

The most recent dataset was created by Georgiadis et al. [181] in 2023 called the NeuMa dataset, collecting diverse data from 42 participants engaging with supermarket brochures. Specific data facets include EEG recordings, capturing real-time brain activity; eye-tracking recordings, shedding light on visual engagement; comprehensive questionnaire responses ranging from demographic details to product-related queries; and computer mouse data, revealing browsing behaviors. Such a combination of dynamic and multimodal data addresses a gap in neuromarketing research, offering a chance for a more thorough exploration.

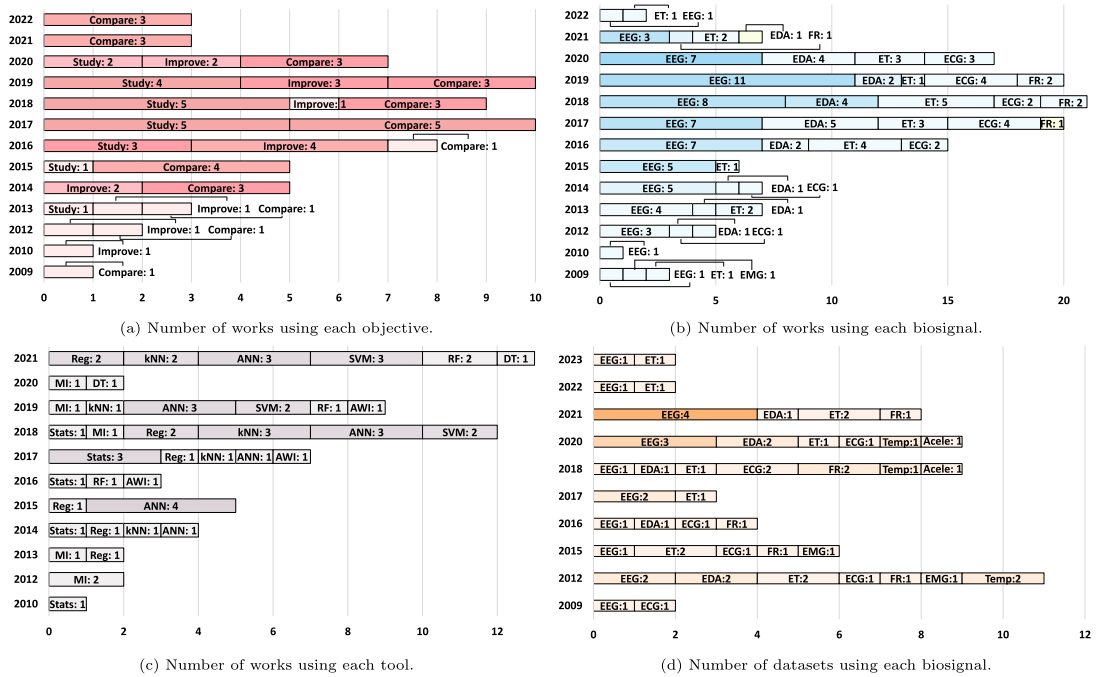
5. How has the role of data fusion in neuromarketing evolved over time, and what are the open challenges?

Based on the different aspects of neuromarketing studied together with the biosignals analyzed in questions *Q1-Q3*, this section answers question *Q4*. To solve this question, lessons learned, trends, and open challenges drawn from current work on neuromarketing are discussed.

5.1. Lessons learned

After reviewing the state of the art, the following lessons learned are summarized:

- **Improving results through data fusion**. Effective data fusion techniques can enhance the accuracy and reliability of neuromarketing studies by combining multiple data modalities, such as EEG signals, eye tracking data, and physiological measurements. This integration allows for a more comprehensive understanding of consumer responses and behaviors.
- **The comparison between advertisements is the most commonly used neuromarketing objective**. As shown in Fig. 3, almost 45% of the works focus on comparing objectives. Its relevance is mainly because different products compete against each other to get the most prominent market quota, so obtaining feedback about the competition is very interesting for companies and, therefore, for research. However, the distribution of works in the rest of the objectives is quite balanced, being 30.4% for the study of an advertisement and 24.8% for the improvement of an advertisement.
- **There is a large number of works following the visual-statistical method**. Many works in the literature used a classification method, collecting statistics from the data, then presenting the results visually. This technique is between 9%–20% among the different objectives, with the improvement objective being the one where it is used the most. This type of classification is very vulnerable to the subjectivity of the person studying the results, which is why ML/DL algorithms are more advisable in these situations.
- **Audiovisual is the most common stimulus in neuromarketing**. These inputs are used in television advertisements, thus perpetuating this kind of stimulus. This category is the most used in the three objectives, exceeding 50% of use in all of them (see Fig. 4(a)). Nowadays, with the popularity of smartphones and tablets, advertisements are still audiovisual, although they add a degree of interaction with the user, which must be studied. After the audiovisual stimuli, some are solely visual through images. Following the same theory as audiovisual stimuli, images shown on television, billboards, and newspapers are the most common way to show a product to a potential consumer. Those works that use more innovative stimuli remain in the background, such as web pages or authentic products for their promotion.
- **EEG and ET are the most widespread biosignals in neuromarketing, with notable differences based on application contexts**. As seen in Fig. 3, the EEG biosignal is used in almost 50% of the works studied. EEG is considered one of the most representative signals for identifying a subject's mental state. However, the ET signal is predominant in specific scenarios, such as the case study of an advertisement. Fig. 4(c) shows the distribution of biosignals in each objective. In objectives aiming to provide a comparison or the improvement of advertisements, the use of EEG exceeds 50%, while in the objective focused on the study of the impact of a stimulus, the ET signal slightly outperforms all other biosignals, being EDA and EEG the second most used signals. The ET signal, it is mainly used in studies that incorporate visual stimuli. In contrast, ET provides visualization patterns or specific points where the user's attention has been focused. Employing these characteristics, it is possible to redesign a stimulus or verify if it fulfills the function for which it has been designed. In the case of, it allows the identification of subjects' stress from the conductivity of the skin.
- **There are no unified data preprocessing techniques for neuromarketing objectives**. In almost all the studied works, the data processing techniques are different. Section 2 shows how the preprocessing and feature extraction techniques are very varied. Some patterns exist, such as using algorithms based on power and frequency to be applied to the EEG signal or the AOI for ET signals. Nevertheless, their combinations and the algorithms used for each pattern vary considerably. In addition, the results are data-dependent, so the definition of a unified set of algorithms for all use cases is an open challenge.
- **Public datasets are scarce and are not designed for neuromarketing objectives**. The public datasets that can be used in this type of work are very scarce (see Table 6). These datasets are mainly aimed at mental state detection, most of which have been created using stimuli to evoke emotional states. Most of the studied works do not provide the data publicly, unable to replicate the experiments performed.



(a) Number of works using each objective.

(b) Number of works using each biosignal.

(c) Number of works using each tool.

(d) Number of datasets using each biosignal.

Fig. 5. Trends in the works and datasets studied per year.

5.2. Current trends

The main trends that can be drawn from the temporal analysis of the published papers and datasets are as follows:

- **The study of advertisements has gained relevance in recent years**. Fig. 5(a) shows how the advertisement comparison objective has been the most commonly proposed. However, in recent years, the study of advertisement has gained relevance, being the most employed in 2017, 2018, and 2019. This is because the possibilities for innovation within this objective are more significant than the rest.
- **The combination of EEG with other biosignals has grown in recent years**. The EEG signal has historically been the most commonly used. However, this signal difficult the interpretation of the data. For this reason, the literature has incorporated the use of other biosignals. Specifically, Fig. 5(b) shows how since 2016, the use of biosignals such as EDA or ECG has increased dramatically. Also, ET has been one of the most used for comparing and studying a particular advertisement, mainly because the primary stimulus used in these works is visual, thus having a close relationship.
- **ML and DL algorithms have gained relevance in recent years**. The emergence of ML and DL algorithms has created a new opportunity for automatic pattern identification in recent years. Historically, this was done by extracting specific features from relevant data and subjecting them to the human eye, but as shown in Fig. 5(c), ML and DL algorithms have gained prominence in recent years, becoming the most widely used.
- **Datasets have not evolved much**. Fig. 5(d) shows how the public datasets analyzed in this work have not undergone many modifications in biosignals, subjects, or stimuli used since their appearance. In these datasets, the EEG signal continues to predominate, followed only by the ET signal.

5.3. Challenges

Based on the study of state of the art, this survey defines below the future challenges for further research that should be taken into account:

- **Unified preprocessing techniques for multiple data sources**. One of the major challenges in data fusion for neuromarketing is the integration of heterogeneous data sources. Different data modalities may have varying sampling rates, noise levels, and feature representations, requiring careful preprocessing and alignment to ensure accurate fusion and interpretation of results.
- **Increase the use of stimuli that resemble those found in real use cases**. The use of stimuli based on sounds and images has been used in more than 90% of the studies, as can be seen in Section 2. Regarding neuromarketing, there is a wide variety of stimuli that can be used to modify a subject's attitude towards a product, such as dealing with other people when shopping or arranging objects in a store [107]. However, these stimuli have not been exploited and studied in most works. This is the reason for the emergence of concepts such as Nanomarketing [18], which aims to study dimensions beyond visual an auditory inputs, such as the arrangement of objects in a store or interacting with the seller.
- **Increased use of cheaper and simpler biosensors allowing real-time response**. One of the most commonly used biosensors is the EEG signal (see Fig. 4(c)). However, although technology

is evolving towards more portable and comfortable devices, the precision these devices can achieve is still reduced. Therefore, biosignals such as EDA and ECG should be considered in situations intended to identify more forthright states, such as stress, rather than an emotional state. These devices report a value easily interpreted by a machine, identifying trivial subject states.

- **Need for data labeling independent of users' subjectivity**. The SAM method is one of the most widely used approaches for labeling data. This method is based on obtaining specific parameters such as valence and arousal from the subject. It is a subjective evaluation that can lead to labeling and classification errors. Due to these errors, it is necessary to develop other methods for labeling data that are more accurate and leave aside the user's personal opinion.
- **The use and proposal of new and more descriptive features for classification**. As shown in Section 2, only sensor biosignals are used as inputs to the classification algorithm. However, other information, such as stimulus-related features, can be used for classification, helping to obtain better classification results.
- **Use of models that ensure the privacy of the user's data.** When publishing public datasets, it is necessary to consider certain aspects regarding the privacy of these data. Because the information obtained from these devices has medical grade, specific private data such as purchase priorities may be extracted. For this reason, it is advisable to anonymize the data and link them only to the information necessary for the study, such as age, gender, or mental health conditions.
- **The optimization of ML and DL models to improve training speed.** The AI models created for biosignal classification have a high training cost because the variability of biosignals is large, so a large amount of data is needed. For this reason, it is necessary to investigate new training systems to improve performance in real use cases. Some techniques, such as transfer learning, have been tested in biosignals like EEG, ECG, or FR, which could help to solve this problem. In another direction, the possibility of training a model with a small group of users, which is generally applicable to all users, should be investigated [182–184]. This enables direct application in a real use case without requiring specific training per user.
- **The creation of more public datasets designed for neuromarketing is needed**. As described in Section 4, the existence of public datasets created based on neuromarketing stimuli is reduced to one. Because of this, the generation of stimuli is not comparable to real-life neuromarketing scenarios, which may cause the methodology designed for that theoretical use case to be inapplicable in a real scenario. In addition, a more comprehensive range of public datasets can help use these datasets for new work, reducing the reliance on data when developing a methodology. In these common data, it is possible to study the proposed methodologies more fairly.

6. Conclusions and future work

Neuromarketing studies have historical importance due to the impact of advertisements on companies sales and profits. However, the techniques used in these studies are very heterogeneous and it is crucial to know which of these techniques are the most appropriate depending on the neuromarketing objective. In order to fulfill this necessity, some surveys compile all this information and concisely indicate the main aspects of each neuromarketing phase. Although these works are useful, there are some shortcomings that still need to be solved. On the one hand, existing surveys need to consider the whole neuromarketing cycle, not leaving aside the technical part. Due to this lack of information, it is difficult to repeat the experimentation of a given study or to apply the methodology proposed by that study in another scenario. On the other hand, the techniques used in these studies are very heterogeneous, being necessary to know which techniques best fit the requirements depending on the neuromarketing objective. To improve these limitations, this paper reviews the phases of the neuromarketing cycle and analyzes the techniques used in the literature. In addition, to facilitate the understanding and selection of techniques, the works analyzed are divided according to the objective for which they have been designed. To achieve these objectives, the following research questions have been answered:

Q1. What are the most applied objectives, biosensors, and processing techniques in neuromarketing? This work shows in a summarized form the most used techniques in each phase of the neuromarketing cycle. For the first phase, focused on the neuromarketing objectives, a predominance of the advertisement comparison objective is observed, while audiovisual stimuli predominate in the second stage. In later phases, the most used biosignal in neuromarketing is EEG, directly conditioning the data preprocessing techniques in subsequent steps. Since the processing is so heterogeneous, the summary of these procedures is complex. However, when conducting a neuromarketing study, one of the most relevant points is the techniques used to recognize a particular state. To get a better overview of these techniques, Fig. 4(d) shows the relationship of use for each of the objectives.

Q2. What combinations of data from biosignals, stimuli, and processing and classification techniques are suitable for each objective? This work reviews which data fusions have been most commonly employed depending on the objective of the work. To better understand these relationships, Fig. 4 shows which stimuli have been the most used in each objective, as well as the biosignals and classification procedures. The results show the predominance of visual stimuli, EEG, and ML algorithms in most neuromarketing studies. In particular cases, the ET biosignal, and techniques such as heat mapping, become relevant for objectives aiming to study and improve advertisements.

Q3. What datasets are publicly available in neuromarketing, and what type of data include? This paper reviews the datasets and the types of data they collect for neuromarketing studies, as well as those that can be applied due to their similarity. In conclusion, there is a need for datasets explicitly designed for neuromarketing studies. Consequently, most authors have used datasets whose labeling corresponds closely to the metrics used in a neuromarketing study. Moreover, the development trend among these datasets is minimal, implying that new datasets do not substantially expand upon or innovate beyond previously existing ones.

Q4. How has the role of data fusion in neuromarketing evolved over time, and what are the open challenges? Historically, the data collected have been used to compare advertisements. However, in recent years, the study and improvement of a stimulus has gained relevance in the literature. The importance obtained by these objectives has caused new challenges related to neuromarketing. One of these challenges is the need for new datasets designed explicitly for neuromarketing and adjusted to the three objectives shown. In the same way, using stimuli that resemble the reality, such as real products or the arrangement of objects inside a store, is a potential need. ML/DL models usually recognize the states generated by these stimuli. Related to these models, the security they apply to users' data is a challenge that remains to be solved, as well as the performance of these when performing classification.

Aligned with current trends and challenges, future work could focus on designing and implementing new systems for predicting mental states in neuromarketing. In addition, there is an opportunity for proposing new stimuli and realistic scenarios for applying the designed techniques, as well as improvements in training and classification algorithms to make them applicable in real time. Finally, a dataset could be designed and made publicly available so that other researchers can use it to develop new research.

CRediT authorship contribution statement

Mario Quiles Pérez: Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Enrique Tomás Martínez Beltrán:** Validation, Funding acquisition. **Sergio López Bernal:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Eduardo Horna Prat:** Validation, Supervision, Conceptualization. **Luis Montesano Del Campo:** Supervision, Funding acquisition. **Lorenzo Fernández Maimó:** Writing – review & editing, Supervision, Methodology, Investigation. **Alberto Huertas Celdrán:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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Data availability

No data was used for the research described in the article.

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2

EEG Channel Reconstruction in Limited BCIs



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Abstract

Neuromarketing is a discipline that combines insights from neuroscience with marketing strategies to gain a profound understanding of consumer behavior through the analysis of physiological data. Electroencephalography (EEG), which provides real-time and direct measurements of brain activity, is increasingly utilized to assess cognitive and emotional responses, offering vital insights for optimizing marketing campaigns. However, the application of EEG via Brain–Computer Interfaces (BCIs) in neuromarketing scenarios encounters specific challenges, particularly with low-cost BCIs. These devices, while expanding the accessibility of EEG technology for mass data collection, typically suffer from limited channel numbers and static electrode configurations, constraining the depth and amplitude of data that can be gathered. This study introduces a novel, a lightweight convolutional neural network model that has demonstrated good performance in reconstructing EEG signals for neuromarketing applications, particularly when employed with limited-channel, low-cost BCIs. The integration of advanced deep learning techniques directly into the EEG device firmware enables the virtual generation of additional EEG channels, effectively overcoming traditional device limitations. Furthermore, this research presents a custom loss function that combines mean squared error and Pearson's correlation coefficient, ensuring high fidelity in signal reconstruction and alignment with the intricate temporal dynamics

of brain activity. This enhancement is crucial for capturing accurate consumer responses. Validation against public EEG datasets demonstrated the superiority of the model in reconstructing EEG channels over traditional signal processing methods. Additionally, rigorous testing of over 1,820 channel configurations has proven the adaptability and precision of the model, making it ideal for diverse neuromarketing scenarios.

Keywords

EEG · Neuromarketing · Brain–Computer Interfaces · Deep learning · Artificial Intelligence

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EEG channel reconstruction using convolutional neural networks in limited BCIs: A proposed method for neuromarketing applications

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ABSTRACT

Neuromarketing is a discipline that combines insights from neuroscience with marketing strategies to gain a profound understanding of consumer behavior through the analysis of physiological data. Electroencephalography (EEG), which provides real-time and direct measurements of brain activity, is increasingly utilized to assess cognitive and emotional responses, offering vital insights for optimizing marketing campaigns. However, the application of EEG via Brain–Computer Interfaces (BCIs) in neuromarketing scenarios encounters specific challenges, particularly with low-cost BCIs. These devices, while expanding the accessibility of EEG technology for mass data collection, typically suffer from limited channel numbers and static electrode configurations, constraining the depth and amplitude of data that can be gathered. This study introduces a novel, a lightweight convolutional neural network model that has demonstrated good performance in reconstructing EEG signals for neuromarketing applications, particularly when employed with limited-channel, low-cost BCIs. The integration of advanced deep learning techniques directly into the EEG device firmware enables the virtual generation of additional EEG channels, effectively overcoming traditional device limitations. Furthermore, this research presents a custom loss function that combines mean squared error and Pearson's correlation coefficient, ensuring high fidelity in signal reconstruction and alignment with the intricate temporal dynamics of brain activity. This enhancement is crucial for capturing accurate consumer responses. Validation against public EEG datasets demonstrated the superiority of the model in reconstructing EEG channels over traditional signal processing methods. Additionally, rigorous testing of over 1,820 channel configurations has proven the adaptability and precision of the model, making it ideal for diverse neuromarketing scenarios.

1. Introduction

Neuromarketing stands as an interdisciplinary field that merges insights from neuroscience with marketing strategies to unlock a deeper understanding of consumer behavior and the effectiveness of advertising campaigns [1]. Unlike traditional marketing methods that often rely on subjective feedback mechanisms such as surveys and interviews, neuromarketing seeks to leverage objective, physiological data to gain a more accurate assessment of a consumer's response to marketing stimuli. Among various physiological techniques, electroencephalography (EEG) has emerged as a cornerstone in neuromarketing research due to its capability to provide real-time and direct measurements of brain activity [2].

The prominence of EEG in neuromarketing is derived from its capacity to capture a wide array of cognitive and emotional responses, including attention, engagement, memory encoding, and emotional valence [3]. These attributes enable a profound comprehension of how consumers process and respond to advertisements, rendering EEG an invaluable instrument for enterprises aiming to design more efficacious campaigns. In contrast to eye-tracking, which assesses visual attention [4], and Electrodermal Activity (EDA), which gauges arousal [5], EEG provides a complete overview of both cognitive processes and emotional states, offering insights beyond mere visual cues or arousal levels. Furthermore, the non-invasive nature and lower cost of EEG compared to other techniques like functional Magnetic Resonance Imaging (fMRI) improves its attractiveness for marketing

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research, allowing for practical applications in real scenarios [6]. However, while EEG is more accessible and suited for large-scale consumer studies, fMRI remains superior in terms of spatial resolution and the ability to capture deep-brain activity, making it a powerful tool for neuromarketing when cost and experimental constraints allow [7].

Despite the potential of EEG in neuromarketing, the practical application of this technology faces challenges, especially when considering the accessibility and usability of Brain–Computer Interfaces (BCIs). Recently, the search of more user-friendly EEG devices, such as textile HALO bands, has opened new opportunities within the field of neuromarketing [8]. These devices, characterized by their ease of use and affordability, offer a practical way to collect EEG data outside traditional lab settings. However, a significant limitation of such devices is their restricted number of channels, which can constrain the amplitude of data collection and the granularity of insights obtained.

