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Multivariate Data Analysis of Consumer Behavior of Functional Products: A Neuroscience and Neuromarketing Approach to Improve Decision-Making

Jesús Jaime Moreno-Escobar[1], Verónica de Jesús Pérez-Franco[2], Ana Lilia Coria-Páez[3], Oswaldo Morales-Matamoros[1], Erika Yolanda Aguilar-del-Villar[1], Mauro Daniel Castillo-Pérez[1]

[1] Instituto Politécnico Nacional,
Escuela Superior de Ingeniería Mecánica y Eléctrica, Zacatenco,
Mexico

[2] Instituto Politécnico Nacional,
Unidad Profesional Interdisciplinaria de Ingeniería y Ciencias Sociales y Administrativas,
Mexico

[3] Instituto Politécnico Nacional,
Escuela Superior de Comercio y Admistración, Tepepan,
Mexico

jemoreno@esimez.mx, acoria@ipn.mx

Abstract. In the market for functional products, identifying the tastes and preferences of consumers is crucial to defining marketing strategies due to its difficult to penetrate nature. This article presents a study using multivariate data by means of Principal Component Analysis (PCA) and Electroencephalogram (EEG) to detect consumers' neuronal response to functional products and predict their purchasing decisions. The usefulness of neuromarketing was examined to evaluate the preferences of 16 subjects aged 20 to 29 years, who evaluated a series of samples through the sense of taste. Due to PCA being associated with frontopolar 1 located in the prefrontal cortex, we used PCA to reduce the dimensionality of the data obtained from EEG, finding that the low beta and low gamma frequency bands, along with the percentages of attention and meditation of the panelists, are the main factors in decision making. In addition, we used some digital image processing tools to support the evidence that there is a difference in the brain activity of the panelists when they taste functional products that they like and dislike. This finding can improve our understanding of decision-making and can be used in the food sector to generate a commercial strategy.

Keywords. Brain–Computer Interface (BCI), analysis of EEG signals, neuromarketing, principal component analysis (PCA), functional products, consumer behavior.

1 Introduction

The study of stimuli that influence consumer purchase decision-making has been a topic of interest for various researchers and entrepreneurs. Marketing departments of companies seek to understand in detail the needs and desires of consumers in order to reduce costs and increase the effectiveness of their advertising campaigns.

This strategic approach aims to optimize resources by improving their understanding of factors that influence consumer purchasing decisions.

The food sector is one of the most important sectors in social, cultural and economic terms for Mexico because it represents 3.9% of the GDP in 2020 [15]. However, in Latin America obesity and overweight have increased by about 58% in

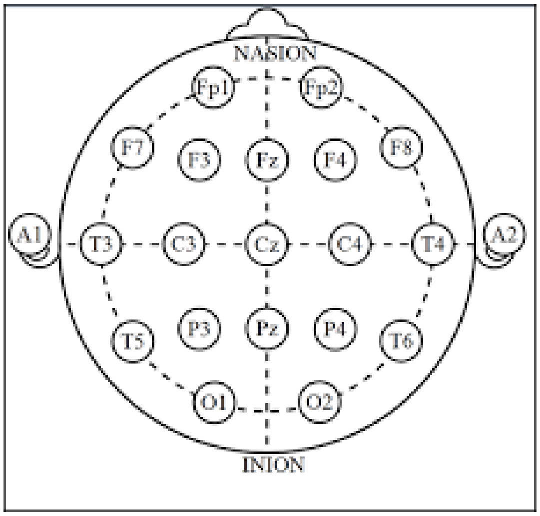

Fig. 1. International Electrode Positioning System 10-20. In this work the F_{p1} electrode is used

Latin America population [26], whilst in Mexico both diseases reached 76.4% in the adult population and 35.6% in children aged 5-11 years [27]. There are feeding patterns in Mexico that promote the increase of these diseases [10].

Obesity and overweight are related to chronic degenerative diseases such as hypertension and type 2 diabetes. This situation has led many consumers to reevaluate their personal wellness needs and has resulted in beneficial dietary changes in the population worldwide. Therefore, the food sector must know the needs and desires of consumers to design commercial strategies that are effective for business and beneficial for consumer health.

In 2023, Mexico has decreased its ranking of obesity in the world, moving from the second place reported in 2020 by ENSANUT to the fifth place currently.

These changes have resulted from actions to take care of the health of the population carried out by the Mexican government, companies, and consumers.

Government agencies from different countries have taken measures to combat obesity and overweight rates. For example, the new label on food packaging reflects the excess of calories and/or fats to encourage the population to have better eating habits [25]. This has allowed consumers to easily observe the quality of a product [11].

