EEG-Based Emotion Recognition in Neuromarketing Using Fuzzy Linguistic Summarization

Ümran Kaya, Diyar Akay, *Senior Member, IEEE*, and Sevgi Şengül Ayan

***Abstract*—In recent years, to increase market share, companies have preferred neuromarketing over traditional methods for better analysis of consumer behavior. Since it easily detects customers' subconscious preferences, electroencephalography (EEG), a brain imaging method, has become widespread within neuromarketing techniques. To make sense of EEG signals, dimensional models are used to convert them into emotions. These steps can reveal emotions and preferences easily but still require an expert for detailed stimulus analysis. This article proposed a fuzzy linguistic summarization approach to provide a decision support tool aimed at presenting detailed analysis to neuromarketing experts. EEG signals were recorded to analyze a hotel's three (audio, video, web page) advertisements (ads). These were converted into fuzzy emotion labels in a modified Russell's circumplex model for more specific analysis. Then, these emotion labels were used in linguistic summarization. EEG data were handled in three types: univariate, multivariate, and multigranular detected time series. Each ad was summarized according to demographic features, such as gender and age, allowing comparisons between ads and their segments. The granular trend detection algorithm was modified to detect the simultaneous effects of ads. This study will inspire future studies with three innovations: fuzzy linguistic summarization technique in neuromarketing, fuzzy emotion recognition, and a modified multigranular trend detection algorithm that detects simultaneous agglomeration that is often overlooked.**

***Index Terms*—Electroencephalography (EEG), emotion recognition, fuzzy linguistic summarization (FLS), multigranular trend detection, neuromarketing.**

I. Introduction

The demand to increase market share drives businesses to compete harder, forcing them to update their marketing strategies. Advertising is the most critical field of investment among marketing methods. Of course, it is vital to research the impact on the consumer and the efficiency of high-budget advertising investments [1]. The main research approaches are traditional and neuromarketing methods. In traditional marketing, surveys and interviews are used to get consumer feedback for advertisements (ads). However, it has been observed that consumers are not always truthful in their preferences and feedback when using them. These mis-diversions indicate an inconsistency between the customer's feedback and their actual perception, understanding, and emotions [2]. Due to the shortcomings of traditional methods and the advancements in neuroscience and imaging technologies, traditional methods have been replaced by neuromarketing, which can detect consumers' subconscious behaviors and emotions [3].

Neuromarketing techniques are more effective than traditional methods in accurately detecting and reflecting the actual impact of ads on consumers [4]. When consumer glances at or focuses on a brochure, audio, or visual ads, the activities in their brain, their subconscious responses, and how they are affected by the advertising document can be understood through brain signals in neuromarketing [5]. Among these signal data, the most commonly used is electroencephalography (EEG) [6], which allows for monitoring brain activity on a millisecond basis during marketing stimuli. Its affordability makes EEG technology the most popular neuroimaging technique for evaluating marketing stimuli [7]. EEG recordings of brain activity can be separated into various frequency bands and categorized [8], and there is a significant relationship between these frequency ranges and behavioral responses and subconscious emotions [9].

In neuromarketing studies on ads, emotion recognition is crucial for understanding the consumer. EEG signals can be transformed into emotions with different categorical and dimensional models [10]. These models aim to identify what emotions the EEG signal subconsciously represents when the customer focuses on an ad [11]. However, since emotions are very limited in categorical models, dimensional models are preferred in studies. In dimensional models, an emotion can be defined as a point, and multiple emotional locations between any two emotions can be allowed [10].

At any moment of an ad, a consumer's subconscious preference and emotion can be detected by dimensional models using EEG. However, extracting all emotions for each moment of an ad creates massive data, making it challenging to interpret the consumer's behavior toward the ad. A more significant challenge than emotion recognition is to find out how ads affect consumers based on age and gender and to interpret the effects

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of ads segments using these emotions. As with data science, some methods can handle Big Data and make it understandable and interpretable. The fuzzy linguistic summarization (FLS) technique, a representative case of the former, can explain and summarize consumers' emotional data efficiently and interpret the brain acts like an expert [12].

FLS is a successful technique for extracting knowledge from big datasets in a daily natural language form [13]. It is more understandable than statistics-based summarization [14]. FLS can compare both ads and ads' segments based on gender and age using emotion labels, with a summary sample as "Most young men are more affected by the first part of the audio ad than the second part."

This study will analyze the effects of three types of ads—web, audio, and video of a hotel with FLS. EEG signals were recorded from participants and then preprocessed. Subsequently, numerical data were converted into emotion labels with Russell's 2-D circumplex model [15]. These labels were then utilized in FLS and presented in structured sentences.

Each ad data were handled within three different types to provide a comprehensive analysis. The first type was univariate EEG data, which enabled each participant to be analyzed individually. The second is the multivariate EEG data, which analyze all participants together for each ad. The last one is granular EEG data, which detected simultaneous emotion aggregations in the multivariate data in a granular format. [16]. It aims to detect how many participants feel the same emotion at any point in ads.

This study contributes three significant approaches to the literature on neuromarketing. First, it combines FLS with neuromarketing for the first time to analyze consumers' big emotion data. Second, the study converts the arctangent of arousal/valence data into an angle in Russell's model, allowing for a fuzzy set to be defined at the determined point to provide a homogeneous transition between two emotions and to determine the emotion's membership degree. Lastly, the study includes modifying the multigranular trend detection algorithm to detect the agglomeration amount and time as well as the number of affected participants in every segment of multivariate data with high precision.

The rest of this article is organized as follows. Section II discusses related works in detail. Section III provides background information that covers EEG, data preprocessing, feature extraction, FLS, and linguistic summary structures. Section IV presents the methodology, including linguistic summarization structures for our cases, as well as new approaches, such as the dimensional model and the multigranular trend detection algorithm with its modification. The experiment's design is detailed in Section V, while Section VI presents important summaries for each data type and their quality validation. Section VII discusses the ads and summaries. Finally, Section VIII concludes this article.