Moreover, the static configuration of the electrodes is critical for specific functionalities of the device. The design of BCIs with fixed electrodes must balance ease of use and rapid deployment with the challenge of optimally positioning these electrodes for a broad range of neuromarketing applications. The placement of electrodes depends heavily on the particular research objectives. For instance, studies focused on emotional responses typically require electrodes to be positioned over the frontal and parietals regions of the brain [9], whereas research into attentional processes might necessitate placement over the parietal areas [10]. Consequently, when designing these devices, it is essential to carefully select not only the number of channels but also their precise locations to ensure both enhanced usability and effective data collection.

Traditionally, EEG reconstruction methods have relied on interpolation techniques and statistical models to estimate missing signals in low-density electrode setups [11]. Although these methods have been useful, they often lack adaptability to dynamic neuromarketing conditions and do not take advantage of the full predictive power of Machine Learning (ML) [12]. Recent advances in DL-based EEG analysis have demonstrated the potential of neural networks to enhance signal reconstruction and even generate virtual EEG electrodes [13]. However, many of these state-of-the-art DL models are computationally expensive, making them impractical for real-time neuromarketing applications.

This study introduces a lightweight Convolutional Neural Network (CNN) model specifically optimized for the reconstruction of EEG channels within neuromarketing contexts, achieving a harmony between computational efficiency and signal fidelity. Unlike previous models that primarily emphasize error minimization, such as mean squared error (MSE)-based approaches, our methodology integrates a correlation-based loss function, thus enhancing the preservation of EEG temporal dynamics. Furthermore, a systematic evaluation of more than 1820 channel configurations is performed, leading to the identification of optimal electrode subsets suitable for commercial BCIs possessing a limited number of electrodes. These developments make significant strides towards bridging the existing gap between academic EEG research and its practical application in neuromarketing.

This paper proposes the following contributions:

- **Development of a CNN-based Model for Channel Reconstruction:** The proposal of a lightweight CNN model with a customized loss function, designed for the reconstruction of EEG channels from the data of other EEG electrodes. This model addresses the pivotal challenge of channel restrictions, proposing a scalable and efficient approach for enhancing data collection capabilities of EEG devices in neuromarketing. Notably, the lightweight architecture of the model makes it a viable candidate for integration directly into the firmware of EEG devices, potentially enabling the virtual generation of EEG channels and enhancing the utility of simplified EEG devices in neuromarketing research.
- **Validation through Public Datasets:** The testing of the proposed CNN model against public EEG datasets to prove its efficacy. This validation entails a thorough comparison of the accuracy in reconstructing EEG channels against traditional signal processing methods and existing techniques in academic literature.
- **Comprehensive Examination of Channels Configurations from Commercial BCIs:** A comprehensive analysis of the current commercial BCI capabilities, with a focus on their applicability across various neuromarketing scenarios. This analysis encompasses an evaluation of channels, scalp localization, and pricing. It is important to note that this evaluation is based on the number and position of electrodes, assuming that a higher number of electrodes correlates with a higher cost. The analysis does not take into account other factors such as the quality of the materials used, the quality of the electrodes, or the precision with which the electrodes function. These factors could affect the final product price and overall performance, but they are beyond the scope of this study.
- **Optimization of Channel Selection for Enhanced Prediction Accuracy:** An extensive evaluation of optimal channel configurations was conducted using combinations of four input channels to predict the remaining EEG channels, employing the previously designed CNN model. The methodical testing of over 1820 combinations identified the most effective configurations for diverse neuromarketing applications. This rigorous approach demonstrated the adaptability of the model and precision in optimizing EEG data collection, even with limited-channel setups, thus contributing significantly to the practical application of BCIs in real-world scenarios.

The paper is structured to delve into the contributions and their significance in neuromarketing. Section 2 covers the relevant literature on neuromarketing, EEG signal processing, and the fusion of AI in neuromarketing practices, laying the groundwork for the proposed approach. Section 3 explains the methodology used to create the CNN-based model for EEG channel reconstruction, including the reasoning behind its design and its potential for integration within EEG device firmware. Section 4 presents the results of empirical testing of the model, comparing it to existing EEG signal processing methods and highlighting its superior capabilities. Section 5 conducts a resource consumption study, evaluating the feasibility of deploying the proposed model within commercial BCI devices and ensuring computational efficiency. Section 6.3 examines the practical deployment of the model in various neuromarketing scenarios, analyzing the examination of commercial BCIs in addition to the required common application design. Section 7 discusses the implications of the findings, challenges encountered, and future directions for research in this field. Finally, Section 8 consolidates the research findings, considering the implications of this research for the field of neuromarketing and suggestions for future scientific pursuits.

2. Related work

This section presents the principal concepts and prior research focused on integrating EEG with AI in the field of neuromarketing. It elucidates pivotal developments in neuromarketing strategies and EEG signal processing, thereby establishing the context for the innovations presented in this paper.

2.1. EEG in neuromarketing: Works and use cases

Transitioning from traditional neuromarketing methods that rely predominantly on subjective self-reports and observational techniques, the integration of biosignals offers an objective insight into consumer behavior and preferences [14]. Among various biosignals, EEG stands out as the most employed within the neuromarketing domain due to

its non-invasiveness, relatively low cost, and high temporal resolution, capturing the electrical activity of the brain in real time [2]. The use of biosignal analysis, particularly EEG, has led to a new era of understanding the complex processes that underlie consumer decisions. EEG allows researchers to explore four key areas in neuromarketing: emotional marketing, attention and design focus, sensory product evaluation, and purchase decisions. Each of these areas utilizes EEG to reveal the subconscious influences on consumer behavior, providing valuable insights that go beyond the limitations of traditional marketing methods.

Emotional marketing, a key aspect of neuromarketing, focuses on understanding and leveraging consumers' emotional responses [15]. For example, Ciorciari, Pfeifer, and Gountas [16] explore the intersection of Emotional Intelligence (EI) and consumer behavior towards advertising, utilizing EEG to measure brain responses to advertisements. It reveals that individuals with varying levels of EI engage differently with advertising content, suggesting that EI significantly influences consumer perceptions and decision-making processes. This research contributes to understanding the ways in which emotional responses can be leveraged in marketing strategies to enhance advertising effectiveness. Another study by Byrne et al. [16], presents a systematic review of EEG measures in neuromarketing, highlighting which EEG components most effectively predict consumer preferences. It highlights the predictive accuracy of frontal alpha asymmetry and Late Positive Potential (LPP) in reflecting emotional responses to marketing stimuli, significantly enhanced by ML, especially when combined with eye-tracking. This research underscores the utility of EEG in capturing the subconscious basis of consumer behavior, offering a sophisticated avenue for anticipating consumer responses and preferences within the neuromarketing domain. Focused on reproducibility in emotional neuromarketing, Apicella et al. [17] introduces a method for measuring emotions using EEG, focusing on emotional valence detection from various stimuli. It showcases the effectiveness of EEG in capturing affective states, employing datasets like SEED, DEAP, and DREAMER for analysis. This research represents a significant methodological contribution, aiming to enhance the precision of emotional measurement in neuromarketing by leveraging advanced data processing techniques and neural network classifiers to achieve high accuracy in emotion detection.

Bridging from the deep insights offered by emotional marketing, attention and focus on design within neuromarketing present a niche for exploration. The systematic review by Bazzani et al. [18] delves into the suitability of EEG for marketing research, providing a comprehensive overview of its application in consumer neuroscience. This review serves to prove the potential of EEG in enhancing our understanding of consumer behavior, particularly in how various design elements captivate attention and influence decision-making processes. Focused on design, the study by Telpaz, Levy, and Boshoff [19] delves into how attentional engagement, driven by design elements, impacts consumer processing of advertising stimuli. By integrating EEG and eye-tracking, this research not only highlights the influence of design on subconscious consumer responses but also underscores the importance of visual attention in enhancing advertising effectiveness. This convergence of neurological measures with traditional marketing research offers an approach to dissecting the layers of consumer attention and its implications for design strategy.

Apart from design, the third use case is the sensory evaluation of products. Park et al. [20] introduce a perspective on sensory product evaluation by utilizing EEG to quantify the emotional impact of fragrances. This methodological approach reinforces the significance of design-focused neuromarketing strategies, highlighting how sensory elements, beyond visual aesthetics, can deeply influence consumer engagement and preference. Similarly, Horská et al. [21] offer a distinctive exploration into consumer preferences when choosing wines, integrating EEG and facial expression analysis to capture emotional reactions during wine tasting. This study exemplifies a sophisticated application of neuromarketing techniques to sensory product evaluation, underlining the importance of sensory elements in shaping consumer perceptions and decisions.

The last use case relates to purchase decisions and the perception of prices. Georgiadis et al. [22] present an approach within the realm of neuromarketing by leveraging brain imaging techniques to enhance the predictive power of traditional marketing tools like questionnaires and focus groups. This study uses neural activity across different brain regions for the analysis of purchase intentions, establishing the suitability of the Riemannian approach for neuromarketing-related problems and proposing a relevant decoding scheme for predicting consumer choices. For the perception of prices, Wang et al. [23] introduce an exploration into the realm of purchase decisions and price perception. This research unveils the "pleasure of paying" when utilizing mobile payment methods, suggesting that mobile payments can significantly influence consumer spending behavior, marking a pivotal shift in understanding the psychological underpinnings of digital payment systems.

Given the diverse neuromarketing use cases, which engage distinct brain areas, the limitation of BCIs with restricted EEG channels becomes apparent. Different use cases may require data from various brain regions not always covered by limited-channel setups. This necessitates the reconstruction of EEG signals to ensure comprehensive analysis across all areas of interest, particularly for specific neuromarketing applications.

2.2. EEG channel reconstruction

EEG reconstruction has been traditionally approached using interpolation techniques and statistical models, aiming to recover missing channels by leveraging spatial and temporal correlations in EEG data. However, recent DL approaches, particularly CNNs, GANs, and transformers, have demonstrated significant advancements in the restoration of EEG signals.

GAN-based EEG augmentation has been explored as a method for generating realistic synthetic EEG signals, reducing class imbalance in classification tasks and enhancing EEG dataset quality [24]. Furthermore, transformer-based models have shown promise in EEG feature extraction and missing channel reconstruction, offering improved spatial and temporal feature modeling while optimizing computational efficiency [25,26].

CNNs have also been widely used in EEG reconstruction. Svantesson et al. [27] demonstrated that CNN-based EEG upsampling methods could outperform spline interpolation, achieving a 22% reduction in mean absolute error (MAE) in EEG restoration. Similarly, Li et al. [28] introduced a Dynamic Evaluation Denoising Network (DEDN) for the removal of EEG artifacts, achieving an improvement in noise reduction 38% over traditional filtering methods.

These recent advances underscore the increasing relevance of DL for EEG reconstruction, paving the way for lightweight architectures such as the proposed CNN model in this study, which is optimized for real-time neuromarketing applications.

2.2.1. Interpolation techniques and statistical methods

The use of advanced statistical and interpolation techniques has greatly improved the reconstruction of EEG signals, providing a more accurate view of neural activity. This approach, initially based on spline interpolation, is extended by contributions that significantly broadened its application and effectiveness in dealing with EEG data. Spline interpolation, a method for smooth approximation of signal trajectories, has been refined by research. Notably, the work of Liu et al. [29] introduced an attention-based EEG interpolation algorithm, which optimizes channel reconstruction by dynamically weighting spatial dependencies between electrodes. This method significantly improves the preservation of signal integrity, outperforming traditional spline interpolation techniques in handling complex artifacts in EEG recordings. These foundational efforts demonstrated the adaptability of spline interpolation to the challenges of EEG data, allowing for more targeted applications.

Building on this groundwork, spatial interpolation techniques have emerged as a critical tool for EEG channel reconstruction [30]. By estimating the signal of a missing or corrupted channel based on the spatial relationships and signal similarities among neighboring channels, spatial interpolation leverages the correlated neural activities due to their proximity to shared neural sources. This method ensures the integrity and utility of the EEG dataset for clinical and research purposes, enhancing the comprehension of neural activity through improved data completeness and quality.

After exploring interpolation methods, the focus shifts to statistical approaches such as ARIMA (Autoregressive Integrated Moving Average), an important model for time series analysis. The usefulness of ARIMA in processing EEG signals is highlighted by its ability to predict missing data by understanding the temporal dependencies within EEG signals. This technique leverages spatiotemporal dependencies in EEG signals, utilizing past signal values, their differences, and error terms to predict missing segments. Recent advancements, such as Transformer-based models, have demonstrated superior performance in preserving continuity and integrity in EEG time-series reconstruction by efficiently modeling long-range dependencies [31]. Following the introduction of ARIMA for predicting EEG signals, the Kalman Filter emerged as another advanced statistical tool, particularly effective for real-time dynamic systems. It iteratively updates predictions and reduces uncertainty through a process that combines prediction and measurement. This makes it highly suitable for EEG data where signals evolve. This method provides a framework for continuously incorporating new EEG data, facilitates the reconstruction of missing values with improved accuracy, and is essential for applications requiring real-time analysis and decision making based on EEG signals [32]. Building upon the filter of Kalman application in EEG signal reconstruction, Bayesian methods further refine the process by integrating prior knowledge into the estimation of missing values. Bayesian approaches adaptively update the posterior probabilities as new data becomes available, making them particularly effective for EEG data that exhibits complex, non-linear dynamics [33]. This probabilistic framework allows for a understanding of the uncertainty associated with signal reconstruction, offering a powerful tool for deciphering the intricate patterns of neural activity inherent in EEG datasets.

2.2.2. Neural networks

Generative Adversarial Networks (GANs) have emerged as a key technology for improving signal reconstruction. Luo and Lu [34] pioneered this approach with a Conditional wasserstein GAN framework. They significantly improved emotion recognition accuracy by generating high-quality EEG data. Xu et al. [24] addressed class imbalance in Rapid Serial Visual Presentation (RSVP) tasks by introducing a balanced isserstein GAN with gradient penalty, which not only mitigates class imbalance problems but also improves classification performance by generating synthetic minority class EEG data. In further research by Mahey et al. [35], GANs are used to synthesize multi-channel EEG data, demonstrating the ability of the technology to replicate the intricate spatiotemporal aspects of EEG signals. This advance holds promise for generating large synthetic datasets for neuroimaging analysis. Furthermore, Zhang et al. [36] and Corley et al. [37] extended the application of GANs in EEG signal processing, focusing on deep EEG superresolution techniques to generate high-resolution data from low-resolution samples. Taken together, these studies underscore the transformative impact of GANs in EEG signal processing, highlighting their potential to overcome traditional challenges and paving the way for novel applications in neuroscience research and the development of BCIs.

Building upon the foundational work of GANs in EEG signal processing, Convolutional Neural Networks (CNNs) have been recognized for their capacity to advance EEG signal reconstruction across a variety of applications. A comprehensive review developed by Roy et al. [38] underscored the advantages of CNNs automated learning, enhancing EEG analysis efficiency. Fickling et al. [39] demonstrated the feasibility of using distant sensor locations, such as the mastoid and forehead regions, for predicting Event-Related Potentials (ERPs) traditionally measured at standard electrode locations like the Cz site, which is often hindered by the presence of hair and requires a time-consuming setup. Utilizing Artificial Neural Networks (ANNs) trained on data from 34 healthy adult participants, the research demonstrates significant improvements in signal prediction accuracy across various stimuli types compared to individual distant channels. The findings reveal that ANNs can effectively reconstruct ERPs from non-standard electrode locations with reduced noise and enhanced signal fidelity, offering a promising avenue for portable, comfortable, and efficient ERP measurement across diverse settings and populations. This advancement could significantly impact the development of wearable EEG technologies for real-time monitoring of brain functions in clinical and everyday environments. This is complemented by studies such as those by Kwon et al. [40], who leveraged CNNs for EEG signal upsampling, markedly improving signal quality. Lastly, Svantesson et al. [27] explores the efficacy of CNNs for enhancing EEG signal quality by upsampling from reduced electrode configurations or restoring missing channels to full 21-channel EEG setups. Utilizing 5144 h of EEG data, the study compares the performance of generative networks against traditional spherical spline interpolation techniques. Results indicate that CNNs not only provide comparable or superior accuracy in signal reconstruction but also generate EEGs with a more realistic appearance, as validated by board-certified clinical neurophysiologists. The study underscores the potential of CNNs to improve EEG signal quality for clinical diagnostics and research, suggesting that incorporating larger datasets and diverse subject samples could further enhance performance.

The studies by Fickling et al. [39] and Svantesson et al. [27] represent significant advances in analyzing and reconstructing EEG signals. However, these works also point out several limitations that constrain a more widespread application. A key issue is the lack of a common metric for comparing results across studies. This makes it difficult to comprehensively assess the relative effectiveness of these approaches. In the case of the first paper, they rely on adjacent electrode placements for accurate prediction. This may limit applicability in scenarios where such configurations are not feasible or the target electrodes are not adjacent. Similarly, in the second work, the focus solely on reconstructing signals associated with event-related potentials (ERPs) limits the usefulness of their approach for continuous monitoring applications, which are common in real-world scenarios. This narrow focus diminishes the practicality of the methods for broader neuromarketing applications and other fields where multiple biosignals are of interest (see Table 1).

Despite significant advances in EEG signal reconstruction using DL techniques, several limitations have been identified in the literature that restrict their more general applicability. A major issue is the lack of a common metric for comparing results across studies, making it difficult to comprehensively evaluate the effectiveness of these approaches. Additionally, many methodologies rely on specific configurations of adjacent electrodes, which may not be feasible in scenarios where such configurations are not possible or the target electrodes are not adjacent [11]. Another limitation is that the majority of studies have focused on reconstructing signals associated with event-related potentials (ERPs), which limits the usefulness of these methods for continuous monitoring applications [13]. Furthermore, the dependency on models that require high-density electrode arrays limits the effectiveness of these methods in low-channel configurations, which are common in low-cost BCI devices [8].

3. Problem statement

A review of existing neuromarketing techniques and EEG applications reveals significant gaps in traditional methods and the functionality of low-cost BCIs. Traditional neuromarketing approaches often

Table 1
Summary of EEG processing studies.

Work	Study focus	Network used	Performance metrics	Results
Luo and Lu [34] 2018	Synthesizing EEG data	GANs	Emotion Recognition, Accuracy	Improved emotion recognition accuracy
Xu et al. [24] 2022	Addressing class imbalance	GANs	Classification, Performance	Enhanced classification performance with synthetic data
Mahey et al. [35] 2023	Enhancing EEG signal quality	GANs	Signal Quality, Metrics	Enhanced signal quality for neuroimaging analysis
Corley et al. [37] 2018 Zhang et al. [36] 2022	Further applications of GANs in EEG	GANs	Varied	Demonstrated ability of GANs across different applications
Fickling et al. [39] 2020	ERP reconstruction	ANNs	Intraclass Correlation, Coefficient, RMS Error	Improvements in predicting ERPs, reduced RMS error
Fox et al. [26] 2024	EEG-based sleep stage classification	Transformer	Classification Accuracy	7% improvement over CNN-based sleep stage classification
Liu et al. [25] 2024	EEG reconstruction for Motor Imagery classification	Transformer	Classification Accuracy	Improved MI classification accuracy to 86.2%
Kwon et al. [40] 2019	EEG signal upsampling	CNNs	Mean Squared Error, Signal Correlation	Significant reduction in MSE, improved signal correlation
Svantesson et al. [27] 2021	EEG signal upsampling	CNNs	MAE	Superior preservation of EEG data integrity
Li et al. [28] 2024	EEG artifact removal	CNNs	Noise Reduction	38% noise reduction compared to traditional methods
This Work 2024	EEG Channel Reconstruction	CNNs	Combination of MSE and Pearson's Correlation	Lightweight model capable of reconstructing EEG channels from a limited set of channels. Optimization of number of channels and positioning for optimal reconstructions.

fail to capture the subtle, unconscious cognitive processes that influence consumer behavior. Moreover, low-cost BCIs, while increasing accessibility, suffer from limited channel capacities and static electrode configurations, restricting the depth and scope of data collection. These limitations underscore the necessity for advancements that can increase data collection and analysis capabilities in neuromarketing. Such enhancements are crucial for obtaining more accurate insights into the multifaceted interplay of emotions and cognition that guide consumer decisions. The integration of EEG signals and AI in neuromarketing represents a significant advancement in obtaining objective, real-time feedback on consumer responses to advertising stimuli. However, the field still faces challenges that limit the efficiency and scalability of current methodologies.