Additionally, there is a tax on sugary drinks, although many more years of research are required to understand the detailed dynamics of individual behavior, since data are scarce to demonstrate whether these policies really influence consumers' purchasing decisions. The nutritional products market has experienced growth in recent decades due to an increase in reflective consumers.

According to Gonzalez [13], this increase is partly due to global phenomena such as the COVID-19 pandemic, which have raised awareness among the population of the consequences of consuming products with low nutritional quality.

This change in consumer attitude has created an opportunity gap for companies that create market-benefiting products for the nutritional health market, such as functional products.

These types of food not only provide nutrients but also act on the body in various ways, such as reducing the risk of chronic diseases, regulating intestinal transit, and the immune system [2]. However, these companies require greater marketing efforts to attract consumer attention and position themselves in the minds of consumers.

The effectiveness of an advertising campaign depends on the commercial strategy used by the company to position itself in the consumer's mind. Understanding consumer preferences is key to the success of any company, however, it is not always easy to achieve this understanding.

In many cases, companies focus on sales and neglect the proper execution of marketing, as noted by Philph Kotler in 1977 [18].

To perform an effective advertising campaign, companies must conduct market research to acquire information to support the design of an appropriate commercial strategy. However, in many cases campaigns become ephemeral and generate high costs for companies.

Therefore, it is important to carry out studies to allow for standardization of the measurement and analysis of acquired data. Additionally, these commercial strategies must be innovative

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and creative in order to capture the consumer's attention and differentiate themselves from the competition.

Although companies often consider consumer behavior as a rational process, the role of emotions and mental patterns in the decision-making process cannot be ignored. Understanding these aspects allows companies to improve their marketing strategies and develop products and services that meet the needs and desires of consumers [20].

Consumers are subjected to several stimuli that cause different levels of motivation, feelings, or reactions to them [8]. Therefore. companies must investigate consumer behavior more thoroughly and select lasting and effective marketing strategies [12].

In this research, the use of computational tools is considered to generate an approach focused on the consumer's mind because computational advances help improve the precision and out-of-sample generalization to predict decisions from brain activity [39].

By conducting research based on neuromarketing, it is possible to acquire information that promotes a better understanding of consumer behavior, and thus achieve lasting marketing strategies for companies that generate and/or market food products with health benefits.

In this work a system for analyzing consumer behavior through the sense of taste is designed to predict their decision-making regarding functional products, using PCA on data obtained from the electroencephalogram (EEG) tool.

In this work, EEG signals are used to detect brain responses associated with each sensation tested, as well as to determine whether these responses are related to the preference of consumers for the samples tested. Data are collected from a group of participants who taste a variety of functional products, and their brain responses associated with each of the four basic taste sensations are recorded. In addition, to analyze the data recorded, a variable synthesis method is used to support better information management.

In the traditional statistical literature, methods have been developed to focus on analyzing only

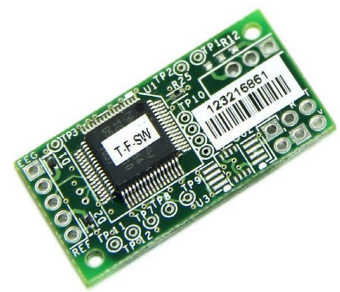

Fig. 2. Sensor ThinkGear ASIC Module v1.0 (TGAM1)

one variable. However, in real life, events often involve multiple features of interest, that is, multiple random variables. To illustrate, a marketing researcher might want to identify the characteristics of individuals that would allow him or her to determine whether a certain person is likely to buy a specific product.

Similarly, an agronomist may be interested in the resistance of new wheat varieties and their resistance to drought and insects. In some cases, researchers have at their disposal a large amount of data related to a large number of variables. This bulk of data can hinder its possible interpretation and therefore provide a solution to the problem that occupies their interest.

Usually a set of variables are related each other, so it is desirable to reduce the number of variables but without losing the information contained in the original ones. In this sense, Principal Component Analysis (PCA) is a useful statistical technique for reducing the number of original variables to a smaller set.

PCA focuses on identifying the linear relationships that exist between the original variables and so generating new variables, known as principal components, to explain the greatest amount of variability possible in the original data. These principal components are ordered in such a way that the first component explains the greatest amount of variability, the second component explains the next greatest amount of variability, and so on.