II. Related Works

In recent years, advertising is undoubtedly an essential part of marketing. It sustains the continuity of the manufacturing and service sectors and is regarded as the most efficient way of presenting and promoting products or services to an unfamiliar audience [17]. To understand the effects of advertising on consumers, companies and researchers have applied traditional and neuromarketing methods in this field [18]. However, it has been observed that traditional methods cannot capture consumers' instant emotions and actual preferences as they are not employed during service delivery [19]. In contrast, neuromarketing has been proven to be more valuable than traditional methods, as it can detect consumers' subconscious decisions that account for 95% of purchasing and preference behaviors [3], [20]. As a result, neuromarketing offers the ability to reach consumers' immediate and genuine preferences, which traditional methods cannot provide [20], [21], [22], [23].

The objective satisfaction evaluation [24], [25], [26] and hidden feedback [27], [28] that traditional methods cannot provide have been subconsciously detected by neuromarketing. It has been shown to be more efficient than traditional methods in evaluating stimuli, such as video [29], [30], [31], [32], [33], [34], [35], audio (such as music) [36], [37], [38], [39], [40], [41], [42], and visual (such as a picture) [43], [44], which are primarily used in ads.

The critical point in neuromarketing is to extract the subconscious emotional preferences of consumers for stimuli. It has been understood that EEG signals are more suitable for emotion recognition and more easily applicable in studies [5], [7], [8], [45], making them the most preferred and highly reliable tool in neuromarketing [6]. EEG signals do not directly recognize emotions but are used in emotion recognition methods.

In the realm of emotion recognition techniques using EEG, there are two primary approaches: categorical and dimensional [46]. Categorical models involve classifying emotions with specific labels. However, compared with the dimensional model, they have a significant drawback in limiting and categorizing emotions poorly [12]. On the other hand, dimensional models recognize emotions based on their locations. Each emotion is located at a point where it is experienced most intensely, and multiple emotions can be defined between each pair of emotion points. Consequently, dimensional models have two types, as two and three dimensions can continuously present the state of mind [11]. 2-D models are more common and effective due to ease of use and recognition [47]. Russell's circumplex model, based on arousal and valence values, is more commonly used in studies [47] and is the most preferred in 2-D models [16]. It is the fundamental model inspired by Thayer's [48] and Whissell's [49] models.

It has been observed that EEG signals are useful in the detection of various emotional states through dimensional models. Depending on the utilized index, a multitude of emotional states can be detected instantaneously. The preferred approach in neuromarketing is the approach–withdrawal (AW) index, which enables the definition of basic emotions, such as positive, negative, and neutral [30], [31], [50], [51]. However, arousal and valence indexes are frequently employed to detect more detailed emotional states, such as happy, surprised, angry, scared, disgusted, and sad. [52], [53].

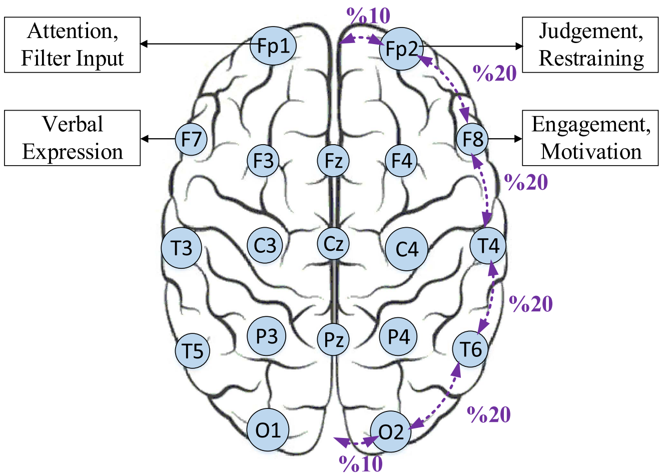

Fig. 1. Neural functions in electrodes and IS [19].

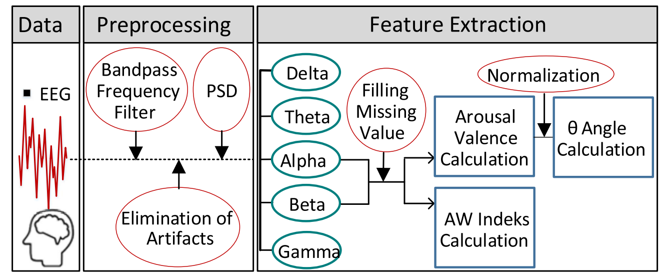

Fig. 2. Data, preprocessing, and feature extraction flow.

In neuromarketing, obtaining subconscious preferences during stimuli is a significant result. However, interpreting all the data completely can sometimes be challenging, even for experts. However, it is easy with FLS, which can provide a ready-made recommendation for experts as an efficient decision support system. This method presents complex data in easy-to-understand natural language, thereby allowing a way to summarize the effects of ads on consumers [13]. This study takes consumer emotional preferences one step further and analyzes ads individually, in general, or in partial communities, depending on temporal, quantitative, gender, and age factors.

III. Background

This section presents a brief background of methods used in the literature upon which we base our study. The section begins with a discussion on how EEG data are preprocessed and which features are selected for our studies. Finally, we provide an overview of FLS and the linguistic summary structures.

A. EEG

EEG signals can be easily received through the electrodes on the device placed on the head [19], [54], [55], [56]. The locations for electrodes on the skull were standardized by the international 10/20 system (IS) [57], [58]. The numbers 10/20 are percentiles used for positioning in the skull. This positioning is standardized by giving letters and numbers. T, C, P, and O letters indicate temporal, central, parietal, and occipital regions, respectively; even numbers indicate the right hemisphere, and odd numbers represent the left hemisphere. This lettering is not limited to these only. The spaces in between have been relettered [58].

Studies show that the preference process required for neuromarketing is done in the medial frontal cortex (see Fig. 1) [8], [19], [59]. The medial prefrontal cortex, nucleus accumbens [59], [60] and medial orbitofrontal cortex regions in the frontal brain regions have been linked to preference [60], [61]. It has been observed that consumers' choice behavior is highly correlated with activation in the nucleus accumbens, and as activation increases in the medial orbitofrontal cortex region, preference tendencies increase [59]. So, the medial frontal cortex is preferred to record EEG signals in the study.