- **Need for a Computationally Efficient AI Model:** One of the primary challenges in advancing BCI technology for neuromarketing is developing an AI model that can be seamlessly integrated into the BCI firmware. This integration is crucial because it ensures that the system can operate efficiently on the limited computational resources available in the BCI hardware. Additionally, computational efficiency is essential for maintaining low power consumption, which is important for portable applications like mobile phones and tablets that could also leverage this technology. This integration enhances the user experience by seamlessly providing access to a greater number of virtual EEG electrodes than those physically present. The real-time data processing that occurs directly within the BCI device allows for the extension of BCI functionality without noticeable changes for the user. Such a model must provide a balance between precision in interpreting EEG signals and computational efficiency to ensure it can operate within the limited processing capabilities of commercial BCI devices. Typically, the training of these AI models occurs on more powerful external systems to leverage advanced computational resources, after which the trained model is deployed within the BCI for evaluation. This approach not only maximizes the accuracy and efficiency of the model but also ensures that the virtualization of electrodes can be performed on any compatible device, enhancing the portability and applicability of BCIs across different neuromarketing settings.
- **General Applicability of Low-Cost BCIs in Neuromarketing:** The challenge in neuromarketing lies not only in capturing detailed cognitive or emotional responses, but also in ensuring that low-cost BCIs can be effectively used across a wide array of marketing studies. These devices must be designed to function reliably under the constraints of limited channels while being flexible enough to cater to the general requirements of diverse neuromarketing applications. The objective is to develop BCIs that offer a balance between affordability and the ability to provide useful insights across different consumer studies, thereby increasing access to advanced neuromarketing tools.
- **Determining Optimal Electrode Configurations:** In the field of neuromarketing, where a variety of consumer behaviors and cognitive responses are studied, identifying the optimal configurations of EEG electrodes is particularly challenging due to the channel limitations inherent in commercially available low-cost BCIs. These devices often have fewer channels, which constrains the amplitude and specificity of data that can be captured. Therefore, a meticulous examination of electrode configurations, tailored to maximize data acquisition within these constraints, is essential. It is of paramount importance to optimize electrode placement in order to enhance the ability of low-cost BCIs to reliably elicit and interpret informative signals across a range of neuromarketing applications.

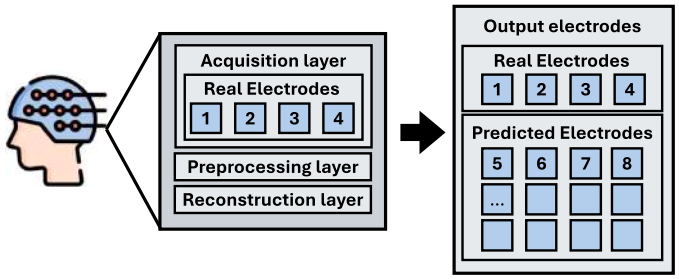


Fig. 1. Application scenario of the model.

By directly addressing these challenges, the study aims not only to improve the technical underpinnings of EEG-based neuromarketing research, but also to facilitate the integration of advanced methodologies into commercial BCI devices. This approach promises to significantly expand the capabilities and reach of neuromarketing, enabling more efficient and consumer-focused marketing strategies.

4. Design and implementation

This section outlines the design and implementation of the model within a BCI. As shown in Fig. 1, the scenario shows the integration of the acquisition, preprocessing, and CNN model layers within the BCI. This model is responsible for inferring the desired channels from the set of available channels. Subsequently, Section 4.3 explores the architecture developed specifically for EEG signal reconstruction. The focus of this section is on detailing the components that enable processing of complex spatial and temporal EEG patterns while maintaining computational viability for potential deployment in commercial BCIs. After the architectural overview, Section 4.4 presents a custom loss function that enhances model performance. The function ensures that reconstructed signals not only minimize prediction error, but also closely match actual EEG signals in their temporal dynamics.

4.1. Acquisition layer

The acquisition layer is responsible for collecting EEG signals using commercial BCI devices. In this study, several commercially configurations of electrodes from available BCI devices, including Bitbrain Diadem, Bitbrain Air, and Emotiv MN8, among others, were evaluated. The selected configuration must provide an optimal balance between channel density and practical applicability in neuromarketing research. This layer serves as the interface between the hardware and the system, ensuring the collection of raw EEG data. Key features of the selected BCI include sampling rate and signal quality. The sampling rates of the EEG signals range from 128 Hz to 512 Hz, depending on the BCI device used. It should be noted that different commercial BCI devices employ various electrode configurations. Another important aspect to consider in this layer is signal quality, which is monitored by assessing the impedance of the electrodes and the levels of baseline noise.

4.2. Preprocessing layer

The preprocessing layer applies signal processing techniques to clean and prepare the raw EEG data for analysis. This step is crucial for reducing noise and artifacts, thus improving the quality of the input data for the prediction model. The key stages include, first include a bandpass filter employed to isolate the frequency range of interest. After that, a notch filter is applied to remove power line interference. The final stage of preprocessing is the removal of artifacts. Blink and muscle artifacts are identified and removed using Independent Component Analysis (ICA). This is followed by baseline correction, which involves the application of linear interpolation to remove DC offset and slow drift. Finally, normalization is performed, where the EEG data are standardized to zero mean and unit variance for each channel to ensure consistency and improve learning during the training of the neural network model. The last step is the segmentation of the data. The continuous EEG signals are segmented into fixed-length time windows of one second (or 512 samples for a 512 Hz sampling rate). Each segment is then labeled based on the neuromarketing use case, such as emotional response, attention focus, sensory evaluation, or decision-making.

4.3. Reconstruction layer

In contrast to other time series applications, where the objective is to predict future states based on past data, the primary goal of this work is to reconstruct a temporal window of EEG data using contemporaneous data from other channels. This unique requirement necessitates an architecture capable of capturing complex spatial and temporal relationships across EEG channels without the need to predict future states. Consequently, while Long Short-Term Memory (LSTM) networks and transformers are both well-suited for this task due to their ability to model long-term dependencies, CNNs are preferred because they can be trained and evaluated more efficiently. CNNs are proficient at extracting hierarchical features and maintaining spatial hierarchies over time, rendering them optimal for the high-dimensional spatial feature extraction required in EEG signal reconstruction.

The created CNN architecture comprises two 1D convolutional layers with 12 filters each one, followed by a dense layer. This configuration is effective in capturing both spatial and temporal patterns, while maintaining a low number of parameters, thus achieving a balance between computational efficiency and reconstruction accuracy. The 1D convolutional layers are specifically designed to process time-series data through the learning of temporal sequences of EEG signals and the application of filters that are capable of identifying short-term dependencies in adjacent time steps. This approach is advantageous for EEG data, which often contain significant information in the spatial arrangement of electrodes that can be effectively learned through convolutional operations. The complete architecture is illustrated in Fig. 2.

The hyperparameters within this CNN were optimized via a Bayesian optimization approach. The optimization was performed using KerasTuner, which allows for the systematic search of optimal hyperparameters, including the number of layers and filters per layer, kernel sizes, regularization techniques, and sizes of dense layers.

Given the application context of commercial BCIs, particularly in Internet of Things (IoT) devices that typically lack GPU capabilities and have limited CPU resources, further optimizations were necessary. The model was converted into a more compact format using TensorFlow Lite, which reduced its size from 4MB to 400KB—a tenfold decrease with minimal loss in prediction accuracy [41]. This conversion is of paramount importance for deployment in real-time

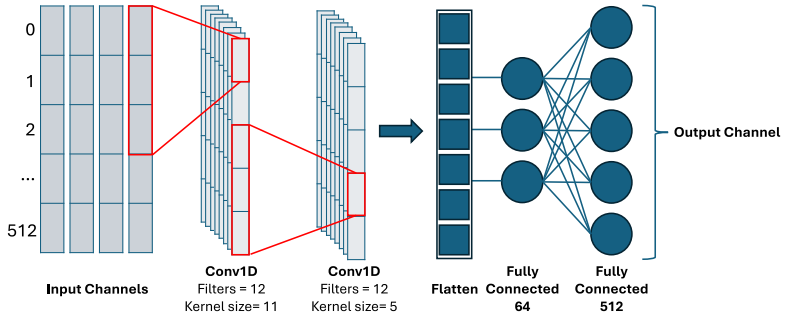


Fig. 2. Model architecture for channel reconstruction.

scenarios, as it ensures that the model can run efficiently on low-resource devices. TensorFlow Lite optimizes the model to operate with a latency of milliseconds, which is essential for real-time EEG analysis in neuromarketing applications.

4.4. Custom loss function

Typical loss functions like Mean Squared Error (MSE) or Mean Absolute Error (MAE) have limitations when used for EEG signal reconstruction, as they can introduce noise that is not relevant to the application. To overcome this, a custom loss function has been devised that incorporates Pearson's Correlation Coefficient in addition to the MSE. While MSE focuses on minimizing the difference in signal magnitude, it can fail to capture the temporal dynamics of EEG signals. By adding Pearson's Correlation Coefficient, the loss function ensures that the predicted signals not only match the true signal magnitudes but also align correctly with the temporal patterns of the EEG data, which is crucial for applications such as neuromarketing.

To ensure the most effective loss function for EEG reconstruction, various time-series similarity metrics were initially evaluated, including Power Spectral Density (PSD), Discrete Wavelet Transform (DWT), Dynamic Time Warping (DTW), Mean Absolute Percentage Error (MAPE), and Cosine Similarity. PSD, while useful for analyzing frequency components, was highly sensitive to noise and variability between subjects, making it unsuitable for consistent evaluation in different EEG datasets [42]. DWT, although capable of multiresolution analysis, introduced high computational costs and a strong dependency on wavelet selection, limiting its feasibility for real-time BCI applications. DTW allowed the alignment of time-shifted signals, but was computationally expensive and often overestimated differences due to minor phase misalignments [43]. MAPE, commonly used in econometrics, was found to be unstable with low-amplitude EEG data, leading to unreliable error estimates [44]. Cosine similarity, although effective in measuring vector alignment, failed to preserve phase information critical to the evaluation of EEG signals [45]. Given these limitations, the combination of MSE and Pearson's correlation coefficient was selected, ensuring both magnitude accuracy and temporal structure alignment while maintaining computational efficiency.

Fig. 3 visually illustrates the differences in predictions generated by the model when using only the MSE (Fig. 3(a)) and a combination of MSE and Person's Correlation (Fig. 3(b)). As illustrated in Fig. 3(a), predictions based on MSE tend to prioritize minimizing squared differences, which may result in satisfactory overall accuracy but may fail to capture the underlying temporal dynamics of the actual signal. The custom loss function, defined in Eq. (1), incorporates both MSE and Pearson's Correlation Coefficient to ensure accurate prediction of signal magnitude while aligning with the temporal dynamics of EEG signals. This combination addresses the limitations of using either metric alone, as shown in Fig. 3(b).

The combination of these two components into a composite loss function, as shown in Fig. 3(b), enables the model to predict the signal magnitude accurately and to correctly align the temporal dynamics of the EEG signal. This duality in the loss function is fundamental for applications in neuromarketing, where understanding the precise temporal dynamics of brain responses is as crucial as signal accuracy.

The use of a simplified model architecture improves the optimization process and the predictive accuracy. A compact architecture reduces computational demands, facilitates faster training, and requires less memory, which is essential for deployment on devices with limited resources. This architecture, in conjunction with the designed loss function, ensures that the model not only predicts accurate values but also preserves the integrity of the temporal patterns of the signal, which are crucial for interpreting consumer responses accurately.

$$\text{loss} = \alpha \text{MSE}(y_{true}, y_{pred}) + (1-\alpha)\left(1 - \frac{\sum (y_{true} - \bar{y}_{true})(y_{pred} - \bar{y}_{pred})}{\sqrt{\sum (y_{true} - \bar{y}_{true})^2}\sqrt{\sum (y_{pred} - \bar{y}_{pred})^2}}\right)^2 \quad (1)$$

Where:

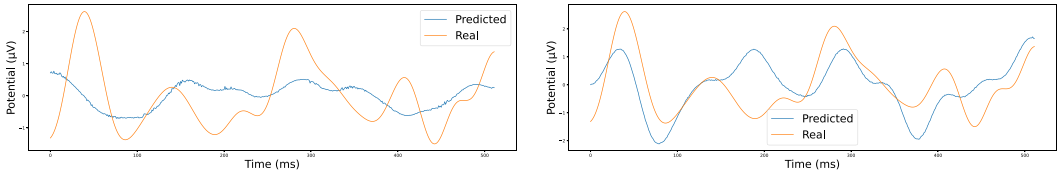
- $\text{MSE}(y_{true}, y_{pred})$ is the MSE between the real and predicted values.
- α is a weighting parameter that controls the importance of the MSE and the correlation, allowing for customization based on specific requirements of the neuromarketing application.

5. Resource consumption study

A resource consumption study is essential to evaluate the feasibility of deploying DL models in commercial BCI devices. The training phase occurs externally, utilizing more powerful hardware to optimize the parameters of the model. In contrast, the evaluation phase is designed to operate directly within the BCI device, leveraging its limited computational resources. The training phase was conducted using an external computer system equipped with a dedicated GPU. The GPU resource utilization enabled efficient optimization, reducing training time significantly. Specifically, the model was executed on Google Colab, utilizing a V100 GPU with 24 GB of VRAM, without CPU acceleration. Table 2 illustrates the resource usage during the training phase.

The evaluation phase was conducted using a TensorFlow Lite (TFLite) version of the model, optimized for real-time execution within BCI devices. The results, shown in Table 3, demonstrate the feasibility of running the model in resource-constrained environments, highlighting its minimal resource consumption and suitability for real-time analysis.

However, deploying DL models in commercial BCI firmware presents additional challenges beyond raw computational efficiency. Although TFLite significantly reduces the memory footprint, further optimizations can enhance performance in low-power devices:



(a) Prediction using only the MSE.

(b) Prediction using the MSE + Person's Correlation.

Fig. 3. Predictions with different loss functions.

Table 2
Resource consumption during model training.

Metric	Value
CPU Usage (%)	10.00
Memory Usage (MB)	29.00
Training Time (s)	122.00
Peak Memory Usage (MB)	100.00
GPU Memory Usage (MB)	32.00
Evaluation Time (s)	0.00

Table 3
Resource consumption during TFLite model evaluation.

Metric	Value
CPU Usage (%)	3.00
Memory Usage (MB)	0.20
Training Time (s)	0.00
Peak Memory Usage (MB)	0.05
GPU Memory Usage (MB)	0.00
Evaluation Time (s)	0.14

- Model Quantization: Converting the model from 32-bit floating point to 8-bit integer precision can further reduce memory usage and inference time while maintaining accuracy.
- Neural Network Pruning: Removing redundant connections in the network can lower the number of computations required per inference step.
- Edge AI Inference Acceleration: Deployment in hardware-efficient frameworks, such as ONNX Runtime, Edge TPU, or TinyML, could further improve execution speed in real-world BCI environments.

The substantial reduction in resource consumption between the training and evaluation phases underscores the potential of employing lightweight models optimized with TFLite for commercial BCIs. This efficiency can significantly enhance the real-time analysis capabilities of neuromarketing BCIs, enabling rapid insights into consumer behavior.

6. Experiments

This section validates the neural network model designed for reconstructing EEG signals in neuromarketing applications. The model is evaluated using a public dataset that reflects the real-world diversity and complexity of EEG data used in neuromarketing. The experiments are structured to assess the model under three key scenarios: use cases specific to neuromarketing, effectiveness across various BCI devices, and optimal channel combinations. The objective of these experiments is to determine the viability of the model in both controlled settings and real-world applications. Furthermore, a resource evaluation confirms the efficiency of the model, thereby demonstrating its operational feasibility within the computational constraints of low-cost BCIs. In-depth analyzes of these aspects are provided, with a view to highlighting both the strengths and areas for improvement in the approach to EEG signal reconstruction.

6.1. Dataset and preprocessing

This section describes the dataset and preprocessing methods used in the study, focusing on a publicly available dataset designed around the P300 spelling paradigm [46]. The choice of this dataset is motivated by the well-established role of the P300 component in neuromarketing research, where it serves as a key neural marker of attentional engagement and decision-making processes. Studies have shown that the P300 wave can be a reliable indicator of consumer engagement and preference [47]. Comprising data from 55 participants and recorded over 32 channels, the dataset provides a robust baseline for evaluating the ability of the neural network model to accurately reconstruct EEG signals. The effectiveness of the proposed method in accurately reconstructing the P300 waveform within this controlled spelling paradigm underscores its potential applicability to other experimental contexts where P300 is integral. This encompasses oddball paradigms frequently employed in neuromarketing.

Data preprocessing included several key steps to ensure the quality and consistency of the input to the model. First, a bandpass filter is applied to the EEG signals to isolate frequencies between 0.5 and 10 Hz, corresponding to the typical frequency range of the P300 component. The data are segmented into one-second time windows, resulting in 512 samples per window. Time windows likely to contain atypical noise, such as those at the beginning or end of recording sessions, are excluded using the criterion of removing any window with amplitudes greater than four times the mean amplitude of the window. The ICA decomposition was performed using FastICA with the number of components set to match the number of EEG channels. The rejection of artifacts was done through manual inspection, specifically removing components with high power in the frontal regions, which were associated with muscle movements and ocular artifacts. Furthermore, the segmentation process was carried out using non-overlapping 1-second windows, ensuring a consistent input structure for the reconstruction model.

In order to further refine the dataset for model training, a standardization process is applied to the data, whereby the signals are normalized to have a mean of zero and a variance of one. This standardization is essential for effective learning by the neural network, as it guarantees that the input features are consistently scaled. The dataset comprises data from 55 participants. For the purposes of this study, a subset of 21 subjects was selected. Extensive research in EEG/P300 paradigms has shown that reliable ERP effects can be obtained with sample sizes exceeding 20 subjects [48–52]. Therefore, our sample of 21 patients is considered adequate to capture the relevant effects of P300 in this study.

The data is partitioned into training, validation, and test sets with careful consideration to maintain the integrity of the experimental evaluation. In particular, cross-validation is employed among the selected subjects. In each iteration, data from 20 subjects is split into a training set (90%) and a validation set (10%) to optimize the model. The test set consists of data from one entirely unseen subject, ensuring that the model is evaluated on individuals it has not encountered during training, thereby assessing its generalization capability. This

cross-validation approach guarantees that each data from the subject is utilized once as a test set, thus providing a comprehensive evaluation of the capacity of the model to generalize to new, unseen data.

6.2. Methodology: Commercial BCI configurations and channel selection

In order to validate the proposed model, several use cases that reflect real-world applications have been selected. In parallel, a number of commercially available BCIs have been identified for potential use in these scenarios. This process is critical in assessing how the model can help to recreate the necessary EEG channels that are not available in the selected BCIs for each specific application. The methodology includes a detailed examination of specific neuromarketing applications, ensuring comprehensive coverage of various aspects such as emotional responses to advertising, attention and focus in design, sensory product evaluation, and the neural mechanisms underlying purchase decisions and price evaluation. For example, in the context of emotional response to advertising, the importance of frontal electrodes (F3/F4) for assessing emotional valence and parietal electrodes (P3/P4) for measuring emotional processing and attention is highlighted. Specific EEG channels has been identified for each application based on their relevance to the cognitive and emotional processes involved:

- Emotional Response to Advertising:
  - Frontal electrodes (F3/F4) for emotional valence assessment [53].
  - Parietal electrodes (P3/P4) for measuring emotional processing and attention [54].
- Attention and Focus in Design:
  - Lateral frontal electrodes (F7/F8) for attention and focus evaluation [55].
  - Occipital electrodes (O1/O2) for analyzing visual activity and attention [56].
- Sensory Product Evaluation:
  - Temporal electrodes (T5/T6) for emotional and sensory response assessment, particularly useful for auditory and olfactory stimuli analysis [57].
  - Central electrode (Cz) for monitoring overall brain activation in response to sensory stimuli.
- Purchase Decisions and Price Evaluation:
  - Frontal electrodes (F3/F4) for emotional processing and valence linked to price perception [58].
  - Central frontal electrode (Fz) essential for decision-making processes and cognitive computations related to price evaluation [58].

This study examines the electrode configurations of commercial BCIs in the context of neuromarketing applications. Rather than merely listing available devices, the focus is on evaluating how well current commercial BCIs align with the optimal EEG channel configurations required for various neuromarketing tasks. By assessing their spatial coverage, this analysis sheds light on the feasibility of using commercial BCIs to reconstruct missing EEG channels for specific applications.

The placement of electrodes is crucial in assessing the appropriateness of a device for neuromarketing applications. Critical EEG channels have been identified for activities such as analyzing emotional responses to advertisements, assessing attention and focus on design, evaluating sensory products, and understanding price perception. Due to the limited number of electrodes available in many commercial BCIs, this study investigates whether current devices offer sufficient coverage and, if necessary, evaluates the feasibility of reconstructing absent EEG channels.

As shown in Table 4, devices such as Bitbrain Diadem, Bitbrain Air, Emotiv MN8, and others are covered. This systematic review emphasizes electrode configurations while acknowledging that an increase in the number of electrodes typically corresponds to higher costs. However, factors such as material quality, electrode precision, and overall device performance, although critical, are beyond the scope of this evaluation. The goal is to identify electrode configurations that best meet the technical and practical demands of neuromarketing, considering both spatial distribution and functional requirements.