Fig. 3. Facial expressions indicating whether they like or dislike a functional product sample

In short, PCA is a useful statistical technique for reducing the number of variables in a data set, making it easier to interpret. PCA makes it possible to identify existing linear relationships between the original variables and to generate a smaller set of new variables, known as principal components, which explain as much variability as possible in the original data. Consequently, PCA is of great importance in various research areas, including statistics, economics, biology, and psychology, among others.

According to the above, this article is structured as follows: in Section 2 we describe our method for collecting electroencephalography (EEG) signals, along with the theoretical framework, including the definition of PCA and related works concerning brain waves.

Subsequently, in Section 3 we present the main outcomes obtained from reducing the dimensionality of EEG signals through PCA. In Section 4 we discuss the primary findings and results obtained from PCA in terms of detecting patterns in the brains of customers when testing functional products. Finally, in Section 5 we present our main thoughts and conclusions.

2 Method

This section is divided into five subsections and addresses the topic of Neuromarketing from a scientific perspective. The first subsection, *Related work*, reviews previous studies to expose how brain waves affect the decision-making process. The second one, *Neuromarketing: First Steps*, exposes how the fusion of neuroscience and marketing led to the creation of the field of neuromarketing.

The third, *Definition of the principal component analysis*, explains how PCA reduces the dimensionality of data and how it is applied in the interpretation of data collected through the acquisition of brain signals. The fourth, *Signal Acquisition*, describes the methods used to acquire data from brain signals, including EEG, and how these data are processed.

The fifth and final, *Experimental Methodology*, explains how the study was conducted, including participant selection, task performed, acquisition of brain signals and how the collected data were analyzed. Together, the method provides a rigorous and scientific framework for investigating the relationship between the brain and decision-making, which is essential for understanding the emerging field of neuromarketing.

2.1 Related Work

Understanding consumer behavior has been a topic of interest since the beginning of consumer psychology in the early twentieth century. The discipline of neuromarketing, which links psychology, marketing, and neuroscience, was consolidated in 2002 when Ale Smidts coined its name.

Bibliometrics show that researchers have paid increasing attention to this discipline in recent years [41]. Although little is still known about the origin of consumer preferences and how they relate to attention and memory processes in purchase decision making, the use of neuroscientific data can minimize existing market research techniques [28].

Several studies have been conducted to analyze consumer preferences in relation to taste, but three works have been of particular relevance to the development of this research. In 2004, in [17] a study was conducted using functional magnetic resonance imaging (fMRI) to detect that purchase decisions are made in the prefrontal cortex and also the perceived value of products lies in that area of the human brain.

In [9] it was determined that consumer neuroscience is an effective tool for evaluating emotional responses, providing information on food characteristics, and improving marketing strategies in food products, using techniques such as fMRI, electroencephalography, and measurement of skin conductance (SCM).

Finally, research conducted in [5] measured brain responses using fMRI while testing combinations of four basic tastes, concluding that the combination of sweet and salty is the one most associated with consumer emotion.

2.2 Neuromarketing: First Steps

It is currently a challenge for companies to emotionally understand the desires of consumers due to consumers being more informed about what they want to purchase. According to Agarwal et al. in [1], neurological research argues that a product or service correlates with the consumer's behavior when making a real purchase.

Analyzing brain activity can provide greater effectiveness in understanding consumer buying decisions. Furthermore, decision making is largely emotional and unconscious, accounting for 85-88% of the process [34, 16, 19]. Advancements in neuroscience have supported the development of more accurate techniques and tools for studying the unconscious processes of an individual's brain when making a purchasing decision.

Therefore, companies can acquire information directly from the consumer's brain during their research, rather than relying on their responses, as it has been shown that consumers' responses to market research may not necessarily reflect what they truly think or feel, leading to false purchases [38].