B. Data Preprocessing

Preprocessing EEG data to improve the signal quality distorted by noise and artifacts are essential [18]. Power line interference, electronic amplifiers, and external interference caused noises. These deviations are mostly eye blinking and some joint movements that contaminate the EEG signals and spread over several channels [6], [62]. For the problems that may occur due to the noise caused by those movements, automatic algorithms based on wavelet decomposition that remove artifacts have been applied [6]. EEG signals were divided using a 0.5–50 Hz bandpass filter [63] to isolate data corresponding to the five bands. The delta band, which indicates deep sleep, is from 0.5 to 4 Hz, the theta band during light sleep is from 4 to 7.5 Hz, the alpha band seen during relaxation is from 8 to 13 Hz, the beta band seen during active thinking is from 14 to 29 Hz, and the gamma band detected in deep thinking and learning range from 30 to 45 Hz [64], [65].

Since the headband device does not fit some forehead shapes, sometimes null values occur in the dataset. These missing values were filled by the moving average method [66].

C. Feature Extraction

Feature extraction should be specific to the purpose of each study. In this study, since emotions are detected by calculating arousal, valence, and AW indexes, which are valuable for neuromarketing, frontal alpha and beta frequency bands were extracted by applying the power spectral density (PSD) method known as Welch method [19].

The arousal, valence, and AW indexes are calculated using alpha and beta signals. The arousal/valence ratio is converted using arctangent to a single angular parameter in Russell's 2-D emotion classification model. This angle is used to express the emotions with fuzzy sets in Russell's model and determine their corresponding fuzzy membership degrees. The overall process, including recording EEG data, preprocessing, and feature extraction, is illustrated in Fig. 2.

1) Power Spectral Density: Based on frequency domain analysis, PSD is the most widely used feature extraction method in neuromarketing [6], [19]. Fast Fourier transform-based method [6], which performs the Fourier transform and vice versa, converts data in the time domain to data in the frequency domain. PSD was used to divide the artifact-free EEG signals into five frequency bands.

2) Arousal and Valence: Frontal EEG asymmetry was utilized as an indicator for arousal/valence indexes [19], along with different frontal asymmetry equations employed to calculate valence/arousal [20], [61]. The arousal value was calculated through the ratio of beta and alpha values [47], while the valence value was determined by the discrepancy between the right and left frontal alpha values [19]. Arousal can be linked to energy level, while valence indicates whether that energy is positive or negative [55]. Various methods have been reported in the literature for calculating arousal/valence [10], [67], [68], [69], [70], [71]. However, (1) and (2) used by Ramirez et al. [70] were adopted for this study

$$\text{Valence} = \text{Frontal\_left}(\alpha) - \text{Frontal\_right}(\alpha) \quad (1)$$

$$\text{Arousal} = \text{Frontal}(\beta)/\text{Frontal}(\alpha). \quad (2)$$

To use arousal valence in Russell's model, their values were compressed between [−1,1] without losing information by normalization [19].

3) AW Index: The AW index has been widely used in neuromarketing literature to identify individuals' approach and withdrawal tendencies for stimulus [19]. The AW index is the frontal alpha asymmetry, which also indicates motivation. The frontal asymmetry theory states that the frontal regions of the left and right hemispheres are responsible for positive/negative feelings (AW motivation) [72]. This index can be computed by taking the difference between the two hemispheres in the prefrontal alpha band, as shown in (3), that is, the relative engagement of the frontal left hemisphere compared with the right. While positive motivation—positive AW values—(approach behaviors) occurs on higher activation of the right frontal cortex, in contrast, negative motivation—negative AW values—(withdrawal behaviors) occurs on higher activation of the left frontal cortex [72], [73], [74], [75]

$$\text{AW} = \frac{\text{alfa}(\text{Frontal\_right}) - \text{alfa}(\text{Frontal\_left})}{\text{alfa}(\text{Frontal\_right}) + \text{alfa}(\text{Frontal\_left})}. \quad (3)$$

D. Fuzzy Linguistic Summarization

Yager [76] proposed the FLS to make large datasets easy for humans to understand in short natural language sentences. Before representing the concept of linguistic summarization, we will define fuzzy sets briefly. A fuzzy subset on *X*, denoted by *A*, is defined as $A = \{\langle x, \mu_A(x)\rangle | x\epsilon X\}$, where $\mu_A(x)$ is the membership degree of *x*. The α-cut of *A* is the crisp set $A_a = \{x\epsilon X\ |\mu_A(x) \geq a\}$.

Let Y be a set of objects $Y = \{y_1, y_2, y_3, \ldots, y_M\}$, V be a set of attributes $V = \{v_1, v_2, \ldots, v_k\}$, and $X_k = \{k = 1, 2, 3, \ldots, K\}$ be the domain of v_k attribute. $v_k(y_m) \equiv v_k^m \in X_k$ is the value of the kth attribute for the mth object. Database $\mathbb{D}$ consists of data about objects belonging to set Y (4). d_m denotes all attributes of mth object

$$\mathbb{D} = \{\langle v_1^1,\ v_2^1, \ldots, v_K^1\rangle,\ \langle v_1^2,\ v_2^2, \ldots, v_K^2\rangle,\ \ldots,\ \langle v_1^M,\ v_2^M, \ldots, v_K^M\rangle\} = \{d_1,\ d_2, \ldots, d_M\}. \quad (4)$$

Yager [76] proposed two protoforms for linguistic summarization. These are type-1 and type-2 quantitative sentences [13], [76]. Apart from them, there are more structures, such as the if–then [77], [78], [79] and tree structure [80], [81], [82].

1) Type-1 Quantified Sentence: Let *Q* be the quantifier, *Y* is the object, *S* is the summarizer, and T is the truth degree. Type-1 quantifier sentence structure is "*Q Y*, *S*." [T]. T is calculated as in (5) and (6) [83]

$$T = \mu_Q\left(\frac{\sum_{m=1}^{M}\mu_s(d_m)}{R}\right) \quad (5)$$

$$R = \begin{cases} M, & Relative\ quantifier\ (\text{“}most\text{”}) \\ 1, & Absolute\ quantifier\ (\text{“}greater\ than\ 4\text{”}) \end{cases}. \quad (6)$$

If *Q* is an absolute quantifier, such as "greater than 4," *R* takes the value 1. If it is a relative quantifier, such as "most," then *R* takes the value of the total number of objects. μ_s represents the membership degree of the *S* summarizer. Summarizers, quantifiers, and qualifiers are modeled with fuzzy sets [84].