In addition to evaluating the configurations of channels from commercial BCIs, an extensive testing procedure was conducted to determine the optimal combination of four EEG channels that best predict the other channels within a neuromarketing context. Given the vast number of potential combinations, which total over 32,000 when considering all 32 channels, a decision was made to reduce the number of channels to 16 in order to facilitate analysis. The selected channels are as follows: ‘Fp1,’ ‘Fp2,’ ‘T7,’ ‘T8,’ ‘O1,’ ‘O2,’ ‘C3,’ ‘C4,’ ‘P3,’ ‘P4,’ ‘F3,’ ‘F4,’ ‘Fz,’ ‘Pz,’ ‘CP5,’ and ‘CP6.’

The selection was based on neurophysiological relevance, suitability for neuromarketing applications, and optimization for EEG signal reconstruction. These channels were chosen to provide a balanced coverage of key brain regions, ensuring robust EEG predictions while minimizing the number of electrodes required:

- Optimized coverage with minimal redundancy: The channels were chosen to ensure a balanced representation of the main cortical areas while avoiding unnecessary duplication of information. This allows for robust EEG reconstruction without requiring a full 32-channel setup.
- Evaluation of Reconstruction Accuracy: A systematic assessment of 1820 different channel configurations was performed, selecting the subset that achieved the best trade-off between minimizing error and maximizing reconstruction fidelity. This ensures that the missing channels can be predicted with high reliability.
- Compatibility with commercial BCIs: The selection is in line with the commonly used low-cost EEG devices in neuromarketing, such as Bitbrain Diadem [68], OpenBCI EEGband [69], and Emotiv MN8 [70]. This facilitates the applicability of the proposed method in real-world scenarios where the number of electrodes available is limited.

Additionally, this selection aligns with common BCI configurations in commercial EEG devices such as Bitbrain Diadem, OpenBCI EEGband, and Emotiv MN8, ensuring applicability in low-cost neuromarketing setups.

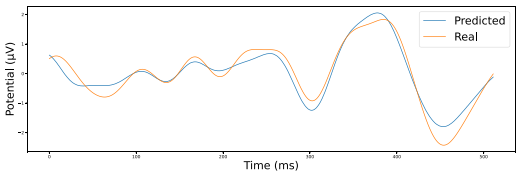
This reduction is based on the premise that neighboring channels are highly correlated, allowing for a more manageable yet effective exploration of channel combinations. The choice of four input channels is a compromise between the constraints observed in commercial BCIs and the need to keep the channel count limited, which is a common scenario in neuromarketing applications. The objective of this approach is to identify the optimal set of four channels that demonstrate the greatest efficacy across a range of use cases. By systematically testing all possible combinations of four input channels for each of the remaining channels, this study aims to identify which combinations are universally effective, providing insights that could influence future BCI designs and neuromarketing strategies.

6.3. Results

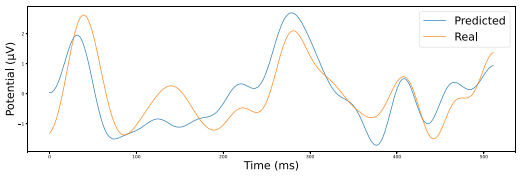
This section validates the neural network model by evaluating its performance in reconstructing EEG signals for diverse neuromarketing applications, directly addressing the challenges outlined in Section 3.

Table 4
Commercial BCIs: Electrode configurations and neuromarketing applicability.

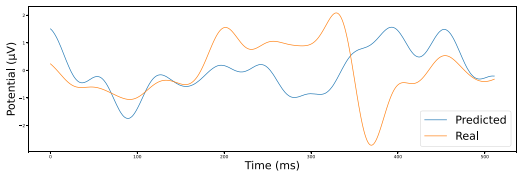
BCI model	Electrode positions	Electrode names	Price	Neuromarketing applicability
Emotiv MN8 [59]	2	Left preauricular, Right preauricular	≤400$	Attention
Open BCI CEEGRID [60]	2	Tp7, Tp8	≤400$	Sensory Evaluation
Bitbrain Ikon [61]	3	AF7, Fp2, AF8	≥400$	Emotional Response
MindRove Strip [62]	3	C1, C2, C3	≥400$	Sensory Evaluation
OpenBCI EEGband [63]	4	Fp1, Fp2, Fpz, Af7, AF8, F7, F8, FT7, FT8, T7, T8, TP7, TP8, P7, P8, PO7, PO8, O1, O2, OZ	≤400$	Emotional Response Attention Sensory Evaluation Purchase Decisions
MuseHeadBand [64]	4	AF7, AF8, TP9, TP10	≤400$	Attention
Brain Access HALO [65]	4	Fp1, Fp2, O1, O2	≤400$	Attention Sensory Evaluation
MindRove ARC [66]	5	C1, C2, C4, C5, C6	≥400$	Sensory Evaluation
Bitbrain Air [67]	7	AF7, Fp2, AF8, P07, O1, O2, P02	≥400$	Emotional Response Attention Purchase Decisions
Bitbrain Diadem [61]	11	AF7, Fp2, AF8, P07, O1, O2, P02, F3, F4, P3, P4	≥400$	Emotional Response Attention Sensory Evaluation Purchase Decisions



(a) Signals with 0.07 loss, corresponding to a low loss value.



(b) Signals with 0.58 loss, corresponding to a medium loss value.



(c) Signals with 3.22 loss, corresponding to a high loss value.

Fig. 4. Examples of loss values with graphical representation.

Utilizing a public dataset, the study demonstrates the efficiency and accuracy of the model, addressing the need for computationally viable solutions in commercial BCIs. Methodically designed experiments assess loss metrics to measure the fidelity of the model in signal reconstruction, as described in Section 4.4. To provide context and clarify their practical significance, Fig. 4 shows three examples of losses with the graphical representation. The subfigures compare EEG signals with model reconstructions, illustrating cases with low, medium, and high loss. This visualization helps to understand the implications of the numerical loss values that will be discussed later.

To evaluate the model performance, this work uses configurations of channels from commercially available BCIs as inputs. This method is particularly relevant for neuromarketing research, where practical application and the ability to deploy scalable solutions are paramount. The analysis covers a range of use cases, including emotions, decisions, and sensory recognition, highlighting the versatility of the model. Table 5 presents the calculated loss values for each of the channels within each case. The values that get a "-" loss are due to the fact that the channel to be reconstructed is in the input channel set.

The Table 5 illustrates the MSE loss values for the emotion, attention, sensory, and decision use cases across a range of BCI devices. Each table corresponds to a specific use case and provides a list of the loss values for the channels of interest within that use case. The reconstruction of each channel is conducted independently, utilizing the nearest available channels from the 32-channel configuration employed in the dataset. The values presented in the tables represent the reconstruction error for each channel, with lower values indicating superior reconstruction accuracy. In the event that a wearable device has already been configured to include the specified sensor, the corresponding value is not reported and marked with a hyphen (-). This comprehensive analysis facilitates a comparative assessment of the performance of diverse BCI devices in reconstructing EEG signals pertinent to neuromarketing applications, offering insights into the optimal configurations for different cognitive tasks.

Table 5
Loss values across BCI devices for different neuromarketing use cases.

BCI device	Emotion use case				Sensory use case		
	F3	F4	P3	P4	T7	CZ	T8
Bitbrain Diadem	0.073	0.062	0.049	0.053	0.075	0.105	0.065
Bitbrain Air	0.035	0.037	0.029	–	0.034	0.047	0.052
Bitbrain IKON	–	–	–	–	0.034	0.043	0.044
Emotiv MN8	0.113	0.120	0.126	0.114	–	0.095	–
OpenBCI EEGBand	0.057	0.058	0.043	0.044	–	0.076	–
OpenBCI CEEGRID	0.065	0.075	0.063	0.054	0.056	0.177	0.066
Muse Headband	0.046	0.047	0.043	0.040	0.036	0.059	0.036
Brain Access HALO	0.052	0.046	0.034	0.053	0.115	0.074	0.116
MindRove ARC	0.111	0.123	0.117	0.095	–	–	–
MindRove Strip	0.153	0.122	0.116	0.124	–	–	0.097
BCI device	Attention use case				Decision use case		
	F7	F8	O1	O2	F3	F4	FZ
Bitbrain Diadem	–	–	0.078	0.101	0.073	0.094	0.062
Bitbrain Air	–	–	–	–	0.035	0.031	0.037
Bitbrain IKON	–	–	–	–	–	0.024	–
Emotiv MN8	0.092	0.088	0.151	0.167	0.128	0.113	0.120
OpenBCI EEGBand	0.048	0.042	0.071	0.096	0.057	0.065	0.058
OpenBCI CEEGRID	0.093	0.107	0.084	0.113	0.065	0.065	0.074
Muse Headband	–	–	0.033	0.053	0.046	0.048	0.048
Brain Access HALO	0.079	0.071	–	–	0.052	0.048	0.047
MindRove ARC	0.074	0.077	0.144	0.145	0.111	0.118	0.126
MindRove Strip	0.084	0.100	0.152	0.148	0.154	0.136	0.120

The analysis of loss values across different electrode configurations in BCI devices for four use cases provides critical insight into the performance of the model in EEG signal reconstruction, addressing the challenge of creating low-cost BCIs that can function effectively across diverse neuromarketing applications. A good configuration is defined as one that achieves a reduced loss when predicting all electrodes across the different use cases. The electrode configuration of the Bitbrain Diadem stands out with relatively low loss values across electrodes F3, F4, P3, and P4 for the Emotion use case, indicating a robust ability to capture emotional states. The configuration in the Bitbrain Diadem shows advanced performance in terms of loss, due to the extensive array of electrodes available. This allows for the electrodes required for each use case to be readily accessible, or for alternative electrodes to be situated nearby, thus facilitating prediction.

In the decision use case, the electrode configurations in the Emotiv MN8 and OpenBCI CEEGRID show remarkable effectiveness, with prominent loss values for electrodes F3, F4, and Fz, highlighting their strength in reconstructing decision-related EEG signals. The variability in performance between configurations for sensory and decision detection is noteworthy. In particular, the configuration in OpenBCI CEEGRID shows exceptional performance in sensory detection, especially at electrode CZ with the lowest loss value, indicating a strong ability to process sensory information accurately. This adaptability is essential for low-cost BCIs aiming to offer broad applicability and reliability in capturing consumer behavior in real-world settings.

To enhance understanding of optimal electrode configurations for neuromarketing applications, the study progressed beyond the initial analysis of commercial BCIs. A focused evaluation was conducted of topographic maps (topomaps) that depict the frequency of electrode selections across various subsets of the best channel combinations. Specifically, these maps illustrated the number of repetitions of each channel within the top 10, 100, 200, and 500 best combinations, providing a detailed visual representation of the brain regions most pertinent to neuromarketing. This visualization helped identify the most effective electrode configurations, emphasizing the strategic importance of certain areas for gathering neuromarketing data.

Fig. 5 illustrates the distribution of selected EEG channels in various optimal combinations, underscoring the strategic importance of specific regions of the brain in neuromarketing research. These optimal combinations denote configurations that have achieved minimal average loss in electrode reconstruction. For enhanced interpretability, the figure incorporates electrode labels along with a color-coded scheme categorizing each channel by its associated brain lobe: frontal, temporal, parietal, occipital, and sensorimotor regions. This representation emphasizes the functional pertinence of the selected electrodes, offering insight into the contributions of distinct brain areas to neuromarketing-related cognitive processes, including decision-making (prefrontal cortex), attention (parietal cortex) and visual processing (occipital cortex). The top 10 combinations shown in Fig. 5(a) highlight a concentrated selection in the temporal regions, which is crucial for sensory processing, along with significant representation in the central and frontal regions typically associated with decision-making and emotional processing. As the number of combinations of EEG channels increases to 100 (Fig. 5(b)) and 200 (Fig. 5(c)), there is a noticeable expansion of the selection towards the temporal and parietal areas, indicating their involvement in sensory processing and attention.

The broadest distribution is observed in the top 500 combinations (Fig. 5(d)), where the selection becomes more evenly distributed across the scalp. This suggests that a wider range of neural networks are engaged when considering a larger pool of combinations, pointing to the complex interplay of multiple brain regions in consumer behavior analysis.

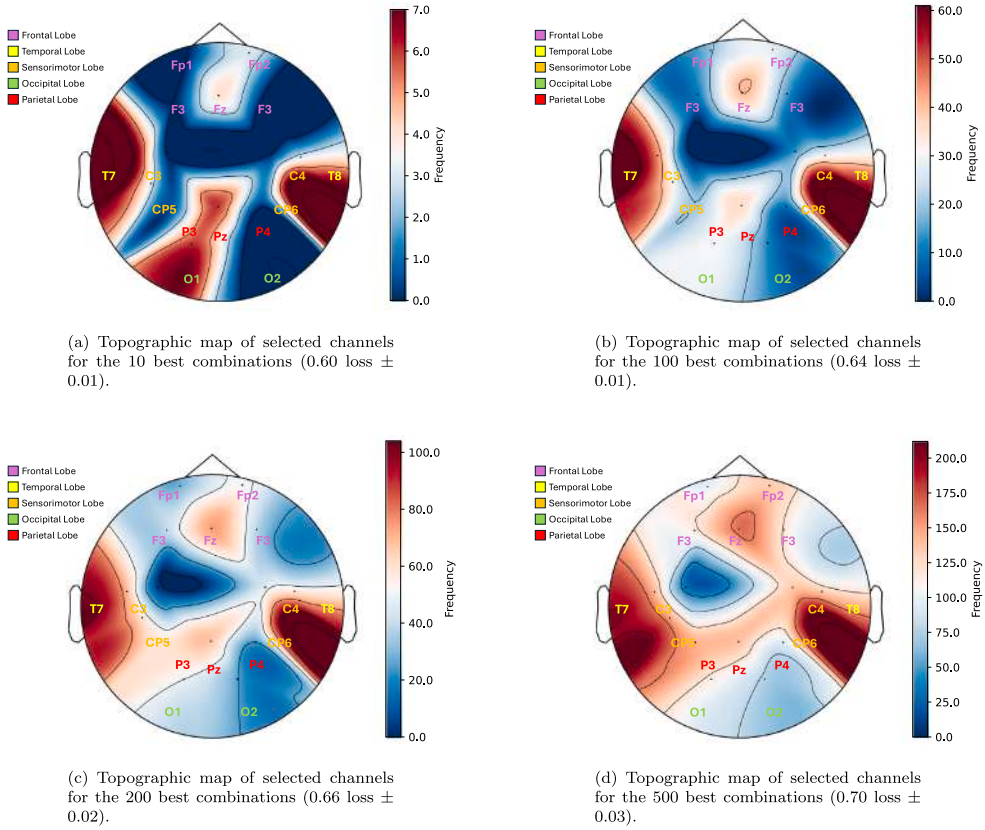
These visualizations demonstrate the adaptability and robustness of the neural network model in handling a variety of neuromarketing scenarios. By mapping the frequency of electrode selections, the underlying neural mechanisms activated in response to different marketing stimuli can be better understood. This comprehensive approach not only improves the interpretation of the predictive capabilities of the model but also helps to optimize the electrode configurations for future neuromarketing studies and for commercial applications of the BCI. Specifically, the focused examination of optimal electrode placements directly addresses the challenge faced in neuromarketing due to the channel limitations inherent in commercially available low-cost BCIs. By identifying strategic electrode configurations that maximize data acquisition within these constraints, this study enhances the ability of low-cost BCIs to reliably elicit and interpret informative signals across a range of neuromarketing applications, thereby increasing the general applicability and effectiveness of these devices in capturing detailed cognitive and emotional responses.

This section concludes with an evaluation of the performance of the model in reconstructing EEG signals across diverse neuromarketing applications. The experiments demonstrates the capability of the model to produce low to moderate loss values across multiple BCI devices, indicating robust EEG signal reconstruction. Notably, the positions of electrodes in devices such as Bitbrain Diadem and Muse Headband exhibited particularly low loss values, showcasing their effectiveness in capturing accurate EEG data for emotional and attention-related use cases. The analysis of loss values across various BCI configurations yielded valuable insights into the optimal electrode placements for specific neuromarketing tasks, thereby enhancing our understanding of effective EEG data collection strategies. Furthermore, the evaluation extended to resource efficiency, affirming the suitability of the model for real-time applications in commercial BCIs without compromising computational performance.

6.3.1. Statistical comparison with baselines

To evaluate the proposed CNN, three baseline methods were chosen based on key conceptual criteria representing the main categories of EEG channel reconstruction techniques:

- **Spherical Spline Interpolation (SSI)** [11]: SSI, the standard method for repairing bad channels in EEG preprocessing, uses the spherical geometry of the scalp to interpolate missing signals. It serves as the strongest purely spatial baseline.
- **Partial Least Squares Regression (PLSR)** [71]: PLSR models linear covariance between retained and missing channels and has been repeatedly reported to outperform ordinary least-squares in multichannel EEG imputation and fusion tasks. It serves as a representative multivariate linear alternative.



(a) Topographic map of selected channels for the 10 best combinations (0.60 loss ± 0.01).

(b) Topographic map of selected channels for the 100 best combinations (0.64 loss ± 0.01).

(c) Topographic map of selected channels for the 200 best combinations (0.66 loss ± 0.02).

(d) Topographic map of selected channels for the 500 best combinations (0.70 loss ± 0.03).

Fig. 5. Topographic maps representing the most frequently selected EEG channels across different numbers of optimal channel combinations. Each map highlights the regions with the highest predictive relevance based on reconstruction accuracy, with color intensity indicating frequency of selection.

Table 6
Reconstruction accuracy of the proposed CNN versus three baseline methods. Values are reported as mean ± Standard Deviation (SD), to reflect inter-subject variability.; p-values from paired two-tailed t-tests are Holm–Bonferroni corrected.

Method	NMSE	Δ vs. CNN	p-value
CNN (proposed)	**0.042 ± 0.009**	–	–
SSI	0.064 ± 0.011	+0.022	<0.0001*
PLSR	0.071 ± 0.013	+0.029	<0.0001*
AE-Shallow	0.055 ± 0.010	+0.013	0.0002*

* Significant at $\alpha = 0.05$ (Holm–Bonferroni).

- **Shallow Auto-encoder (AE-Shallow)** [72]: Auto-encoders constitute the simplest deep-learning approach to generative reconstruction. A shallow variant with a single hidden layer offers a parameter-matched neural baseline that captures non-linear relationships while avoiding the depth and inductive biases of the proposed CNN.

Each baseline was trained and evaluated under the same preprocessing pipeline, data splits and channel-mask scenarios as the CNN to guarantee a controlled comparison. The resulting normalized mean-squared errors (NMSE) and paired statistical tests are reported in Table 6.

Table 6 shows that the proposed CNN achieves the lowest NMSE (0.042 ±0.009), outperforming all three baselines by statistically significant margins. In particular, the CNN reduces NMSE by 34% relative to Spherical Spline Interpolation and 41% relative to PLSR, demonstrating clear advantages over classical spatial and multivariate linear techniques. Compared with a parameter-matched shallow auto-encoder, the CNN still yields a 24% improvement, indicating that architectural depth and convolutional inductive bias provide additional benefits beyond simple non-linear projections.

7. Discussion

This section examines the results of the experiments, discussing the significance of the findings, the distinct advantages of the proposed neural network model, and areas where further investigation is necessary. This comprehensive analysis aims highlight the contributions of the model to the field, its practical utility, and the roadmap for future research efforts.

7.1. Results interpretation

The analysis of the performance of the model, as demonstrated by the loss values obtained across different brain regions for each neuromarketing use case, reveals the complex dynamics of EEG signal reconstruction. This investigation not only validates the potential of the

model in neuromarketing applications, but also provides key insights for its optimization. The graphical representation of the loss values across different BCI devices brings to light several critical observations, including:

- **Impact of Channel Density and Spatial Distribution on Reconstruction Quality:** The results underscore a significant correlation between the number of channels in BCI devices and the decrease in loss values, indicating that a higher channel density enhances the accuracy of EEG signal reconstruction. Devices equipped with a greater number of electrodes, such as the Bitbrain Diadem, consistently demonstrate superior performance across all neuromarketing applications. For instance, the Bitbrain Diadem shows loss values as low as 0.05 in emotional response scenarios, compared to 0.15 in devices with fewer channels, such as the MindRove Strip. This evidence reinforces the claim that increased electrode coverage augments resolution and forecast accuracy. Beyond the total channel count, a higher electrode density increases the probability of having a proximate reference channel for reconstruction, which markedly impacts prediction quality. When electrodes are spatially proximate, the model can exploit the high correlation between adjacent signals to enhance reconstruction accuracy. Analysis of critical electrode positions, such as F3, F4, P3, and P4, reveals that closely spaced electrodes provide more robust reconstruction support due to overlapping neural information, whereas widely spaced configurations introduce greater loss values. In the decision-making application, the F3 electrode in the MindRove Strip recorded a loss of 0.154, while in the Bitbrain Diadem, which offers denser coverage in that region, the loss was significantly lower at 0.059. These findings illustrate that an increased number of channels not only supplies more data but also raises the likelihood of achieving an optimal spatial arrangement for precise EEG signal prediction.
- **Enhanced Performance with Circumferential Configurations:** The analysis of the topomaps, particularly Fig. 5(a) with the ten best combinations, demonstrates that circumferential ring configurations show significant effectiveness in reducing loss values. This effectiveness can be attributed to the fact that these configurations provide a holistic view of brain activity, which is critical for mitigating the source localization problem. The topomap of the 10 best combinations clearly indicates that the most frequently selected electrode positions form a circumferential pattern, highlighting the strategic importance of these locations. Such configurations ensure a balanced and comprehensive dataset that facilitates the discrimination of neural impulse sources, ultimately enhancing the overall performance of the model in predicting EEG signals accurately.
- **Topographic Insights on Electrode Selection:** The topomaps reveal that electrode selection frequency varies significantly with the scope of channel combinations examined. The concentration of selections in central and frontal areas for the top 10 and 100 combinations underscores their importance in neuromarketing tasks. As the range of combinations expands, so does the spatial distribution, indicating the engagement of additional cognitive and sensory processes across broader brain areas.
- **Cross-hemisphere prediction challenges:** The difficulty of the model in making cross-hemisphere predictions is evidenced by the higher loss values for lateral predictions. For example, in Table 5, the loss values for electrode CZ are relatively high in some BCI configurations, indicating challenges in predicting signals across different hemispheres. This suggests a complex interplay between signal propagation and brain hemisphericity, highlighting areas where the model needs improvement. Additionally, as shown in the topographic maps in Fig. 5, the model demonstrates lower accuracy in cross-hemisphere reconstructions, as evidenced by the higher frequency of errors in temporal regions when compared to other areas.
- **Variability Across Use Cases:** Observations indicate significant variability in model performance across different neuromarketing scenarios. This variability not only illustrates the adaptability of the model but also its current limitations, suggesting a tailored approach to model training and application based on the specific neuromarketing use case.
- **Difficulty of reconstructing specific EEG signatures:** A closer inspection of the per-channel losses (see Table 5) reveals that signals originating from cortical areas with intrinsically higher signal-to-noise ratios and strong inter-hemispheric correlations—particularly the frontal (F3/F4) and parietal (P3/P4) sites are reconstructed with markedly lower error (0.04–0.06). These channels capture high-amplitude, low-frequency components such as frontal-alpha asymmetry and the P300, which present clear temporal templates that the CNN can exploit. In contrast, lateral temporal electrodes (T7/T8), edge-occipital sites, and channels dominated by higher-frequency activity exhibit loss values that can exceed 0.10. Their weaker cross-channel correlation and lower amplitude make them more vulnerable to polarity ambiguity and over-smoothing during reconstruction. Therefore, spatial proximity and signal strength jointly set the practical upper bound for the proposed model, indicating that additional spatial priors or frequency-specific loss terms may be required when applications demand faithful recovery of low-amplitude gamma activity or lateralised temporal dynamics.

Observations from the performance of the model not only validate its potential in EEG signal reconstruction for neuromarketing applications, but also highlight critical areas for refinement. Future work should aim to improve cross-hemisphere predictions, explore the impact of electrode proximity, and further exploit circumferential electrode configurations to effectively address the challenge of source localization.

7.2. Model advantages

The proposed neural network model brings several noteworthy advantages to the field of EEG signal reconstruction for neuromarketing, as underscored by the analysis:

- **Scalability and Efficiency:** The model is optimized for computational efficiency, making it suitable for commercial BCI devices with limited processing power. This ensures broader applicability in real-world neuromarketing scenarios beyond laboratory settings.
- **Robust Performance Across Use Cases:** The model demonstrates versatility by maintaining strong performance across various neuromarketing applications, from emotional response analysis to decision-making, ensuring adaptability to diverse research needs.
- **Innovative Use of Circumscribed Configurations:** Effective model use of circumferential electrode configurations addresses the challenge of source localization, a notable hurdle in EEG signal analysis. This approach improves the accuracy of signal reconstruction and provides a more holistic view of brain activity.
- **Data-Driven Electrode Optimization:** Insights from topographic maps guide data-driven electrode placement, prioritizing the most informative regions and refining EEG setups for improved data quality and efficiency.
- **Customizable Channel Configurations:** The analysis of topographic maps across different subsets of combinations illustrates the capability of the model to adapt its performance based on the specific configuration of electrodes. This flexibility allows for customized setups that are tailored to the specific needs of each neuromarketing study, maximizing the effectiveness of EEG data acquisition.

7.3. Ethical considerations in EEG-based neuromarketing

The integration of EEG and DL into neuromarketing research raises several critical ethical considerations, particularly regarding data privacy, informed consent, and responsible application of neurophysiological insights.

Informed consent is a fundamental requirement. Participants must be clearly and comprehensively informed about how their neural data will be collected, processed, and stored, as well as the potential implications of EEG-based analysis. Given that EEG signals can reveal sensitive information related to cognitive and emotional states, explicit consent must be obtained before utilizing brain activity data in marketing research. Transparency in data usage policies is essential to uphold ethical research standards.

Data privacy and security are equally crucial concerns. Unlike other physiological metrics, such as heart rate or skin conductance, EEG signals capture intricate patterns of brain activity that could potentially be used for personal identification or cognitive profiling. To mitigate these risks, robust anonymization, encryption, and secure storage protocols must be implemented. Regulatory compliance with data protection frameworks, such as the General Data Protection Regulation (GDPR) or the California Consumer Privacy Act (CCPA), should be prioritized to ensure the ethical handling of EEG data.

Beyond individual rights, the broader societal and ethical implications of EEG-based neuromarketing must be critically evaluated. While these technologies aim to enhance consumer experience and optimize marketing strategies, their application must not cross ethical boundaries into subconscious manipulation or exploitation of consumer vulnerabilities. Establishing stringent ethical guidelines and regulatory oversight will be essential as EEG-based neuromarketing expands, ensuring that innovation progresses alongside respect for autonomy, privacy, and fairness.

7.4. Limitations and future work

Despite its advances, the development of the model highlights several areas for future exploration and improvement:

- **Cross-hemisphere reconstruction:** The model currently presents opportunities for improvement in cross-hemisphere EEG signal predictions, influenced by both neurophysiological and computational aspects. Exploring advanced techniques such as Transformer-based architectures or Graph Neural Networks (GNNs) could effectively capture long-range dependencies and account for functional asymmetries in cognitive processes like attention, language, and emotional regulation [73]. Moreover, refining artifact mitigation methods—particularly for ocular and muscular artifacts—may further enhance signal accuracy and reliability in high-precision neuromarketing and cognitive neuroscience applications [74,75].
- **Dependence on Channel Density:** Although the current model performs well with higher channel densities (e.g., Bitbrain Diadem with 11 channels achieving mean loss of 0.05), optimizing its performance for configurations with fewer channels remains an open opportunity. Developing methods tailored specifically for low-density setups could significantly broaden the model's applicability.
- **Generalization Across Diverse Datasets:** Future research could benefit from evaluating the model on diverse EEG datasets beyond the P300 Speller Dataset. Assessing its performance with EEG signals associated with emotional responses and consumer decision-making processes would ascertain the robustness of the model and practical relevance across multiple neuromarketing paradigms. Ensuring the retention of key features such as frequency bands and event-related potentials will enhance the general applicability of the reconstruction methodology.
- **Advanced Deep Learning Architectures Exploration:** Exploring Transformer-based models presents a valuable opportunity, as they have demonstrated potential improvements in similar contexts by reducing loss values compared to convolutional architectures. Optimizing these architectures for compatibility with low-resource BCI devices could facilitate their practical implementation in real-world scenarios.
- **Real-World BCI Integration:** Integrating the model into commercial BCI platforms represents an essential step forward. Collaboration with BCI manufacturers and neuromarketing professionals would enable translating the research developments into practical tools, significantly advancing consumer neuroscience applications.
- **Adaptive Electrode Configuration Models:** Developing adaptive mechanisms capable of dynamically selecting optimal electrode configurations based on real-time EEG data presents a promising area for future work. Such adaptive approaches, informed by current findings on optimal electrode placement from topomaps, could substantially enhance prediction accuracy and usability, particularly in scenarios with limited electrode availability.
- **Improved Polarity Preservation Strategies:** Addressing the potential ambiguity of the model in EEG polarity predictions offers another direction for improvement. Future research may explore novel loss functions or architectures explicitly designed to preserve signal polarity, ensuring accurate reconstruction of ERPs crucial for EEG interpretation.
- **Development of Standardized Evaluation Metrics:** Given the diversity of currently utilized evaluation metrics, such as MSE, correlation coefficients, and classification accuracy, there is a significant opportunity to establish a standardized metric for EEG reconstruction evaluation. Developing a unified assessment criterion would enhance comparability across studies, facilitating more rigorous and reproducible benchmarking of reconstruction methodologies.

8. Conclusions

This work presents a lightweight CNN model equipped with a custom loss function, representing a significant advancement in the reconstruction of specific EEG channels from a constrained dataset. The model proposes a novel approach to addressing the limitations of current EEG devices by integrating AI methods directly into the firmware of the EEG device, enabling virtual generation of EEG channels. The effectiveness of the model was validated using a public dataset. Moreover, comprehensive testing of over 1820 channel configurations showcased the adaptability and precision of the model, rendering it suitable for a range of neuromarketing applications.

The evaluation indicates that commercial BCIs are efficacious for neuromarketing research by filling the gap between the limited channel capabilities of existing devices and the demands of comprehensive neuromarketing research. The study conducted a series of experiments on the reconstruction of signals using a custom loss function that combines MSE and Pearson's correlation coefficient. This process ensured that the reconstructed signals exhibited temporal dynamics closely resembling those of the actual EEG signals. Additionally, over 1820 channel configurations were rigorously tested, highlighting the model's adaptability and precision in various neuromarketing scenarios. The experiments underscored the critical importance of the custom loss function in accurately extracting consumer insights.

Furthermore, the study highlighted the potential of this model as a robust tool for neuromarketing applications, emphasizing its computational efficiency and scalability. Efficiency is an important factor to consider when integrating advanced signal processing capabilities into commercial BCI platforms. This approach has the potential to significantly enhance neuromarketing strategies by enabling more in-depth and personalized consumer analysis.

Future research could enhance the adaptability and performance of the model by optimizing cross-hemisphere predictions, reducing dependence on channel density, and exploring more sophisticated DL architectures. The integration of the model into practical BCI applications has the potential to expand the impact of EEG-based neuromarketing research. The contributions of this work extend beyond immediate improvements in EEG signal reconstruction, potentially ushering in a new era of neuromarketing research where advanced AI and signal processing techniques offer deeper, data-driven insights into consumer behavior, ultimately enhancing the effectiveness of marketing strategies.

CRediT authorship contribution statement

Mario Quiles Pérez: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Sergio López Bernal:** Writing – review & editing, Validation, Conceptualization. **Eduardo Horna Prat:** Writing – review & editing, Supervision, Conceptualization. **Luis Montesano Del Campo:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Lorenzo Fernández Maimó:** Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Alberto Huertas Celdrán:** Writing – review & editing, Supervision, Methodology, Conceptualization, Funding acquisition.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mario Quiles reports financial support was provided by Fundación Séneca. Mario Quiles reports was provided by Cybersecurity National Institute. Alberto Huertas reports was provided by Swiss Federal Office for Defense Procurement. Alberto Huertas reports financial support was provided by University fo Zurich. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data used is a public dataset.

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3

EEG Dataset Quality Assessment



Title:	Scalable Framework for Multidimensional Quality Assessment and Benchmarking of EEG Datasets
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Abstract

Ensuring the quality of datasets containing electroencephalography signals remains challenging due to heterogeneous acquisition protocols, diverse preprocessing practices, and inconsistent annotation standards. Existing toolboxes mainly focus on signal cleaning and pipeline checks, while generic data quality frameworks lack domain specificity and do not provide an interpretable dataset-level score for electroencephalography datasets used in tasks such as affect recognition and event-related paradigms. This work introduces a platform for dataset-level quality assessment of electroencephalography collections tailored to these downstream tasks. The platform computes a set of indicators that capture session completeness, consistency of session length, class balance, annotation timing, signal-to-noise ratio, outlier prevalence, feature information content, and class separability. It then combines these indicators into a normalized global Quality Score ranging from 0 to 100. The aggregation relies on order-preserving mappings and subject-wise summarization to enable robust comparisons across datasets and to prevent longer recordings from dominating the score. The evaluation uses six public datasets from affect recognition, event-related paradigm and motor imagery, all processed under identical protocols. Classification performance is reported using Balanced Accuracy and Area Under the ROC Curve. The global score reflects differences in data integrity, temporal consistency, and separability while

remaining interpretable across heterogeneous collections. In addition, correlation analyses indicate positive associations between separability-oriented indicators and downstream performance, and negative associations with a higher prevalence of outliers. Targeted training adjustments guided by these indicators, including the removal of highly contaminated windows and loss reweighting based on class priors, consistently improve performance. Implementation and configuration files are publicly available to support reproducibility and adoption.

Keywords

Benchmarking · Brain–computer interfaces · Datasets · Data quality assessment · Electroencephalography

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RESEARCH ARTICLE

A Scalable Framework for Multidimensional Quality Assessment and Benchmarking of EEG Datasets

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ABSTRACT Ensuring the quality of datasets containing electroencephalography signals remains challenging due to heterogeneous acquisition protocols, diverse preprocessing practices, and inconsistent annotation standards. Existing toolboxes mainly focus on signal cleaning and pipeline checks, while generic data quality frameworks lack domain specificity and do not provide an interpretable dataset-level score for electroencephalography datasets used in tasks such as affect recognition and event-related paradigms. This work introduces a platform for dataset-level quality assessment of electroencephalography collections tailored to these downstream tasks. The platform computes a set of indicators that capture session completeness, consistency of session length, class balance, annotation timing, signal-to-noise ratio, outlier prevalence, feature information content, and class separability. It then combines these indicators into a normalized global Quality Score ranging from 0 to 100. The aggregation relies on order-preserving mappings and subject-wise summarization to enable robust comparisons across datasets and to prevent longer recordings from dominating the score. The evaluation uses six public datasets from affect recognition, event-related paradigm and motor imagery, all processed under identical protocols. Classification performance is reported using Balanced Accuracy and Area Under the ROC Curve. The global score reflects differences in data integrity, temporal consistency, and separability while remaining interpretable across heterogeneous collections. In addition, correlation analyses indicate positive associations between separability-oriented indicators and downstream performance, and negative associations with a higher prevalence of outliers. Targeted training adjustments guided by these indicators, including the removal of highly contaminated windows and loss reweighting based on class priors, consistently improve performance. Implementation and configuration files are publicly available to support reproducibility and adoption.

INDEX TERMS Benchmarking, brain-computer interfaces, datasets, data quality assessment, electroencephalography.

I. INTRODUCTION

Electroencephalography (EEG) is widely used in neuroscience and Brain–Computer Interface (BCI) research to measure brain activity and study mental processes such as attention, perception and emotion [1]. However, ensuring proper dataset quality remains challenging because research groups often design studies to answer specific questions, leading to various approaches in acquisition, preprocessing, and labeling. As a result, EEG datasets

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frequently differ in their protocols, hardware, preprocessing pipelines, artifact handling, label definitions, timing, and experimental paradigms [2]. These differences reduce data reliability and limit the performance and generalization of Machine Learning (ML) and Deep Learning (DL) models [3], [4]. Consequently, Dataset Quality Assessment (DQA) is essential to enable robust and reproducible EEG studies and to reduce avoidable failures in downstream AI pipelines. This role aligns with Healthcare 5.0, which emphasizes human-centric, resilient, and sustainable AI-enabled care grounded on reliable data streams [5]. In this context, multidimensional EEG dataset quality assessment can support trustworthy and ethical model development by providing transparent and comparable evidence of completeness, integrity, and annotation/label reliability before training.

The number and diversity of EEG datasets continue to grow, including multimodal studies and large-scale collections [6], [7]. This growth also increases heterogeneity: incomplete sessions, inconsistent sampling rates, and mismatched event labels complicate benchmarking and cross-study comparisons [8]. Integrating public and proprietary data to increase the sample size or broaden validation can increase these problems [9].

The EEG tools for data quality assessment are classified into two groups. First, domain libraries such as EEGLAB [10] and MNE [11] that support comprehensive preprocessing and analysis. Building on these libraries, automated pipelines such as Automagic [12], HAPPE [13], Autoreject [14], RELAX [15], and FASTER [16] provide standardized cleaning workflows, including filtering and rereferencing, channel inspection, Independent Component Analysis (ICA) or Artifact Subspace Reconstruction (ASR), and adaptive rejection and interpolation, with batch execution that improves repeatability. Secondly, general-purpose data quality platforms, such as Great Expectations [17] and Talend Data Quality [18], provide an extensibility schema, type and rule-based checks.However, these tools operate at the signal/pipeline or generic data level and typically do not (i) produce a simple, normalized dataset-level score, (ii) expose EEG-specific metrics with actionable thresholds, (iii) validate annotation timing and class balance for each paradigm, for example P300 class prevalence, or (iv) quantify links between quality indicators and downstream performance for cross-dataset benchmarking. Extending general-purpose platforms to cover EEG is possible through custom plugins, but such extensions are ad hoc and not available out of the box. A comparative summary of representative EEG preprocessing/QC tools and general data-quality platforms is provided in TABLE 1, highlighting assessment level, scalability, automation, and the dimensions covered.

To address these gaps, this article introduces a framework for assessing the quality of complete EEG datasets used in affect recognition and event-related paradigms. The framework computes a heterogeneous set of indicators that capture session completeness, temporal consistency through session-length statistics, class balance, annotation timing, signal-to-noise ratio, outlier prevalence, feature information content, and class separability. These indicators cover completeness, temporal consistency, signal quality and separability, annotation validity, and feature relevance at the dataset level. Next, the framework consolidates all indicators into a normalized Quality Score (QS) between 0 and 100 for pre-training evaluation and reporting. In this context, QS should be interpreted as a comparative, pre-training ranking under a fixed evaluation protocol rather than as an absolute measure of dataset quality. To be precise, cross-paradigm comparisons are meaningful only when the same preprocessing, enabled indicator set, and weights are used. Therefore, when paradigms differ, QS should be interpreted together with the dimension-level profile, and paradigm-dependent indicators (e.g., class balance, annotation validity, and feature–label measures) should only be enabled when comparable labels or event markers are available; otherwise, they should be treated as unavailable and the remaining weights are renormalized. The mapping uses order-preserving transforms with caps for extreme values and applies subject-wise aggregation to avoid dominance by long recordings and to enable comparison across datasets. In addition, the framework is implemented as a reusable platform, and the codebase, configuration files, and automated execution scripts are publicly available to enable reproducibility and independent verification [19]. Finally, the framework is evaluated under identical protocols on six public datasets, linking metric profiles to downstream classification performance with subject-stratified validation.

Six public datasets were analyzed: DEAP, SEED, and DREAMER for emotion recognition, BCI Competition III together with RSVP/P300 Speller for the P300 paradigm and EEG Motor Movement/Imagery Dataset (EEGMMIDB) for motor imagery. The platform links metric values to downstream performance in terms of balanced accuracy and area under the curve, examines robustness to window size and repetition count, and reports simple ablations that act only on training folds. The proposed framework complements existing EEG preprocessing pipelines by shifting the focus from recording-level cleaning to dataset-level quality characterization and benchmarking. It provides an automated and scalable set of EEG-aware indicators and a composite Quality Score (QS) intended for comparative, pre-training diagnosis rather than an absolute notion of dataset quality. Note that the scope of this article is restricted to EEG datasets and to the predefined indicator set formalized in Section III. The presented validation focuses on affect recognition and ERP/P300 case studies under a fixed evaluation protocol. Therefore, QS should be interpreted as a comparative, pre-training diagnostic ranking under the enabled indicators and weights, rather than as an absolute measure of dataset quality across paradigms. Extending the framework to other EEG paradigms requires selecting the indicators that match the target labels and metadata and verifying that the required annotations and protocol information are available.

The remainder of the article is organized as follows: Section II reviews dataset-quality tools for EEG and general data-quality platforms. Section III formalizes the assessment framework, defines the metrics used, and introduces the composite QS. Section IV outlines the platform architecture and the technological stack used. Section V describes the datasets, preprocessing, evaluation protocols, and statistical tests. It also reports quantitative results, robustness analyses, and ablation studies. Section V-G discusses implications, limitations, ethical considerations for data handling, and generalization to other EEG settings. Finally, Section VI concludes the study.

II. RELATED WORK

The quality of EEG datasets is critical across EEG applications, including cognitive neuroscience, BCIs, affective computing, clinical-oriented studies, and other applied EEG settings. In this article, neuromarketing is used only as an illustrative application scenario rather than as the primary domain of the proposed framework. Inconsistent acquisition, preprocessing variability, and labeling differences hinder reliability and reproducibility [7]. They also affect model performance and complicate cross-study comparisons and data integration [20]. Standards for organizations such as EEG-BIDS [21] support scalable sharing and validation, but a reproducible dataset-level assessment with actionable thresholds remains limited in practice.