A summary sentence, such as "most time of the audio ad, participants are excited," [0.75] can be generated. Here, "most" is the quantifier, "audio ad" is the object, "excited" is the summarizer, and "0.75" is the *T* of the summary.

2) Type-2 Quantified Sentence: Protoform is "$Q\ w_g(S_g)\ Y$, *S*." [T]. In this protoform, distinct from the type-1 structure, $w_g(S_g)$ qualifier (predefined summarizer) is added. Qualifiers are adjectives that characterize the object [85]. Qualifiers enrich the summaries by adding detail and are modeled based on fuzzy sets, such as summaries and quantifiers. *T* of the summaries in the type-2 quantifier protoform is calculated as in (7) [14], [86]

$$T = \mu_Q\left(\frac{\sum_{m=1}^{M}\left(\mu_{w_g(S_g)}\left(v_g^m\right) \otimes \mu_s(d_m)\right)}{\sum_{m=1}^{M}\mu_{w_g(S_g)}\left(v_g^m\right)}\right). \quad (7)$$

The function employed in the intersection of fuzzy sets is known as t-norm (⊗), and it must meet the axioms listed as: $\forall x_1,\ x_2,\ y_1,\ y_2\ \in [01] : \otimes\ (x_1, 1) = x_1$ (Boundary), $y_1 \leq\ y_2$ implies that $\otimes(x_1,\ y_1) \leq \otimes(x_1,\ y_2)$ (Monotonicity), $\otimes\ (x_1,\ y_1) =\ \otimes(y_1,\ x_1)$ (Commutativity), and $\otimes(x_1,\ \otimes(x_2,\ y_2)) = \otimes(\otimes(x_1,\ x_2),\ y_2)$ (Associativity). The well-known t-norm used in this study is minimum $(\otimes_{\text{Min}}\ (x_1,\ y_1) = \min(x_1,\ y_1))$.

"At least half of old men are affected positively by audio ad" [0.85] is an example of this protoform, where "old" is the qualifier [13]. A set of fuzzy labels is also created for qualifiers [87].

IV. Methodology

This section provides an overview of our methodology. Initially, the conversion of angles to emotional labels using fuzzy sets in Russell's model will be discussed in detail. This will

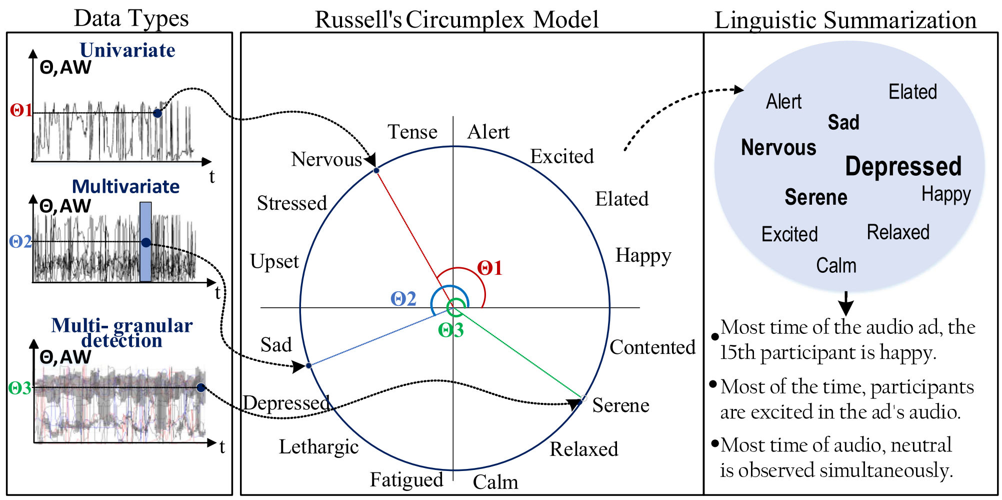

Fig. 3. Flowchart of the methodology (left-hand side: data types, middle: Russell's circumplex model, right-hand side: linguistic summarization).

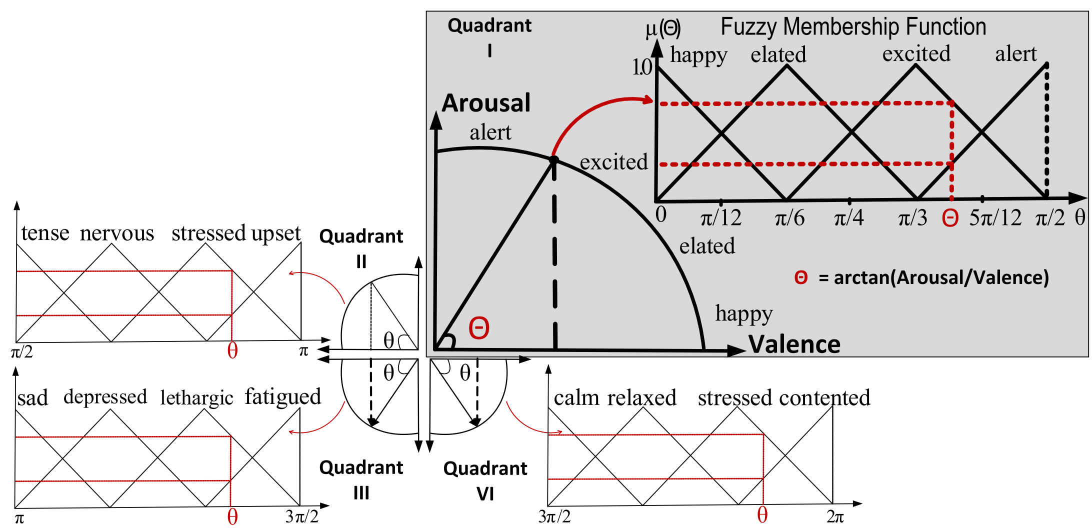

Fig. 4. Conversion of emotions to fuzzy membership function in Russell's model.

be followed by a description of the summary structures created using these labels. Finally, the multigranular trend algorithm and its development using the sliding window approach will be presented. The three summary structures were obtained using different data handling methods (univariate, multivariate, and multigranular detected trends). The data types, Russell's circumplex model, and workflow of the developed methodologies are illustrated in Fig. 3.

A. Dimensional Model of Emotions

Emotion recognition with EEG signals was studied with different models and emotions [6], [11], [47], [62], [88]. Basic emotions [89] and dozens of complex situations derived from combining several basic emotions [90] have been proposed and are classified by different dimensional models in the literature. In Russell's circumplex model [11], [16], emotions are homogeneously distributed according to their valence and arousal values (see Fig. 3).

The arousal/valence values ratio is converted into arctangent to determine the angle in Russell's circumplex [47]. This angle converts the EEG signal to Russell's model and is used in fuzzy set definition by detecting the membership degree of the emotion to which the signal corresponds. The angle (8) is calculated between the horizontal plane and the ray extending from the center to the points in the circle (the intersection of the arousal/valence values)

$$\theta = \arctan\left(\frac{\text{Arousal}}{\text{Valence}}\right). \tag{8}$$

Ruspini condition-based triangular fuzzy set is preferred [79]. Because Russell's model has a homogeneous transition between two emotions [91], Ruspini condition can only provide this homogeneous transition. The representation of the angle calculated for each quadrant in the coordinate plane and the labels defined in the generated fuzzy sets are shown in Fig. 4.

B. Summarization Structure

The summarization is structured in three types, illustrated in Fig. 3. First, all ads are summarized on an individual basis. The purpose here is to see and compare the impact of the whole ad and segments for each participant. Second, these structures are extended to encompass all participants for each ad, including gender and age factors. This step seeks to examine the overall impact of the ads on the participants and facilitate intercomparison between them. Finally, a multigranular trend detection algorithm is employed to detect and summarize simultaneous emotional agglomerations for each ad. If the populous experiences the same emotion at the same points in the ad, it is evident that the relevant part truly makes them feel those emotions. However, observing the same emotions for the populous in the second structure may not provide this information since emotion may have arisen at different times for each individual, not simultaneously.

In Russell's model, with θ angle, four basic emotions {excitement, distress, depression, relax}, 16 extended emotions {happy, elated, excited, alert, tense, nervous, stressed, upset, sad, depressed, lethargic, fatigued, calm, relaxed, serene, contented}, and AW index-based three emotions {negative, neutral, positive} are defined in fuzzy sets. The summaries are defined in two ways: general and comparative. According to the summaries structure, type-1 and type-2 quantitative protoforms were used. All protoforms and quantifiers' membership functions can be accessed via the following link.[1]

1) Univariate Structure: In this section, a total of eight structures were developed. Two examples of protoforms below explain the notations:

> "(Q) time of the (Y_{segment}) quarter of (Y) ad, (person$_{\text{N}}$) has (S) tendency for the ad. [T]"

> "For (person$_{\text{N}}$), the (Y) ad has a more positive impact than the (Y') ad. [T]"

where Q is the quantifier (few, half, at least half, most, and all), Y_{segment} is the ad segment (first, second, third, and fourth), S are the emotions, person$_{\text{N}}$ is the person, Y/Y' is the ad, and T is the truth degree.

2) Multivariate Structure: In this section, EEG signals are summarized with 15 structures. The example protoforms are as follows:

> "(Q) ($W_g(S_g)$) (G) is (S) in the (Y_{segment}) quarter of the (Y) ad. [T]"

> "($W_g(S_g)$) (G) are more affected more positively than the ($W_g(S_g)$)' (G) by (Y) ad. [T]"

where Q is the quantifier, G is gender (men and woman), ($W_g(S_g)$)/ ($W_g(S_g)$ ') are qualifiers (mature, adult, and young), (Y) is ads, Y_{segment} are ads' segments, S are emotions, and T is truth degree.

[1] [Online]. Available: https://github.com/umrankaya/-mran-Kaya/blob/main/all_structures.docx

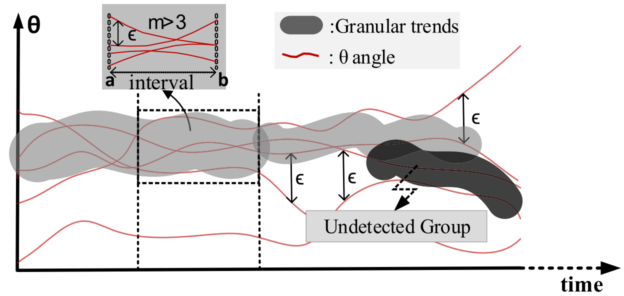

Fig. 5. Multigranular trend detection algorithm.

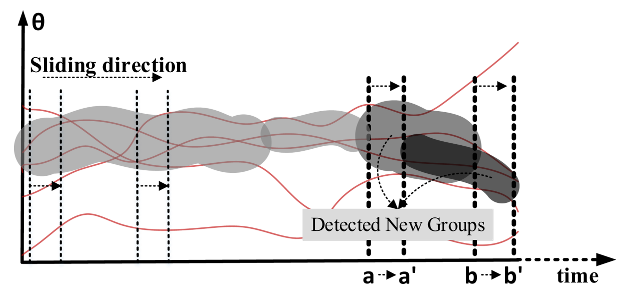

Fig. 6. Modificated version of the algorithm.