A. IMPORTANCE OF DATA QUALITY IN PRACTICAL APPLICATIONS

High-quality datasets are essential for the development of reliable ML and DL models across EEG applications, including cognitive neuroscience, BCIs, affective computing, and clinical-oriented studies. The quality of the datasets directly affects the performance, generalization, and interpretability of the model. Key attributes such as completeness, accuracy, and representativeness determine the reliability of analyzers and predictions [4].

In applied EEG scenarios, ensuring these attributes is important because datasets support the study of cognitive processing, affective responses, and stimulus-locked neural dynamics under controlled conditions. The same data-quality requirements arise across cognitive neuroscience, BCI, affective computing, and clinical-oriented EEG benchmarking. In this article, neuromarketing is referenced only as one illustrative applied case in which these requirements become visible. The reliability of these datasets directly influences the validity of analyses in areas such as cognitive processing and affective response modeling. P300 datasets, for instance, enable the evaluation of cognitive processes like attention and memory during exposure to stimuli, which are often associated with marketing strategies [22]. Similarly, datasets for emotion recognition provide critical insight into affective responses, allowing campaigns to be customized to suit consumer preferences [20].

However, many of these datasets are contaminated by noise, inconsistencies, and variations in collection protocols, which challenge their effective integration and analysis [23]. An additional challenge lies in the need for datasets that support comparative studies across diverse experimental setups and conditions.For example, comparing multiple experimental conditions across groups requires standardized frameworks to evaluate datasets and ensure consistent metrics for cross-study benchmarking. In addition, advertising-campaign studies represent one applied case where these requirements are visible [4].

Addressing these challenges requires the development of scalable platforms that integrate dataset evaluation, exploration, and comparison tools. Such platforms are important for maintaining high dataset quality and advancing ML applications across EEG domains, including cognitive neuroscience, BCI, affective computing, and clinical-oriented studies.

B. CHALLENGES IN EVALUATING AND COMPARING DATASETS

The evaluation and comparison of datasets are critical for ensuring the reliability of ML models across EEG applications, including cognitive neuroscience, BCI, and clinical-oriented benchmarking. However, this process is complicated by several challenges that stem from the inherent variability of experimental conditions and the lack of standardized methodologies to assess the quality of datasets.

One of the primary challenges is the variability between studies introduced by differences in experimental designs, data acquisition protocols, and sensor configurations. For example, datasets collected using various EEG devices or under varying environmental conditions can exhibit significant inconsistencies, making direct comparisons difficult. Such discrepancies often lead to biases that compromise the reproducibility and generalization of the findings, especially when trying to integrate data from multiple studies [8].

Another major challenge lies in the lack of standardized metrics to evaluate the quality of datasets. Although general criteria such as completeness, consistency, and validity are commonly used, their interpretation and implementation can vary significantly between studies. This variability limits the ability to benchmark datasets or draw meaningful comparisons between experimental setups. For example, neuromarketing datasets often lack uniformity in labeling conventions, signal preprocessing techniques, or even the granularity of recorded data, further complicating cross-study evaluations [24].

The heterogeneity of the datasets also poses a significant obstacle to the development of scalable AI models. Combining public and private datasets, often essential for broadening the scope of neuromarketing studies, requires robust frameworks that can handle differences in data format, resolution, and collection methodologies. Without such frameworks, researchers face considerable difficulties in

harmonizing datasets, leading to potential loss of information or the introduction of additional biases [9].

Addressing these challenges requires the creation of platforms and methodologies that facilitate the evaluation and comparison of datasets. Such solutions must incorporate standardized metrics and automated tools capable of handling heterogeneous datasets while ensuring data quality. Recent efforts emphasize the development of scalable and interoperable systems, which are critical for enabling reliable cross-study comparisons and supporting the development of generalized machine learning models tailored to diverse consumer populations [8].

C. EXISTING TOOLS FOR DATASET ANALYSIS

DQA continues to be a fundamental aspect in guaranteeing the reliability of AI models. The scientific literature delineates the essential dimensions of DQA, such as completeness, consistency, accuracy, and validity. These dimensions are evaluated through specific metrics that have been extensively implemented in both general-purpose tools and domain-specific platforms, each providing solutions to distinct challenges. However, current tools face limitations when applied to biosignal data, such as EEG, which require additional evaluations for temporal alignment, artifact detection, and annotation validity.

General-purpose data quality tools provide a useful baseline for structured data pipelines. Great Expectations offers reusable rules-based checks that cover completeness, consistency, and validity and can be integrated into CI workflows [17]. Talend Data Quality and Pandas Profiling support large-scale profiling, indicators, and anomaly detection for tabular data [18], [25]. These frameworks are extensible where Great Expectations allows custom expectations and plugin-based checks, while Talend supports user-defined indicators and rules [17], [18]. These systems are practical for database-style inputs, but are not EEG-aware: they do not model multichannel structure or time-locked events, they do not test event–signal alignment, and they do not provide a normalized dataset-level score. Extending them to EEG is possible through custom code, yet such extensions remain ad hoc and are not available out of the box.

EEG libraries and pipelines focus on signal preparation and artifact handling. EEGLAB and MNE expose building blocks for filtering, referencing, artifact removal, visualization, and I/O, and are widely adopted in research and practice [10], [11]. On top of these libraries, pipelines standardize cleaning and add basic quality reporting. PREP (EEG-Clean-Tools) addresses early steps such as referencing and line noise handling and generates QS summaries [26]. FASTER applies automated statistical thresholds at channel, epoch, and ICA levels to reduce manual intervention [16]. Automagic provides configurable batch workflows (including filtering, rereferencing, channel inspection, and ICA) and produces quality reports suitable for large studies [12]. HAPPE targets high-artifact and developmental data with conservative defaults and post-processing metrics [13]. Autoreject learns the rejection thresholds per sensor and performs adaptive interpolation on a data-driven basis [14]. RELAX integrates recent cleaning modules into a reproducible workflow and surface cleaning metrics to help inspect the results [15]. These contributions improve repeatability and transparency at the level of recordings and preprocessing runs, but their outputs remain tied to a specific pipeline and are typically local to each session.

Other frameworks extend coverage across biosignal processing and BCI lifecycles. BioSig offers a wide range of I/O and processing utilities in all modalities and presents long-term community use [27]. NeuronLab provides a web-based environment that supports parts of the BCI workflow, including preprocessing, prediction, and experiment management [28]. These systems support end-to-end studies, yet they do not deliver a normalized dataset-level score, nor do they test annotation timing or paradigm-aware class balance by default.

Across these tools, two patterns explain why they are not suited for assessing the quality of the dataset. First, quality evidence is reported at the signal or session level e.g., per-channel flags, rejection counts, or variance retention and is not aggregated into a single normalized score that can be used to compare datasets. Second, EEG-specific checks that matter for downstream modeling, such as event-signal alignment and class imbalance adjustments that reflect paradigm priors e.g., P300 target to nontarget ratios are rarely formalized, and links between quality indicators and model performance are seldom quantified.

TABLE 1 provides a comparative analysis of these tools, highlighting their strengths and limitations. Although general-purpose frameworks excel in standard data quality metrics, they lack EEG-specific capabilities. In contrast, EEG processing tools focus on artifact detection, but omit comprehensive dataset quality evaluation. These gaps demonstrate the need for an integrated solution providing EEG-specific quality metrics, annotation validation, and cross-dataset comparison tools, which are essential to advance EEG and biosignal-driven research.

Existing EEG pipelines focus on signal cleaning and analysis, whereas general data quality systems emphasize schema- and rule-based validation. In contrast, this work provides a dataset-level assessment that aggregates a compact set of EEG-aware indicators into an interpretable 0–100 QS, with a paradigm-aware option for P300 studies. Consequently, the approach complements EEGLAB and MNE-based pipelines and extensible data-quality frameworks by providing standardized, reproducible evidence for cross-dataset comparison and reporting.

III. FRAMEWORK DESIGN

This section details the design of the proposed platform for automated quality assessment and comparison of EEG datasets. The quality assessment framework acts as a pipeline layer that remains agnostic to downstream models and

TABLE 1. Comparison of representative EEG preprocessing/Quality Control (QC) tools and general DQA platforms, highlighting assessment level, covered dimensions, automation level, and scalability. ✓ = yes, ✗ = no, △ = partial/indirect (e.g., via plugins).

Tool	Assess.	Dimensions covered	Auto.	Scal.	Comp. score	EEG	Down.	Ref.
EEGLAB	Rec./sess.	Visual inspection; artifact handling (plugins)	Man.	Med.	✗	✓	✗	[10]
MNE	Rec./sess.	Preprocessing; artifact correction/rejection (code)	Man.	High	✗	✓	✗	[11]
FASTER	Rec./sess.	Automated rejection based on thresholds (noise/artifacts)	Auto	High	✗	✓	△	[16]
Automagic	Rec./sess.	Cleaning pipeline with QC summaries and metrics	Semi	High	✗	✓	△	[12]
HAPPE	Rec./sess.	Automated cleaning with QC summaries and metrics (dev.)	Auto	High	✗	✓	△	[13]
Autoreject	Rec./sess.	Automated artifact rejection using learned thresholds	Auto	High	✗	✓	△	[14]
RELAX	Rec./sess.	Cleaning pipeline with artifact/noise QC summaries	Semi	High	✗	✓	△	[15]
BioSig	Rec./sess.	Biosignal I/O; basic preprocessing utilities	Man.	Med.	✗	✓	✗	[27]
NeuronLab	Rec./sess.	Web-based BCI workflow with basic QC summaries	Semi	Med.	✗	✓	✗	[28]
Great Expectations	Dataset (gen.)	Completeness, validity, and consistency checks (tabular)	Semi	High	✗	✗	✗	[17]
Talend DQ	Dataset (gen.)	Profiling plus validity/consistency indicators (tabular)	Auto	High	✗	✗	✗	[18]
Pandas Profiling	Dataset (gen.)	Descriptive dataset profiling and summaries (tabular)	Man.	Med.	✗	✗	✗	[25]
This work	Dataset (EEG)	Completeness; temporal cons.; signal integrity/noise; annot. validity; feature relevance	Auto	High	✓ (0–100)	✓	✓	–

Note: Automation is categorized as Man. (user-driven building blocks), Semi (configuration-driven pipelines), or Auto (end-to-end automated checks). Scalability (Low/Med./High) reflects suitability for large studies via batch execution. "Down." indicates whether indicator values are explicitly related to model performance under a standardized evaluation protocol.

training protocols: it receives preprocessed or formatted EEG data, computes the fixed set of quality metrics defined below, normalizes them to a scale of 0-100 and outputs per-metric scores together with a composite QS. FIGURE 1 summarizes this data flow. Feature extraction is required only for feature-based indicators (MI, Overlap, and Homogeneity) and is applied only when precomputed features are not available. All quality dimensions are then combined through a weighted aggregation to obtain a single QS value. The implementation details (file upload, parameter form, caching and API) are presented in Section IV [19].

A. QUALITY DIMENSIONS AND METRICS

The framework evaluates datasets along complementary dimensions that capture completeness, temporal consistency, signal integrity and noise robustness, annotation validity, and feature relevance/separability under a fixed representation. To improve readability, the terminology is used with specific meanings. In this paper, "quality" denotes the comparative evidence produced by the indicators and the resulting QS under a fixed evaluation protocol, rather than an absolute property of a dataset. In this context, "signal integrity" refers to the degree to which neural activity is preserved relative to artifacts and noise. Furthermore, "informativeness" refers to the statistical dependence between the chosen representation and the labels, whereas "separability" refers to how well classes can be distinguished under the same representation. These terms are mapped to specific dimensions in TABLE 2 and to specific indicators in TABLE 3.

This article proposes this unified set of metrics as a dataset-level assessment within the framework. Each metric is computed at the subject level (and per session when applicable) and then macro-averaged across subjects to prevent dominance by longer recordings. All metrics are

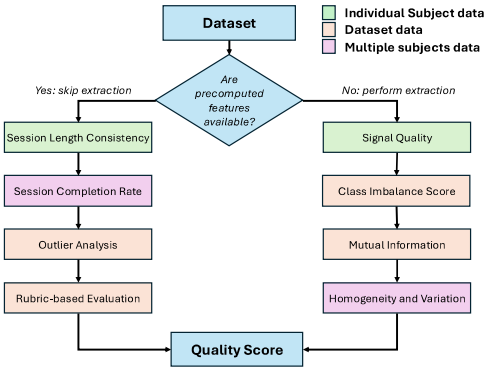


FIGURE 1. Workflow of the proposed framework for EEG dataset quality evaluation. The pipeline starts from a standardized data set organized by subject and session. If pre computed features are available, feature extraction is skipped. Otherwise, features are computed only for feature-based indicators (mutual information, class overlap, and homogeneity). The remaining indicators are computed from recordings and meta data, mapped to a 0–100 scale at the subject level, and macro-averaged to obtain data set scores. Finally, dimension-level scores are aggregated with user-defined weights to produce the composite Quality Score (QS) and the per-metric report.

mapped to $[0, 100]$ so that higher values indicate better quality. TABLE 2 defines the quality dimensions and their role in downstream EEG analysis tasks, while TABLE 3 lists the metrics used to operationalize these dimensions, including directionality and normalization.

Completeness covers the expected subject and session coverage as well as sufficient recording duration. When data are missing, the effective sample size decreases and results can become biased. Temporal consistency then captures whether

subject-level patterns remain stable across sessions, including whether session durations are comparable. As a result, higher temporal consistency supports cross-session generalization. Signal integrity and noise robustness focus on preserving neural activity in the presence of artifacts and noise. In practice, this dimension can be reflected by SNR, filtering efficiency, and outlier prevalence. If integrity is low, spectral, ERP, and connectivity features can degrade. Annotation validity, in turn, relates to label and event-timing reliability when this information is available. This aspect is especially important for time-locked paradigms because it reduces label noise. Finally, feature relevance and separability capture two related but distinct aspects of the selected representation. Mutual information quantifies feature relevance as statistical dependence between the representation and the labels, whereas class overlap quantifies separability as the extent to which class-conditional distributions remain distinguishable under that same representation. Therefore, this dimension provides a comparative, pre-training diagnostic under a fixed representation.

In downstream tasks, completeness and temporal consistency mainly affect statistical power and generalization; signal integrity/noise robustness affects feature quality and reduces spurious correlations; annotation validity improves ERP alignment and supervision; feature relevance/separability summarizes the discriminative structure that models can exploit when datasets are compared under the same evaluation settings.

TABLE 2. Formal definition of quality dimensions and alignment with downstream EEG analysis tasks.

Dimension	Definition and downstream alignment
Completeness	Expected subject/session coverage and sufficient recording duration; supports statistical power and reduces sampling bias.
Temporal consistency	Stable subject-level patterns and comparable session duration across sessions; supports longitudinal analysis and cross-session generalization.
Signal integrity / noise robustness	Neural signal preserved relative to artifacts/noise (e.g., SNR, filtering efficiency, outliers); supports reliable PSD/ERP/connectivity features.
Annotation validity	Label and event-timing reliability (when available); supports time-locked analysis and reduces label noise in supervised learning.
Feature relevance / separability	Representation informativeness with respect to the labels (e.g., mutual information) together with class discrimination under the same fixed representation (e.g., class overlap); supports comparative, pre-training diagnosis under fixed features.

1) SESSION COMPLETION RATE

Missing sessions under-represent specific neural states and bias group statistics [29]. The score is the percentage of expected recordings that are present:

$$M_c \;=\; 100 \times \frac{\#\,\text{completed sessions}}{\#\,\text{expected sessions}}\,.$$

Higher values indicate better completeness.

2) SESSION-LENGTH CONSISTENCY

Large variability in recording length introduces unequal signal content and potential confounders such as fatigue [29]. Let $d_{u,s}$ denote the duration of session s for subject u. For each subject, the coefficient of variation is $\mathrm{CV}_u = \mathrm{SD}(d_{u,\cdot})/\mathrm{Mean}(d_{u,\cdot})$. The dataset-level score maps the macro-average CV to [0, 100]:

$$M_l \;=\; 100 \times \max\!\big(0,\; 1 - \overline{\mathrm{CV}}\big), \qquad \overline{\mathrm{CV}} \;=\; \frac{1}{U}\sum_{u=1}^{U} \mathrm{CV}_u\,.$$

Higher values denote more uniform session durations.

3) ANNOTATION VALIDITY

Misaligned or imprecise event markers degrade label reliability and confound learning. This indicator assumes that ground-truth event markers (and the corresponding event definitions) are available and that dataset documentation provides an expected event timestamp for each event type. For each subject, let Δ_i denote the absolute temporal offset between the recorded marker and the expected event time for event i. The subject-level alignment error is the median offset $\widetilde{\Delta} = \mathrm{median}_i(|\Delta_i|)$. The score maps the error to [0, 100] using a tolerance anchor τ (e.g., 50 ms):

$$M_v \;=\; 100 \times \max\!\big(0,\; 1 - \tfrac{\widetilde{\Delta}}{\tau}\big).$$

The tolerance τ should reflect the expected timing jitter for the paradigm and acquisition setup. If the expected timestamp is not defined or is not comparable across recordings, M_v should be disabled or configured with a paradigm-appropriate τ to avoid penalizing valid protocol jitter. Dataset-level annotation validity is the macro-average of subject scores. Higher values indicate more accurate event–signal alignment.

4) OUTLIER ANALYSIS

EEG is susceptible to high-amplitude artifacts caused by blinks, muscle activity, or poor electrode contact [30]. For each subject and channel, a sliding window of length w and hop h is used with overlap, under the constraints $w \geq f_s/4$ and $w \leq N$, where f_s is the sampling rate and N the number of samples. Let $\mu_{|x|}$ be the mean absolute amplitude over the entire channel recording. A window is flagged as outlier if at least one sample satisfies $|x_t| > 4\,\mu_{|x|}$. If N_{out} and N_{tot} denote the numbers of outlier and total windows, respectively, the outlier rate is $\mathrm{OR} = N_{\text{out}}/N_{\text{tot}}$, and the score is

$$M_o \;=\; 100 \times \big(1 - \mathrm{OR}\big).$$

The $4\mu_{|x|}$ rule is a conservative amplitude-based screen that flags large transient artifacts while keeping the computation simple; threshold-based artifact detection is common in automated EEG preprocessing pipelines [31]. Subject-level scores are macro-averaged across subjects. Higher values indicate cleaner data with fewer artifacts.

TABLE 3. EEG quality metrics (all mapped to [0, 100]). Dir. indicates whether higher (↑) or lower (↓) raw values imply better quality.

Metric	Symb.	Dir.	Transform	What it measures
Session completeness	M_c	↑	$100 \cdot \frac{\#\text{completed}}{\#\text{expected}}$	Expected vs. observed sessions
Session-length consistency	M_l	↑	$100 \cdot \max(0,\ 1 - \overline{\text{CV}})$	Session-duration uniformity
Class balance	M_b	↑	$100 \cdot (1 - \Delta/(2f^{\text{tot}}))$	Label distribution balance
Class overlap	M_{bhat}	↓	$100 \cdot (1 - BC)$	Separability under fixed features
Outlier prevalence	M_o	↓	$100 \cdot (1 - \text{OR})$	Outliers as artifact/stability proxy
Mutual information	M_{mi}	↑	$100 \cdot \text{clip}(\text{MI}^{\star}/(0.6\,H(Y)),\ 0,\ 1)$	Feature–label dependence
Filtering efficiency	M_{fe}	↑	$100 \cdot \frac{\#\text{removed}}{\#\text{detected}}$	Cleaning effectiveness
Homogeneity	M_h	↑	$100 \cdot \max(0,\ 1 - \text{SD}(\bar{x}_u)/\mu_{\text{global}})$	Cross-subject similarity
Signal-to-noise ratio	M_{snr}	↑	$100 \cdot \text{clip}(\text{SNR}_{\text{dB}}/30,\ 0,\ 1)$	Signal clarity vs. noise

5) CLASS IMBALANCE SCORE

Imbalanced label distributions bias classifiers toward majority classes and reduce generalization, a frequent issue in EEG where some states (for example, targets in oddball paradigms) are rare [32]. Let f_k be the count of class k and K the number of classes. Deviation from perfect balance is

$$\Delta = \sum_{k=1}^{K} |f_k - f_{\text{avg}}|, \qquad f_{\text{avg}} = \frac{1}{K}\sum_{k=1}^{K} f_k .$$

The dataset-level score maps this deviation to [0, 100]:

$$M_b = 100 \times \left(1 - \frac{\Delta}{2f_{\text{total}}}\right), \qquad f_{\text{total}} = \sum_{k=1}^{K} f_k .$$

The dataset-level score is the macro-average across subjects to avoid dominance by larger subjects. For P300 datasets, a paradigm-aware variant compares the observed target ratio to the protocol prior when available (see Section III-B). For K=2, M_b reduces to $100 \times \left(1 - |f_{\max} - f_{\min}|/f^{\text{tot}}\right)$, matching the binary display used in the user interface.