3) Granular Detected Structure: This section focuses on detecting emotions that co-occur for each ad using a modified multigranular trend detection algorithm. The detected simultaneous emotions are subsequently summarized for each ad, ad section, person density, and timely basis.

a) Multigranular trend detection algorithm: This method is based on topological grouping, which aims to present clear information by reducing uncertainty and complexity with the aggregation method while preserving the information in the input data [92], [93]. Time series is grouped according to the determined distance (ϵ), density (m), and time interval (δ) parameters. The minimum number of members required in the group is represented by m, while ϵ denotes the maximum allowable distance between two successive members in the group. In addition, δ represents the minimum time interval of the group and is shown in Fig. 5.

b) Modificated multigranular trend detection algorithm: In the model presented by Goethem et al. [17], groups combined over time could not be detected because of the principle that "groups can be separated but not combined." It causes severe data loss later in time. This problem has been overcome by modifying the algorithm with a sliding window approach. In this modification, the fundamental grouping principle was repeated for each time interval and continued until the end of the series as a sliding interval. When all groups are detected, they are combined by looking at adjacent intervals. As shown in Fig. 6, it was grouped in the a–b interval, then grouping continued with the a'–b' interval by sliding, and thus all groups were detected. Finally, the groups at each time point are combined the whole time. In this way, aggregation data for each time point were obtained ideally. It is evident in Fig. 5 that some groups (shown with a black line) could not be detected with the basic version of the algorithm at later times. However, this missing knowledge

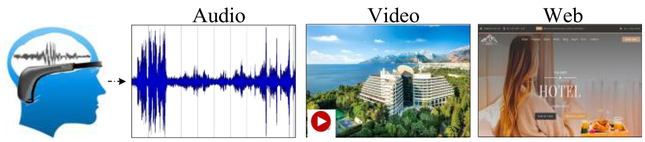

Fig. 7. Ads used in the experiment (audio, video, and web).

(two black lines) was recovered by the sliding window modification (see Fig. 6). Agglomeration levels are determined and summarized by the number of people.

c) Structures: In this section, summaries based on the ads, ads' segments, emotions, and agglomeration levels were created. Four protoforms were built. These are

"(Q) time of (Y) ad, (S) emotions are observed simultaneously as a group [T]"

"(Q) time of the ($Y_{\text{seg.}}$) quarter of (Y) ad, (S) are observed simultaneously as a group [T]"

"(Q) time of (Y) ad, S was observed by a (C_{granuls}) crowd [T]"

"(Q) time of ($Y_{\text{seg.}}$) quarter in (Y) ad, (S) was observed by a (C_{granuls}) crowd [T]"

where Q is the quantifier, (Y) are ads, $Y_{\text{seg.}}$ are ads' segments, S are emotions, C_{granuls} is agglomeration level (small, normal, big, and very big), and T is truth degree.

V. Experimental Design

It is an experiment in which 17 people participated. Some of the data obtained were unusable since the device used during the experiment did not appropriately fit the participants' head shapes. For this reason, the data of 17 participants with complete data could be used. This number may be small, but it is sufficient to implement and verify the methods. The number of users will be increased in future studies.

Two EEG signals were recorded per second (sample rate is 2Hz) while each ad was presented. The audio ad source file is a 256 Kbit mp3, and the length is 4.15 min. For the 4-min video ad, the frame is 853×480, and the quality is 720P in MP4 format. For an easy-navigate hotel web page, it is stated that just three segments were examined for nearly 4–5 min. These segments are "discover hotels," "our offers," and "activities in hotels." The experiment is illustrated representatively in Fig. 7.

Brain signals were recorded using a MUSE 2 headband that measures the electrical activity of the four-channel (TP9, AF7, AF8, TP10) brain contacting the forehead [18]. Furthermore, the Mind Monitor app saved EEG data in CSV file format. The experiment occurred in a free-of-sound room without any external factors that would affect the participants. Participants were healthy people who were not under the effects of any medication. Before or during the experiment, there was no direction to the participants. The order in which the participants watched the ads was selected randomly. Different age groups (nearly 50%, upper 30 year old) and genders (nearly 60% men and 40% women) are included heterogeneously in the experiment in neuromarketing due to their diverse preferences [66]. For this reason, the experiment was carried out by selecting the participants by paying attention to demographic characteristics, such as age and gender.

TABLE I
Linguistic Summaries of Univariate Data

Summaries	T
At least half time of the audio ad, the 15th participant is happy.	1
At least half time of the web ad, 15th participant has a positive tendency toward the ad.	1
At least half time of 1st quarter of the video ad, 15th participant has a neutral tendency toward the ad.	1
First quarter of the video ad has a more positive impact than the second quarter for the 15th participant.	0.73
For the 15th participant, the video ad has a more positive impact than the web ad.	1
For the 15th participant, stress emotion is observed most often in both the video and web ads.	0.97

VI. Result

EEG data are converted into CSV format and transferred to MATLAB for further preprocessing [45]. Three different linguistic summary structures are coded separately in MATLAB.[2] The summaries are created according to the truth degree threshold. To get the linguistic summaries with all details, the threshold value was chosen as 0.1, and ads were analyzed in four segments. The codes have been prepared functionally for more detailed examination. It contains as many combinations as the product of the quantities of features for each linguistic structure. As a result of the study, thousands of summaries were created, but the ones with the highest degree of truth were selected.

A. Univariate Summaries

Summaries that show the effects of the whole and segments of the ads on participants are presented. A few samples of summaries with the highest T are given in Table I.

Here, only a few summaries belonging to the 15th person have been presented. The most striking point in the summaries is that the first and second segments of the video affect positively, while the person is generally stressed. These contrasting emotions detected by partial analysis show that they are not due to the person's mood but are entirely due to the influence of the ads. If the person's mood was more dominant than the ad effect, the same emotion would be seen through all segments.

B. Multivariate Summaries

Summaries that show the effects of whole and segments of the ads on all participants based on age and gender are presented. The most valuable summaries appeared in this section (see Table II).

It is understood from the summaries that website ad has a more positive impact than others. While videos are considered entertaining, some studies [94] suggest that reading increases

[2][Online]. Available: https://github.com/umrankaya/LS-codes-in-MATLAB-for-EEG.git

TABLE II
LINGUISTIC SUMMARIES OF MULTIVARIATE DATA

Summaries	T
Most of the time, participants are excited during the ad's audio.	1
Few times of first quarter of the web ad, participants are excited.	0.96
At least half the time of the web ad, people have positive tendencies.	0.8
Few times of second quarter of the web, people have negative tendencies.	0.95
At least half of young women are excited in the web ad.	0.86
The first quarter of the audio ad has a more positive impact than third quarter.	0.06
In general, web ad has a more positive impact than video ad	0.46
While a positive emotion is observed most of the time in the audio, as opposed to this, neutral emotion is observed most of the time in the video ad.	0.51
At least half of old men are more affected by first quarter of audio than the third quarter.	0.46
In general, web ad affects women positively more than video ad.	0.56
Old women are more affected positively by video than young women.	0.15
Men are more affected positively by video ad than women.	0.23

Fig. 8. Word cloud with all emphasized emotion labels for multivariate summaries (audio, video, and web).

TABLE III
LINGUISTIC SUMMARIES OF MULTIGRANULAR DETECTED DATA

Summaries	T
At least half time of the audio ad, neutral emotion is observed simultaneously as a group.	1
At least half time of second quarter of the video ad, neutral emotion is observed simultaneously as a group.	1
At least half the time of the video ad, positive emotion was observed by a big crowd.	1
At least half time of third quarter in the video ad, excitement was observed by a big crowd.	1
The positive impact seen as a group in the web ad is more than in the audio ad.	0.37

positive emotional activity in the brain, supported by the summaries.

To look over the summaries that emphasize the ads' effects in general at once, a word cloud was drawn with the truth degree corresponding to the size of each emotion label in summary (see Fig. 8). Although a clear distinction between web and audio ad in the summaries is not visible here, it is expressed in general with all emotions.

C. Multigranular Detected Summaries

Summaries that show the simultaneous emotional agglomeration and the amount of agglomeration of the whole and segment of the ads are presented. A few samples with the highest T are given in Table III.

The multivariate data summaries did not reveal a significant difference between the web and audio ads. However, the web ad was found to have a more relaxing and positive impact on participants in simultaneous emotion recognition. On the other hand, the video ad had a negative effect on the participants in

Fig. 9. Word cloud with all emphasized emotion labels for granular detected summaries (audio, video, and web).

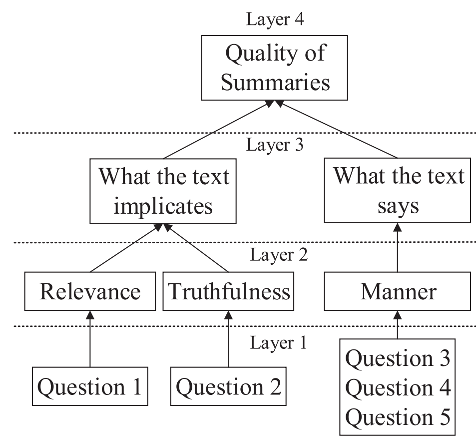

Fig. 10. Schema of the validation composition.

all data types. These results indicate that the type of ad and its content can significantly impact the audience's emotional responses. It also suggests that using simultaneous emotion recognition can provide valuable insights into the effectiveness of ads. A word cloud was created with the truth degree for each summarized emotion label to focus on the ads' overall effects for this data type (see Fig. 9).

D. Quality Validation

A questionnaire that follows the approach presented in [95] was provided to three marketing experts to evaluate the quality of the generated summaries. This questionnaire is based on three key dimensions of the summaries, as shown in Fig. 10

1) *Relevance:* Do the summaries provide all the information an expert wants?
2) *Truthfulness:* Do the summaries accurately represent the data?
3) *Manner:* Are the summaries expressed neatly and clearly?

The summaries that have the highest truth degree in Tables I–III are presented to each expert, and the following questions were asked for three important validation keys.

Question-1: What is the informative level of the summaries?
Question-2: How accurately do the summaries express the ads?
Question-3: How simple and understandable are the summaries?
Question-4: At what level is the content richness of the summaries?
Question-5: How useful is it to have summaries based on general, comparative, and demographic characteristics?

Experts were asked to evaluate the questions on a scale of 1–10 (1 "very negative" to 10 "very positive"). The results were

TABLE IV
VALIDATION QUESTIONNAIRE SCORE

Questions	Average Score	Standard Deviation
Q1	8.3	0.47
Q2	9	0.81
Q3	8.3	0.47
Q4	8.3	0.94
Q5	9.3	0.94
GQ	8.64	0.72

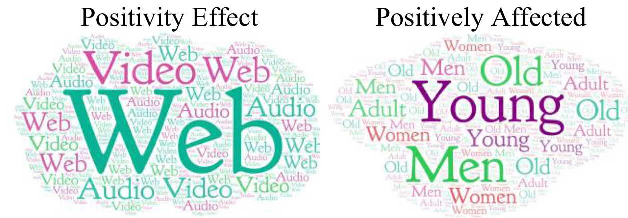

Fig. 11. Positivity effects of ads (left-hand side) and more positively affected participants' age and gender (right-hand side) emphasized with a word cloud.

calculated according to the following formulas:

$$Q_{S_i} = \frac{\frac{\overline{P1}+\overline{P2}}{2} + \frac{\overline{P3}+\overline{P4}+\overline{P5}}{3}}{2} \quad (9)$$

$$GQ = \sum_{i=1}^{n} \frac{Q_{S_i}}{n}. \quad (10)$$

The terms $\overline{P1}$, $\overline{P2}$, $\overline{P3}$, $\overline{P4}$, and $\overline{P5}$ are the average of the answers to questions 1–5, respectively, received from experts. Thus, the global quality (GQ) score for generated summaries is obtained as the average of the validation. Q_{S_i} is defined as the arithmetic mean of the two dimensions in Layer-3, and n is 23 (number of summaries presented to experts) in our case.

The assessments are given in Table IV. According to these values, the summaries' GQ score was 8.64 out of 10. This score indicates that summaries' quality is high enough.

VII. DISCUSSION

With three different data types, tens of summary structures and thousands of summaries were created. These summaries were filtered by their degree of truth, and the most accurate sentences were selected. Subconscious effects on customers are interpreted with these sentences.

One of the aims of the study was to conduct emotion analysis with broader and more sensitive measurements. Russell's model allowed for emotion diversity and fuzzification allowed for precise measurement. So, Russell's model and arousal and valence indices became inevitable. This diversity and sensitivity increased the summaries' semantic capacity and analysis ability. Otherwise, restricted emotion labels would not provide such rich summarization.

In univariate data, ads and their segments were summarized individually for each participant. At the same time, in comparative sentence structures, ads and segments were described as comparing. For instance, for the 15th participant, the second quarter of the video ad had a more positive impact than the first quarter, and the video ad was the most impressive for this participant. This summary structure has no general opinion about the ads, but it is very convenient for individual analysis. The most emphasized phenomenon in these summaries is that sometimes the person's mental state is more dominant than ad's effect. If the stimulant effect does not suppress the participant's mood and cannot rise above the threshold, EEG data cannot present the effect of the ad. It only shows the participant's instant mood. Analyzing ads person by person is critical to understanding whether the ads or the participants' moods are dominant.