6) SIGNAL-TO-NOISE RATIO (SNR)

Low SNR limits the extraction of neural information from EEG [33]. Channel-level SNR in decibels is calculated as

$$\text{SNR}_{\text{dB}} = 10 \log_{10}\left(\frac{P_{\text{signal}}}{P_{\text{noise}}}\right),$$

where P_{signal} and P_{noise} are defined consistently across datasets; band definitions and spectral estimators are specified in Section IV. Channel values are averaged per subject and then macro-averaged across subjects. The mapping to [0, 100] uses the clamped linear transform from Section III-B.

7) FILTERING EFFICIENCY

Filtering performance is estimated as the fraction of detected artifact segments that are effectively removed by the filtering or cleaning stage. For subject u, let A_u^{det} be the count of detected artifact windows and A_u^{rem} the subset removed after filtering. The subject-level efficiency is

$$\text{FE}_u = 100 \times \frac{A_u^{\text{rem}}}{A_u^{\text{det}}},$$

with $\text{FE}_u = 100$ when $A_u^{\text{det}} = 0$ (no detected artifacts). The dataset score M_{fe} is the macro-average between subjects. Higher values indicate a more effective artifact suppression.

8) MUTUAL INFORMATION

Mutual information (MI) quantifies the statistical dependence between features and the labels of interest [34]. Labels of interest include, for example, target vs. nontarget in P300 or high vs. low valence in emotion tasks. Continuous features use the Kraskov–Stögbauer–Grassberger (KSG) k-nearest neighbor estimator with k=5. A label-shuffle null with B=1000 permutations provides a bias estimate. The bias-corrected MI is

$$\text{MI}^{\star} = \max\left(0,\ \widehat{\text{MI}} - \mathbb{E}[\widehat{\text{MI}}_{\text{null}}]\right).$$

MI is computed per subject and per feature, then averaged across features to obtain a subject-level value. Subject-level values are macro-averaged across subjects. The mapping from $\text{MI}^{\star}$ to the [0, 100] score is defined in Section III-B.

9) CLASS OVERLAP

Class separability is estimated via the Bhattacharyya coefficient between class-conditional feature densities. For $K > 2$ classes, the pairwise coefficients are averaged per feature and subject, normalized within the dataset, and inverted to obtain a [0, 100] separability score; higher values indicate greater separability.

10) HOMOGENEITY

Homogeneity quantifies the cross-subject similarity after subject-wise scaling. For a given feature family, let $\bar{x}_u$ denote the mean magnitude at the subject level and let μ_{global} be the mean across subjects. The score is calculated as follows

$$M_h = 100 \times \max\left(0,\ 1 - \frac{\text{SD}(\bar{x}_u)}{\mu_{\text{global}} + \varepsilon}\right),$$

where ε is a small positive constant (e.g., 10^{-8}) to ensure numerical stability. Higher values indicate a more homogeneous magnitude across subjects. A complementary variation index

$$\text{Var}_u = \frac{\text{SD}(x_{u,\cdot})}{\text{Mean}(x_{u,\cdot})}$$

is reported as a diagnostic at the subject level but is not included in the QS by default.

B. NORMALIZATION, WEIGHTING, AND QUALITY SCORE

This section introduces the normalization strategy and the aggregation rule used to compute the QS at the dataset level. Order-preserving mappings place all metrics on a [0, 100] scale (TABLE 3). Clamped transforms are specified for unbounded metrics (SNR and MI). These saturation anchors are not claimed to be universal. They keep the score interpretable and limit the influence of extreme values, similar to robust clipping (winsorization) described in statistics [35]. For SNR, 30 dB is treated as a high-SNR reference point; values above 30 dB are mapped to 100. For mutual information, the normalization by $H(Y)$ follows common normalized-MI practice in feature selection [36], [37]. The factor 0.6 sets a practical saturation point so that typical MI values do not saturate early; it can be adjusted when a different label entropy or estimator is used. Weighted aggregation uses dynamic weights with renormalization when a metric is unavailable, and macro-averaging across subjects.

1) SCORE MAPPINGS FOR BOUNDED METRICS

For bounded metrics with highest value is better $M \in [a, b]$,

$$\text{score} \;=\; 100 \times \frac{M - a}{b - a}\,;$$

for lower-is-better,

$$\text{score} \;=\; 100 \times \frac{b - M}{b - a}\,.$$

Metrics with heavy tails, that is, distributions with many extreme values, use robust anchors: the median as the lower anchor and the median plus two interquartile ranges (IQRs) as the upper anchor. The values are then linearly mapped to the [0, 100] scale, with the clipping indicating that observations below the lower anchor map to 0 and observations above the upper anchor map to 100. The class overlap uses the normalized Bhattacharyya coefficient $\widetilde{BC} \in [0, 1]$ and is scored as $100, (1 - \widetilde{BC})$. For the P300 paradigm, the class balance can be scored against the prevalence of the protocol class when available. If a metric is unavailable, it is omitted, and the remaining weights are renormalized.

2) SCORE MAPPINGS FOR UNBOUNDED METRICS

SNR (dB) and MI (bits) use clamped monotonic transforms. For SNR,

$$\text{Score}_{\text{SNR}} \;=\; 100 \times \text{clip}\!\left(\frac{\text{SNR}_{\text{dB}}}{30},\; 0,\; 1\right),$$

so that $0\,\text{dB} \mapsto 0$, $30\,\text{dB} \mapsto 100$, and higher values saturate. For MI, with $H(Y)$ the empirical label entropy,

$$\text{Score}_{\text{MI}} \;=\; 100 \times \text{clip}\!\left(\frac{\text{MI}^{\star}}{0.6\,H(Y)},\; 0,\; 1\right),$$

which preserves comparability across datasets with different label entropies.

3) AGGREGATION AND DYNAMIC WEIGHTS

The final QS aggregates rescaled metric scores $S_i \in [0, 100]$ with non-negative weights:

$$\text{QS} \;=\; \sum_{i=1}^{n} w_i\, S_i, \qquad \sum_{i=1}^{n} w_i = 1\,.$$

Default setting: the eight indicators $M_c, M_l, M_o, M_b, M_{bhat}, M_h, M_{mi}, M_{fe}$ use equal weights ($w_i = 1/8$). This choice is a neutral baseline for cross-dataset comparison. Equal weights act as a neutral prior when no community-agreed importance weights exist, and they avoid injecting paradigm-specific preferences into the default ranking. If an indicator is unavailable, it is removed and the remaining weights are renormalized to sum to 1. SNR (M_{snr}) and annotation validity (M_v) are reported but use weight 0 by default because they are not consistently available across datasets/paradigms and may depend on acquisition/reference choices and on reliable timing metadata. When the compared datasets share comparable acquisition settings, reference choices, preprocessing definitions, and spectral estimation settings, Msnr can be assigned a non-zero weight. Likewise, Mv should be enabled only when trustworthy protocol-defined event timing is available and comparable across datasets. Otherwise, these indicators should remain disabled because they can introduce protocol-dependent shifts that reduce cross-dataset comparability. In particular, annotation validity is assigned weight 0 by default because a comparable reference for expected event timing is not always available: many datasets provide event markers without a trustworthy protocol-defined timing reference, and timing uncertainty can be paradigm-dependent. When expected event timing is uncertain or markers are unreliable, M_v is treated as unavailable and QS is computed from the remaining enabled indicators with renormalized weights. Subject-level values are first averaged within each subject and then macro-averaged across subjects to prevent dominance by longer recordings.

4) INTERPRETATION AND USE OF QS

QS is a 0–100 summary score used for comparative, pre-training diagnosis and ranking under a fixed protocol. For feature-based indicators, this protocol includes the selected preprocessing and the chosen feature representation. Therefore, QS should be interpreted as a comparative ranking under these evaluation settings rather than as an absolute notion of dataset quality. Under the default setting, QS is the weighted average of the mapped indicator scores (equal weights by default, renormalized if an indicator is missing). Consequently, a 10-point QS difference corresponds to a 10-point difference in this weighted average under the same settings.

Equal weights are a neutral default and can be changed when a task needs to prioritize specific dimensions. A lower-QS dataset can still be preferable when it better matches the research question, for example when it provides the required

labels or event timing, targets a specific population, contains rare events, has higher ecological validity, or matches the intended acquisition setup. In such cases, the dimension-level profile should guide mitigation instead of using QS as an acceptance threshold.

IV. IMPLEMENTATION

This section presents the technical details of how the proposed platform has been implemented. It covers the overall architecture of the system, the specific tools and libraries employed, and the procedures implemented for dataset handling. Through an examination of the system architecture, the intricate interactions among the frontend, backend, and processing layers are clarified, which together facilitate the automated evaluation of EEG datasets. Then, this section describes the technology stack employed and how it ensures scalability and modularity to integrate new metrics or functionalities. Finally, it outlines the dataset integration process, focusing on how public and private datasets are standardized and incorporated into the evaluation pipeline.

A. SYSTEM ARCHITECTURE

The platform follows a web-based modular architecture structured into three primary layers: frontend, backend, and processing modules. Each layer is responsible for different aspects of the system, ensuring scalability and efficient dataset evaluation.

- Frontend: it provides a user interface for uploading datasets, configuring analysis parameters, and visualizing results. It ensures an interactive and accessible experience for researchers working with EEG data.
- Backend: it manages data flow, processes user requests, and orchestrates dataset evaluations. It handles the coordination of quality assessment tasks and interacts with a file storage service to optimize data retrieval and processing.
- Processing Modules: they perform dataset quality evaluations, including session completeness, noise detection, class balance analysis, and feature relevance assessment. These modules are designed to operate asynchronously, allowing efficient processing of large EEG datasets while maintaining system responsiveness.

The architecture of the platform is illustrated in Fig. 2, providing an overview of the interaction between the frontend, backend, and processing modules.

B. TECHNOLOGICAL STACK

The platform has been developed following a modular and scalable approach, which enables seamless addition or removal of processing components as needed. The backend, implemented using Python 3 and Flask, manages the routing and execution of processing tasks by dynamically loading independent modules responsible for different quality assessment metrics. This modularity facilitates the efficient integration of new functionalities without affecting the core structure of the system.

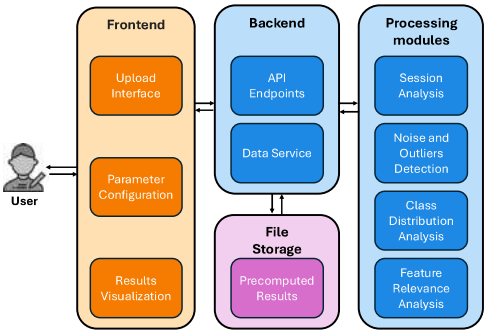


FIGURE 2. System architecture of the EEG dataset evaluation platform. The frontend supports dataset upload, parameter configuration, and result visualization. The back end exposes API endpoints and orchestrates evaluations. A data service and file storage handle retrieval and caching, while processing modules implement session analysis, noise and outlier detection, class distribution analysis, and feature relevance analysis. Modules are executed asynchronously to keep the interface responsive. Outputs include per-subject and dataset-level scores and the composite QS.

Each processing module, such as session analysis, noise detection, and feature variability assessment, is designed as an independent function that can be activated based on user-defined parameters. The processing pipeline is orchestrated using Python threading capabilities to keep module orchestration and I/O responsive during evaluation. This design should not be interpreted as unrestricted CPU-bound parallelism, since the Python Global Interpreter Lock (GIL) can limit concurrency in pure-Python sections. In the current implementation, threading was retained as a lightweight deployment choice, whereas multiprocessing or asynchronous task execution remain suitable alternatives for heavier CPU-bound workloads. A formal benchmark against these alternatives was not conducted in this version. Additionally, extracted features are cached temporarily using the Pickle library [38], reducing redundant computations and significantly improving efficiency when reprocessing datasets with the same parameters.

For data manipulation and numerical processing, the platform is based on Pandas [39] and NumPy [40], which provide the ability to handle the temporal characteristics of EEG data and perform statistical evaluations. Visualization components within the frontend utilize JavaScript to dynamically present processed results, offering users interactive insights into dataset quality.

The combination of these technologies ensures that the platform is both efficient and adaptable, serving the evolving needs of EEG data quality assessment while maintaining a user-friendly experience.

C. DATASET INTEGRATION

The platform supports EEG datasets, focusing on Event-Related Potentials (ERPs) and affective responses. An ERP

is a time-locked brain response to a stimulus. The P300 component is a well-known ERP that appears around 300 ms after infrequent or target stimuli. To ensure interoperability and systematic evaluation, all datasets must conform to a hierarchical data structure with dictionaries indexed first by subject and then by session. Within each session, EEG recordings are stored as two-dimensional matrices, where columns correspond to channels and rows correspond to samples.

The P300 component is widely used in ERP research to study attention and target detection and to support stimulus-locked analysis in BCI settings. It has also been used in neuromarketing as one application example [41]. To extract robust features that describe the magnitude and reliability of this response, the platform implements a temporal segmentation window typically within 250-500 ms after the stimulus [9]. Within each window, the following features are computed:

- Mean amplitude: The average voltage over the selected time interval.
- Standard deviation: A measure of variability in amplitude.
- Kurtosis: An indicator of potential peaks or heavy tails in the signal distribution.
- Alpha power: Estimated using the Welch method [42], which reduces variance in Power Spectral Density (PSD) estimation and facilitates the assessment of cortical activity in the alpha band (8-13 Hz) which helps measure the cognitive status.

Mathematically, each window is represented as $x \in \mathbb{R}^N$, where N is the number of samples in the window:

$$\text{Feature}_{P300} = \{\mu_x, \sigma_x, \text{kurt}(x), P_\alpha(x)\} \quad (1)$$

where μ_x represents the average of all elements in the window, σ_x is the standard deviation of all elements in the window, $\text{kurt}(x)$ denotes kurtosis values, and $P_\alpha(x)$ represents the power of the alpha band estimated by the Welch method.

For experiments aimed at capturing affective responses, the platform considers relevant EEG frequency bands including Delta (δ, 1-4 Hz), Theta (θ, 4-8 Hz), Alpha (α, 8-13 Hz), Beta (β, 13-30 Hz) and Gamma (γ, 30-45 Hz) [43]. A sliding window approach is used to dynamically compute PSD estimates for each frequency range, allowing real-time tracking of changes in power. The extracted EEG features for emotion-related analyses are defined as:

$$\text{Feature}_{Emotions} = \{P_\delta, P_\theta, P_\alpha, P_\beta, P_\gamma\} \quad (2)$$

where each P corresponds to the average power in the specified band, also estimated by the Welch method. These features are essential for analyzing arousal, valence, and consistency between subjects with respect to affective stimuli [43].

To assist researchers in preparing their datasets, the platform provides conversion scripts designed to enforce the required data structure. These scripts perform tasks such as:

- Validating the hierarchical format (Subject × Session × EEG Matrix)
- Harmonizing the sampling rate across experiments with differing acquisition frequencies.
- Identifying and handling missing data or incomplete sessions.
- Ensuring correct event segmentation and labeling, which is critical for feature extraction in stimulus-locked analyses.

The reliability of quality metrics, such as inter-subject homogeneity and MI analyses, is highly dependent on consistent data labeling and dimensionality. Consequently, this preliminary conversion and validation phase is essential. Therefore, the platform adopts a standardized protocol that facilitates enhanced comparability between publicly accessible datasets and proprietary datasets submitted by users.

The platform ensures rigorous and reproducible quality assessment through a consistent data structure and unified processing pipeline. This allows researchers to integrate datasets and obtain consistent performance scores and visualizations, supporting evidence-based decisions in EEG studies across cognitive neuroscience, BCI, affective computing, and clinical-oriented benchmarking. The implementation described in this work is openly available at [19].

V. RESULTS AND VALIDATION

The proposed platform was evaluated through a pool of experiments designed to assess its effectiveness for EEG dataset quality analysis. The validation focused on two aspects: (1) the ability to provide useful, comparable quality scores across heterogeneous datasets and (2) the ability to highlight differences in data integrity, temporal consistency, and feature relevance under a fixed evaluation protocol. All datasets were processed in identical settings to ensure comparability (Section III). Preprocessing used subject-wise standardization and fixed feature sets. The models were linear classifiers evaluated with five-fold cross-validation grouped by subject (all samples from a subject stay in the same fold to avoid leakage). Within each training fold, class proportions were preserved. The five-fold procedure was repeated ten times with independent random partitions, yielding 50 train–validation runs per model. Performance is summarized at the subject level with Balanced Accuracy (BA) and Area Under the ROC Curve (AUC), and 95% bias-corrected and accelerated bootstrap intervals.

A. BENCHMARKING PROTOCOL

This subsection describes dataset selection, preprocessing/standardization, and parameter settings used in the benchmarking case studies. Datasets were selected based on public availability and wide use, access to raw EEG organized by subject and session, and heterogeneous paradigms and acquisition settings. The evaluation pool includes DEAP [44], SEED [7], DREAMER [45], BCI Competition III [46], RSVP/P300 Speller [47], and the EEGMMIDB [48],

covering emotion recognition, P300, and motor-imagery paradigms. TABLE 4 summarizes the main dataset characteristics. The benchmarking pool was kept to six widely used public datasets to keep the protocol fixed and the comparisons reproducible. The pool focuses on emotion recognition, P300, and motor imagery because these paradigms match the target use cases and provide heterogeneous acquisition settings (channel density, sampling rate, recording structure, and class balance). This validation does not claim full representativeness across all EEG applications.

To support comparability, all datasets were standardized using the integration scripts described in Section IV-C. The hierarchical format was validated, sampling rates were harmonized when required for feature extraction, missing or incomplete sessions were flagged, and event segmentation and labeling were enforced for stimulus-locked analyses. Parameter settings were controlled through the public configuration files and kept constant across datasets unless constrained by dataset metadata (sampling rate, channel list, and event markers). Downstream performance was evaluated under a fixed protocol using subject-level aggregation with BA and AUC, 95% BCa bootstrap intervals (2000 resamples), and permutation tests with Holm correction.

The selected datasets represent real-world EEG variability because they differ in paradigm (affective vs. ERP), channel density, sampling rate, recording structure, class balance, and availability of event timing. These factors reflect common sources of variability that affect both dataset-level indicators and downstream performance, supporting a realistic benchmarking setting.

TABLE 4. Datasets used in the bench marking protocol and key sources of EEG variability.

Dataset	Paradigm	Subj.	Ch.	f_s	Variability sources covered
DEAP	Emotion	32	32	128	Audiovisual trials; self-reports; trial-based structure.
SEED	Emotion	15	62	200	Higher channel density; multi-class labels; session structure.
DREAMER	Emotion	23	14	128	Lower channel density; audiovisual stimuli; different recording setup.
BCI Competition III	P300	2	64	240	ERP epochs; event timing; structural class imbalance.
RSVP/P300 Speller	P300	55	32	512	Large scale; high sampling rate; ERP timing and repetition effects.
EEGMMIDB	Motor imagery	109	64	160	Motor/imagery runs; different run types; event timing and baseline runs.

B. DATASET ASSESSMENT CASE STUDIES

This subsection reports dataset-level quality results under the benchmarking protocol described in the previous subsection and using the dataset pool summarized in TABLE 4. The pool involves emotion recognition, P300, and motor-imagery paradigms, covering differences in label structure, channel density, sampling rate, and recording organization that commonly affect both quality indicators and downstream performance.

TABLE 5 summarize the dimension-level indicators and the composite Quality Score (QS, 0–100) defined in Section III for the six datasets. The indicators correspond to the full set listed in TABLE 3. The final column reports the composite QS.

To contextualize quality with downstream behavior under the fixed protocol, TABLE 6 reports the median BA and AUC at the subject level for each dataset. These baselines enable subsequent tests to support conceptual validity. These interpretations should be read with respect to the present preprocessing, enabled indicator set, feature representation, and weights. Consequently, expressions such as higher, lower, or stronger quality refer to comparative QS values and dimension-level scores under this fixed protocol, rather than to an absolute property of the datasets.

1) DEAP

Under the fixed protocol, DEAP attains one of the highest QS values and shows strong separability with informative features. Acquisition is uniform and cleaning is already effective, so aggressive filtering is unnecessary. Comparative studies should emphasize representation and separability rather than denoising. Under the present preprocessing, enabled indicators, and weights, DEAP is a useful benchmark when model differences are expected to come primarily from feature learning.

2) SEED

Under the fixed protocol, SEED attains a high QS and shows good cross-subject consistency, with highly informative features but intermediate separability. The main gains are likely to come from feature engineering and representation learning. Dataset stability enables comparable evaluations without complex cleaning adjustments.

3) DREAMER

DREAMER provides informative features but shows variability in session duration and limited denoising. The most direct gains come from light, artifact-focused adjustments within training folds, while keeping the evaluation protocol fixed. The dataset is appropriate for studying robustness to session variability.