With the multivariate data, the more expected and critical knowledge was extracted. With these summaries, the effect of each ad on all participants was obtained. For instance, an "excited" emotion was detected mainly for the audio ad, while a "positive" effect was for the web page. Moreover, these summaries compared the ad's segments. For example, while the participants generally felt "relaxed" in the video ad, it was realized that they were actually "stressed" in the first part.

Another curious piece of information is the AW index-based positivity effect. It was detected in web, audio, and video ads, respectively. The positive impact of the web page is quite high, but audio and video are close to each other. The positivity of web ad supports the theory that reading affects the brain more positively than watching it [94].

Another analysis feature is gender. The positivity of ads based on gender was determined as web, audio, and video for women and web, video, and audio for men. Web shows the most positive effect for both genders, but for audio and video, it is nearly identical. The result shows that to make the hotel more attractive, it should focus on web ad. However, if marketing is planned to develop based on gender, attention should be paid to audio ads for men and video ads for women. From a different point of view, it was realized that men were more affected than women in all three ads. It shows gender sensitivity and presents the potential customer's gender. This knowledge is vital in marketing to determine investments field.

For marketing, another critical feature, "age," was analyzed. Summaries presented that the most positively affected ages were young, old, and adult, respectively (see Fig. 11). Within the scope of these results, mostly men and young should be considered while updating the ad's contents, and more attractive content should be used for women.

Strangely, it was observed that although ads appear to have a significant positive impact compared with others, a closer analysis of ad segments revealed that this is not the case. This also applies to the web page.

However, these summaries are beneficial for hotel promotion and marketing strategy. By guiding marketing investments, it presents which ads should be emphasized more and which segments of the existing ads need improvement. Among the ads discussed in this study, it is observed that audio and video ads, especially the first quarter of video, need improvement. Furthermore, it also states that web page and ads placed on it should be designed for young men most positively affected by web ads. When the summaries are examined in more detail, they provide more knowledge on which part of the ad should be developed for which gender and age group.

Finally, multigranular detected summaries present the simultaneous impact of the ads and their segments on a community. In the summaries, the audio ad shows a simultaneous neutral preference, while the video and web ads generally indicate positive. However, the web page is more positive. The audio ad appeared more positive in the second structure, but it was understood with the multigranular structure that video is more favorable than audio. This is because the positive effect in the audio was not simultaneously and distributed over time. This clear comparison could be made only by multigranular structures. Individual preferences distributed over time may not reflect reality, but the stimulus that simultaneously affects a large proportion of participants may be a good hint for neuromarketing.

The multigranular algorithm has a significant role. The neuromarketing expert can analyze the ads from emotions, but revealing the number of people feeling the same emotions simultaneously within a specific interval throughout the entire data is challenging, and as the data enlarge, it becomes impossible. It is an approach that can extract significant information in neuromarketing data analysis. It can even correct information overlooked or misunderstood in other analysis methods. The positivity effect analysis between video and audio ads is an example.

This study reveals a critical fact that may seem odd at first glance. While a hotel ad is expected to relax people, trigger their imagination, and activate feelings of excitement and happiness, participants experienced intense stress and pessimism toward ads. This highlights a crucial point that people are initially biased toward presentations or things designed to sell them something. It can be argued that the intensity of this bias may vary depending on one's income level. When good things offered cannot be afforded economically, it has a negative effect on the person, and likewise, unsolicited presentations or ads do not have a positive effect on people as a result of this study.

Two main data-to-text (D2T) approaches exist in the literature: fuzzy-based and neural-based natural language generation methods. Although the FLS, a fuzzy-based approach used in the current study, has limited summary templates/structures and does not provide long and fluent text, it can extract comprehensive knowledge from the domain-specific data, and its accuracy can be measured via the degree of truth, and more, it is very effective in using vague terms in communication. In this respect, it was thought that its use in neuromarketing would be advantageous. The other approach, neural D2T, constantly improving itself in text generation over time and creating fluent and lengthy complex summaries, is examined in two categories. These are neural modular and neural end-to-end approaches. While the heuristic-based former is good at probabilistic linguistic generation, it is not scalable or adaptable to new domains. However, the latter approach reduces error propagation compared with neural modular by directly modeling the corresponding relationship between the structured data and the reference text and achieves flowing texts. However, it still has problems, such as insufficient controllability and poor truthiness [96]. In addition, neural approaches are not so efficient in measurability of vague terms [97]. Thus, if the FLS method is used in neural D2T, it can both improve the text quality with fuzzy expressions and contribute to the accuracy of the text being more measurable. In the future, the naturalness and truthiness of neural D2T's complex and fluent summaries could be improved [98].

VIII. Conclusion

This article presents the use of the FLS in analyzing the effect of hotel ads on consumers, intending to help neuromarketing experts. FLS provides clear information about the effectiveness of each ad, the emotions elicited in each segment, and how the ads affect different genders and age groups. FLS and neuromarketing combination studied for the first time within this study will shed light on future studies.

Since FLS is fuzzy set based, EEG signals were converted into fuzzy emotion labels in Russell's circumplex by fuzzified angle conversion modification. This approach also allowed a homogeneous transition between fundamental emotions and provided more realistic results in emotion detection by calculating their fuzzy membership value. Fuzzified emotion recognition has paved the way for good studies in the field by offering a different and more realistic perspective on neuromarketing and emotion recognition.

The semantic value of linguistic summaries varies according to the knowledge presented by the sentences. Although summarizing univariate and multivariate data provide significant knowledge, revealing simultaneous emotion with agglomeration amount by modificated multigranular detection algorithm is more realistic in ad analysis. This approach will provide a different perspective in neuromarketing data analysis and will be able to present the strongest points of the stimulus to experts in future works.

Inspired by this study, more extensive and innovative research will be carried out in neuromarketing. In the future, an excellent decision support system will be developed for neuromarketing experts, incorporating experiments with larger participants and more complex linguistic summaries.

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