4) BCI COMPETITION III

BCI Competition III is affected by strong class imbalance inherent to the oddball design and by signal instability. Priority should be prevalence-aware training, including class reweighting and calibrated decision thresholds. Additional cleaning is likely less beneficial than improving separability and tuning decision criteria.

5) RSVP/P300 SPELLER

Under the fixed protocol, RSVP/P300 Speller attains a comparatively high QS despite scarce target events and frequent outliers. The most effective strategy is prevalence-aware training and proper calibration to reduce decision bias.

TABLE 5. Summary of dimension-level results for the evaluated EEG datasets. Final: composite quality score (0–100).

Dataset	Session	Length	Outlier	Class Imb.	Filter Eff.	Overlap	MI	Homog.	Final
DEAP	100.0	100.0	53.63	74.20	87.47	96.69	100.0	82.34	86.80
SEED	100.0	91.21	94.72	100.0	32.70	65.32	100.0	90.88	83.72
DREAMER	100.0	56.68	94.42	62.50	0.05	62.21	100.0	74.57	69.17
BCI Competition III	100.0	100.0	96.35	0.09	40.06	65.25	75.0	99.32	63.85
RSVP/P300 Speller	100.0	100.0	97.29	20.00	52.95	87.99	100.0	92.89	81.39
EEGMMIDB	100.0	100.0	68.16	98.34	10.25	57.26	2.75	96.83	66.70

TABLE 6. Downstream performance by dataset under the protocol followed (subject-level median [95% BCa CI]).

Dataset	BA (%)	AUC
DEAP	79.1 [77.0, 81.0]	0.87 [0.85, 0.89]
SEED	77.0 [75.1, 78.8]	0.85 [0.83, 0.87]
RSVP/P300 Speller	74.2 [72.0, 76.3]	0.83 [0.81, 0.85]
DREAMER	70.1 [68.0, 72.1]	0.80 [0.78, 0.82]
BCI Competition III	66.2 [64.0, 68.3]	0.78 [0.76, 0.80]
EEGMMIDB	68.0 [66.5, 69.5]	0.79 [0.77, 0.81]

Further filtering tends to yield diminishing returns relative to improvements in representation and imbalance handling.

6) EEGMMIDB

EEGMMIDB was evaluated by separating runs with different motor-imagery label meanings to avoid mixing labels; results are reported for Group A (R03–R04) and Group B (R05–R06). Both groups achieved Mc=100.0 and Ml=100.0. Outlier prevalence was similar (Mo=68.242 vs. 68.087) and class balance remained high (Mb=98.342). Homogeneity was high (Mh=98.291 vs. 95.376). However, separability-related indicators were limited under the selected feature set (Mbhat=57.841 vs. 56.686; Mmi=0.859 vs. 4.650), and filtering efficiency was low (Mfe=10.928 vs. 9.576). The resulting QS values were similar (66.813 vs. 66.590).

C. DATASET COMPARISON CASE STUDY

Beyond individual assessments, the platform enables direct comparisons. To illustrate, Figure 3 shows the class balance scores for DREAMER and DEAP. Each bar represents the score at the subject level based on the distribution of the labels within those recordings of the subjects. Higher values indicate more balanced datasets. DREAMER exhibits a lower overall balance score (62.5) than DEAP (74.2), suggesting a more consistent label distribution in DEAP.

Having established dataset-level baselines and profiles, the next section tests the validity of the platform by quantifying associations between quality indicators and performance, followed by analyses that evaluate practical impact under fixed evaluation settings.

D. STATISTICAL VALIDATION

This subsection validates that the indicators and the composite QS are relevant to downstream performance under the fixed protocol. The uncertainty for BA and AUC is summarized with 95% bias-corrected and accelerated bootstrap intervals computed at the subject level (2000 resamples). Associations between QS or individual indicators and performance are quantified with Spearman's correlation on subject-level aggregates, significance is assessed by permutation with Holm adjustment across tested associations. SNR and annotation validity are reported indicators; they are not included in the default QS unless explicitly enabled.

TABLE 5 and TABLE 6 show a consistent result: datasets with higher QS also achieve higher BA and AUC with limited overlap in confidence intervals. The pooled associations in TABLE 7 indicate that the separability-oriented indicators, namely mutual information and Bhattacharyya-based overlap, exhibit the strongest positive links with AUC, while the prevalence of outliers negatively correlates. To be precise, the associations between QS and downstream performance correspond to moderate positive effects under the fixed protocol (QS→BA: $\rho = 0.62$; QS→AUC: $\rho = 0.65$ in TABLE 7). Therefore, the reported significance is accompanied by non-trivial association strength rather than being driven only by uncertainty reduction from resampling. These findings support QS as a pretraining proxy for downstream performance.

TABLE 7. Associations between quality and performance (pooled across datasets). Spearman's ρ with 95% BCa CIs (subject-level bootstrap). p_{adj} by holm.

Association (pooled)	ρ [95% CI]	p_{adj}
QS → BA	0.62 [0.47, 0.73]	<0.001
QS → AUC	0.65 [0.50, 0.76]	<0.001
M_{mi} → AUC	0.58 [0.41, 0.71]	<0.001
M_{bhat} → AUC	0.55 [0.37, 0.69]	<0.001
M_o → AUC	-0.52 [-0.67, -0.33]	<0.001
M_{snr} → AUC	0.41 [0.20, 0.58]	0.001

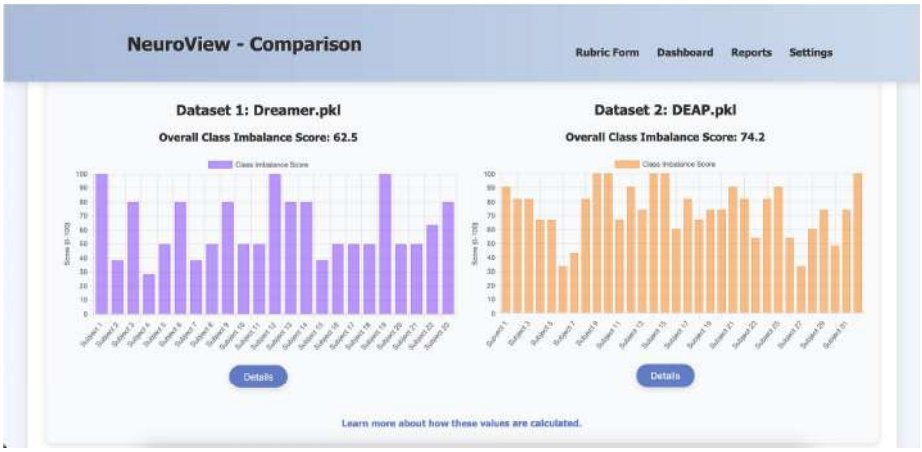


FIGURE 3. Comparison of subject-level class-balance scores for DREAMER and DEAP as displayed in the web-based platform. Each bar corresponds to one subject and reflects the within-subject label distribution, where higher values indicate more balanced classes. DREAMER exhibits lower overall balance than DEAP (62.5 vs 74.2), indicating stronger label skew in DREAMER under the fixed protocol.

E. ABLATION STUDIES

This subsection reports a QS dimension ablation to quantify the contribution of each quality dimension, robustness tests under simulated perturbations, and training-only interventions that test whether quality-oriented actions translate into performance gains without altering the test data. Dimension ablation recomputed the QS after removing one quality dimension at a time and renormalizing the remaining weights over the available metrics. Robustness was tested by injecting controlled noise and by simulating missing data, and the resulting QS degradation and ranking stability were summarized. TABLE 8 reports the dimension ablation, robustness, weight-sensitivity, and feature-set sensitivity results. In the weight-sensitivity analysis, QS was recomputed under three alternative reasonable weight configurations that emphasized different indicator families while keeping the same enabled indicator set for comparability. Ranking stability was quantified with Kendall's τ relative to the default QS. A feature-set sensitivity check was also performed on DEAP by recomputing the feature-based indicators under two alternative band-power feature sets while keeping preprocessing and weights fixed. Subject-level QS ranking stability remained high (Kendall's $\tau = 0.86$–0.90) and dataset-level QS changed by at most 1.1 points

Two training-only manipulations were evaluated under identical preprocessing, features, and hyperparameters. First, the top five percent of windows with the worst outlier score were discarded from training folds, leaving test folds unchanged. Second, class reweighting applied inverse-frequency weights in the training loss, reflecting task priors for P300 where available. Paired permutation tests on subject-level deltas provided significance, and Cliff's delta quantified effect sizes with bootstrap intervals.

TABLE 9 summarizes the training-only results. Discarding the noisiest windows leads to small but consistent improvements. In addition, class reweighting gives modest gains for emotion datasets and larger gains for ERP/P300 datasets, where class imbalance is inherent. To be precise, Cliff's δ indicates a small-to-moderate effect for discarding the noisiest windows ($\delta = 0.36$), a small effect for emotion reweighting ($\delta = 0.21$), and a larger effect for P300 reweighting ($\delta = 0.62$) (TABLE 9). Furthermore, TABLE 8 shows that QS rankings are stable under mild noise and limited missing data, while stronger perturbations reduce QS and may change the ranking when datasets have similar baseline QS. Sensitivity analyses on window length and repetition count do not change these conclusions. Therefore, the indicators remain useful under fixed evaluation settings. Finally, a feature-set sensitivity analysis was also performed for DEAP by recomputing the feature-based indicators and QS under two alternative band-power feature sets. Subject-level QS ranking stability remained high (Kendall's $\tau = 0.86$–0.90) and dataset-level QS changed by at most 1.1 points (TABLE 8).

F. SCALABILITY AND RESOURCE PROFILING

This subsection reports the computational complexity of the proposed indicators and provides indicative runtime and peak memory usage across datasets of different sizes under the default configuration. Let U denote the number of subjects, S the number of sessions per subject, C the number of channels, and N the number of samples per session. Metadata-based indicators (session completeness, session-length consistency, and class balance) scale as $\mathcal{O}(US)$. Signal-scanning indicators (outlier prevalence, filtering efficiency, and SNR) scale as $\mathcal{O}(USCN)$. Feature-based indicators (mutual information,

TABLE 8. QS dimension ablation, robustness, and weight sensitivity under simulated perturbations (default: equal weights, renormalized in ablation). Kendall's τ reports ranking stability relative to the default QS across the six datasets; QS change is averaged across datasets; feature-set sensitivity is reported for one dataset only (DEAP).

Setting	Kendall's τ	Mean QS change
Dimension ablation (removed dimension)		
Completeness	1.0	3.0
Temporal consistency	1.0	3.8
Signal integrity / noise robustness	1.0	4.6
Annotation validity	0.2	4.8
Feature relevance / separability	0.6	2.7
Robustness (perturbation)		
Noise injection ($\alpha = 0.05$)	1.0	-1.8
Noise injection ($\alpha = 0.10$)	0.8	-5.5
Noise injection ($\alpha = 0.20$)	0.6	-12.0
Missing sessions (10%)	1.0	-1.5
Missing sessions (20%)	0.8	-3.2
Missing channels (10%)	0.8	-2.5
Missing channels (20%)	0.6	-6.0
Weight sensitivity (alternative weights)		
Metadata-prioritized (Mc, Ml, Mb)	0.8	0.6
Signal-integrity-prioritized (Mo, Mfe, Mh)	0.6	-0.5
Feature-relevance-prioritized (Mmi, Mbhat, Mh)	0.6	5.5
Feature-set sensitivity (DEAP; fixed preprocessing and weights)		
Log-band power (log transform)	0.90	-0.7
Relative band power (normalized)	0.86	-1.1

TABLE 9. Training-only ablations. Paired permutation on subject-level deltas; 95% BCa CIs.

Ablation	Effect on BA/AUC	δ
Discard top 5% worst windows by M_o	ΔBA: +0.8% [0.3, 1.3] ΔAUC: +0.012 [0.005, 0.020]	0.36 [0.18, 0.52]
Class reweighting (inv. freq.), Emotion	ΔBA: +0.6% [0.0, 1.1] ΔAUC: +0.008 [-0.001, 0.017]	0.21 [0.02, 0.39]
Class reweighting (inv. freq.), P300	ΔBA: +1.8% [1.0, 2.6] ΔAUC: +0.026 [0.015, 0.038]	0.62 [0.44, 0.76]

class overlap, and homogeneity) operate on a feature matrix with n windows and d features and scale as $\mathcal{O}(nd)$ (and $\mathcal{O}(ndK)$ when computed per class with K classes). Peak memory is bounded by the largest subject/session loaded at once, i.e., $\mathcal{O}(CN_{\max})$, plus the feature matrix required by the selected indicators. TABLE 10 reports runtime and peak memory usage across datasets of different sizes.

G. DISCUSSION

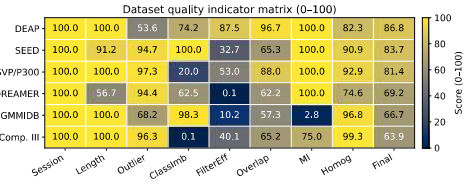
The validation results confirm that the proposed platform offers a comprehensive assessment of the quality of EEG datasets by integrating multiple domain-specific metrics, including session completeness, filtering efficiency, and class

TABLE 10. Indicative runtime and peak memory usage of the end-to-end quality assessment pipeline under the default configuration (single-process Python execution on an AMD Ryzen 7 7800 CPU with 32 GB RAM).

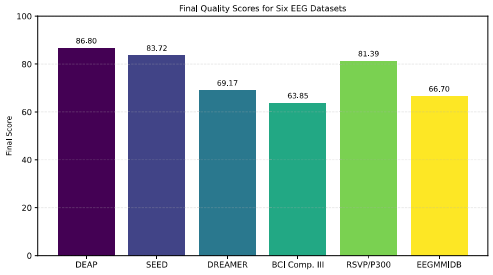
Dataset	Subj.	Ch.	f_s (Hz)	Runtime (min)	Peak RAM (GB)
DEAP	32	32	128	3.4	1.9
SEED	15	62	200	17.0	4.8
DREAMER	23	14	128	2.1	1.2
BCI Competition III	2	64	240	2.4	1.6
RSVP/P300 Speller	55	32	512	44.6	8.5
EEGMMIDB	109	64	160	52.0	7.5

overlap. FIGURE 4a and ab illustrate these findings for six widely used EEG datasets. Specifically, the heatmap (FIGURE 4a) shows the dimension-level scores (0–100) for each dataset, making differences in session structure, signal quality, and feature–label indicators easy to compare. Meanwhile, the bar chart (FIGURE 4b) condenses this multidimensional evaluation into a single final score per dataset, offering a convenient point of comparison. To support quantitative comparison, the QS-based ranking is DEAP (86.80), SEED (83.72), RSVP/P300 Speller (81.39), DREAMER (69.17), EEGMMIDB (66.70), and BCI Competition III (63.85) (TABLE 5 and FIGURE 4b). In addition, the gap between the highest and lowest QS is 22.95 points, which indicates substantial differences in the overall indicator profile across the evaluated datasets. Although specialized preprocessing routines may further optimize certain metrics (e.g., artifact removal or balanced class distributions), the current unified scoring system presents a robust preliminary framework for researchers to gauge dataset viability before undertaking more in-depth analyses.

Despite these strengths, the platform has certain limitations. Regarding weighting, the framework is intended to remain user-configured because different paradigms and scientific questions prioritize different dimensions. However, optional presets can be provided as starting points, and future releases may include community-agreed presets per paradigm while keeping full configurability. Such presets would be optional starting points rather than a single universal default. Its current design is tailored exclusively for EEG data, limiting its applicability to multimodal research that integrates additional physiological signals such as electrocardiography (ECG) or Galvanic Skin Response (GSR). Moreover, the platform relies on a predefined set of scoring dimensions and mathematical formulas, which may restrict its adaptability to EEG paradigms beyond the affective and ERP case studies considered in this validation. Another limitation is representativeness: the current validation used six public datasets covering emotion recognition, P300, and motor imagery, and it did not include other applications such as sleep staging or epilepsy detection. The proposed indicators are computed at the dataset level and most of them are paradigm-agnostic (session completeness, session-length consistency, outlier prevalence, and filtering efficiency). Paradigm-dependent indicators (class balance, annotation



(a) Dimension-level performance of the six EEG datasets studied.



(b) Overall final quality scores for each EEG dataset.

FIGURE 4. Side-by-side comparison of the six EEG datasets analyzed under the fixed bench marking protocol. (a) Heatmap (indicator matrix) reporting the dimension-level indicator profile. (b) Bar chart reporting the final composite QS, where DEAP (86.80) and SEED (83.72) score highest, RSVP/P300 Speller is intermediate (81.39), DREAMER (69.17) and EEGMMIDB (66.70) are lower, and BCI Competition III (63.85) scores lowest. Together, the two panels summarize the main drivers of each dataset profile and the resulting ranking.

validity, and feature-label measures such as mutual information or overlap) apply when labels or event markers are available. Feature-based indicators (mutual information, class overlap, and homogeneity) depend on the selected feature representation, which may differ across paradigms and studies. Therefore, the feature relevance/separability dimension reflects the joint effect of dataset properties and the chosen representation. QS should be interpreted as a comparative, pre-training ranking under the fixed evaluation protocol rather than as an absolute notion of dataset quality. Although the inclusion of weighted scoring provides a degree of flexibility, researchers cannot yet define entirely custom dimensions or introduce alternative feature evaluation methods, which may be necessary for specific analytical frameworks. Additionally, while the platform processes multiple datasets in parallel efficiently, more optimizations are required to improve its scalability for larger datasets and real-time EEG processing scenarios.

Various directions for future advancements can effectively address existing limitations and expand the scope of the platform. Primarily, the integration of user registration alongside secure data handling protocols would enable the confidential uploading, processing, and reanalysis of datasets across multiple sessions. This would allow researchers to track the progress over time, review previous evaluations, and iteratively refine data quality assessments.

Furthermore, enabling researchers to define and integrate custom feature extraction methods will enhance the flexibility of the platform. Providing a modular interface where users can upload precomputed features or develop custom processing pipelines would accommodate various experimental requirements and facilitate the adaptation to novel EEG-based studies.

Another major step is the deployment of the platform as a publicly accessible online web application, beyond simply making the code available as open-source software. This implementation would provide researchers worldwide with direct access to the platform without the need for local installation, further promoting large-scale collaborative research. To support this, scalable cloud-based computing resources and an intuitive user interface will be integrated to ensure accessibility, ease of use, and efficiency in the evaluation of datasets.

Finally, the long-term vision includes expanding the platform to support additional biosignals, such as the electrocardiogram and galvanic skin response, to extend its applicability beyond EEG research. By incorporating these advances, the platform aims to establish a standardized, flexible, and widely accessible tool for biosignal data quality assessment.

VI. CONCLUSION

This study introduces a unified, implemented platform that automates the evaluation and comparison of the quality of electroencephalography datasets. The platform combines generic indicators of completeness and session consistency with electroencephalography-specific measures of outlier prevalence, feature relevance, and artifact contamination into a single interpretable Quality Score. In contrast to existing toolboxes, it provides a unified implementation that standardizes preprocessing, scoring, and reporting across heterogeneous datasets. Consequently, researchers can systematically evaluate and benchmark both public and private datasets using consistent, domain-sensitive criteria, which current signal cleaning tools and generic data quality frameworks do not fully support.

Case studies using six well-known EEG datasets (DEAP, SEED, DREAMER, BCI Competition III, RSVP/P300 Speller, and EEGMMIDB) demonstrated the ability of the platform to identify key differences in data integrity, class distributions, and signal cleanliness. The results of the case study underscore the strengths and weaknesses of different datasets across affective and ERP paradigms. In this sense, the proposed framework supports benchmarking for cognitive neuroscience and BCI research and can inform clinical-oriented dataset selection when appropriate labels and meta-

data are available. DEAP and SEED exhibited strong session completeness and signal quality, making them suitable for affective computing tasks. DREAMER showed moderate consistency but lower filtering efficiency, suggesting potential improvements in preprocessing. BCI Competition III and RSVP/P300 Speller datasets demonstrated high class separability but also extreme class imbalances, reflecting the challenges in training robust P300 classifiers. These insights emphasize the importance of selecting datasets based on task-specific requirements and highlight the need for standardized quality assessment frameworks to improve the reproducibility of EEG research.

Unlike general-purpose data quality frameworks, this platform is specifically designed for EEG research. It includes EEG-specific metrics and supports automated or semi-automated preprocessing, reducing the manual workload for artifact rejection and feature extraction. Furthermore, its ability to handle multiple datasets in parallel addresses a key challenge in neuromarketing and related fields, where the combination of public and private data is essential to increase sample sizes and ensure robust cross-subject comparisons.

ETHICS STATEMENT

In this study, only publicly available EEG datasets were used. Ethical approval and informed consent were handled by the original data collectors and are reported in the corresponding dataset publications. This article performed only secondary analysis of de-identified data and did not involve new data collection or contact with human participants.

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