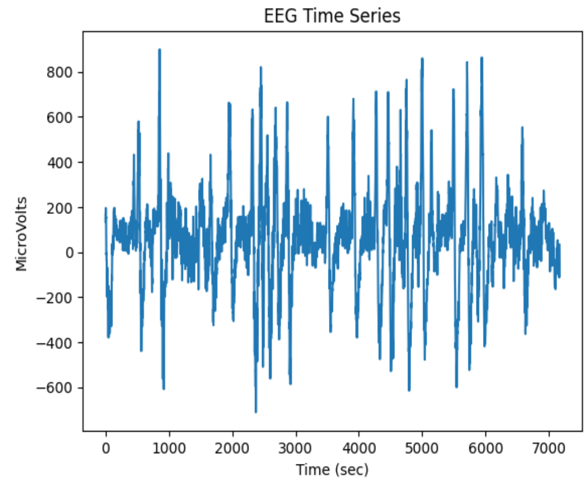

Fig. 4. Example of brain activity when a panelist eats a functional product

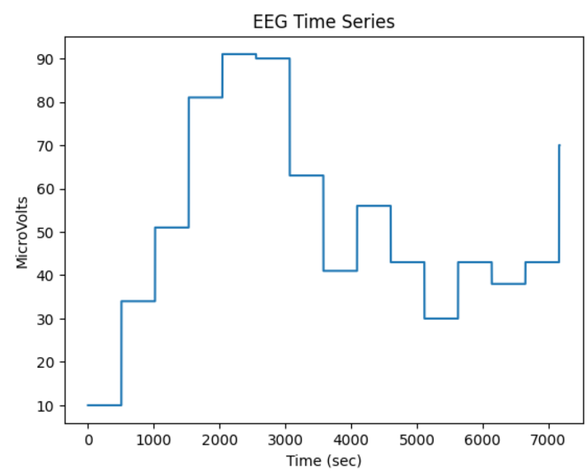

Fig. 5. Example of a panelist's attention when eating a functional product

These advancements have opened the door to neuromarketing, which is derived from consumer neuroscience.

The latter is considered the science that offers the most possibilities for recording brain activity by regions because it provides precise information for determining which neurons are activated by certain stimuli provided to different consumers.

Moreover, this interdisciplinary field detects that purchasing decisions can be influenced

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Fig. 6. QR code on Google Drive where the EEG Database can be downloaded

by subconscious processes in certain areas of the brain [23]. When the beta brain waves observed in the frontal regions of awake individuals coincide with the gamma waves that detect the characteristics of an object, activity is associated with perception.

In addition, Roopun et al. in [30] found that these waves interact through wave concatenation, able to merge, mentioning that this interaction is important for cognitive function and plays a role in human sensory perception and selective attention, supporting the purchase decision.

It was also found that low-frequency oscillations in the prefrontal cortex are related to decision-making as follows:

– Low beta. The magnitude of gradual accumulation over time in this frequency band correlates with the accuracy of choice in decision-making. This suggests that it could be an internal signal in the brain that predicts what movement will be chosen before a person makes a conscious decision [7].

– Low gamma. Specifically in the prefrontal cortex, activity in this frequency band correlates with evidence accumulation during a specific task, suggesting that it may reflect information integration for decision-making [21].

The purchasing decision is located in the cerebral cortex, where complex cognitive functions are performed such as thinking, perception, and judgment.

More specifically, in the subdivision of the cerebral neocortex responsible for decision-making, where the frontopolar 1 of the prefrontal cortex is located, located in the front of the brain, just behind the forehead. This is the main reason why EEG was considered the relevant tool for this study.

In addition to allowing real-time measurement of brain activity, EEG identifies emerging patterns and turns them into a tool to investigate how consumers process and evaluate marketing stimuli, as well as how they respond to them emotionally, in order to predict consumer preference [6].

2.3 Definition of Principal Component Analysis

Principal Component Analysis (PCA) is a fundamental statistical technique in multivariate data analysis. PCA aims to transform a set of p highly correlated variables into other new variables whose number is less than p and are not correlated with each other. The importance of PCA lies in its ability to reduce the complexity of the original data set, thereby facilitating its interpretation and further analysis.

In addition to reducing the dimensionality of the data, PCA is used to identify hidden patterns and structures in the original data. In this way, PCA can be used as an exploratory technique to identify important underlying variables and their relationship to the data set. By identifying these variables, a better understanding of the structure of the data and its relationship to the original variables can be obtained.

Although PCA generates new variables from the original variables, it is not guaranteed that all these new variables are significant in terms of their interpretation.

However, even when the new variables are not significant, their use remains valuable for tasks such as data collection and cluster verification. These tasks allow one to identify patterns in the data to be used for a wide range of applications.

Consider that each individual is described by k variables. Data from n subjects can be represented by the matrix $n \times k$ X. The data in the matrix make

Table 1. EEG sample of Panelist 3 when tasted something sweet and liked it, ten first rows

RAW	Delta	Theta	Low Alpha	High Alpha	Low Beta	High Beta	Low Gamma	High Gamma	Attention	Meditation
26	77896	11953	5560	4568	5512	4890	5572	1635	26	34
39	77896	11953	5560	4568	5512	4890	5572	1635	26	34
20	77896	11953	5560	4568	5512	4890	5572	1635	26	34
-2	77896	11953	5560	4568	5512	4890	5572	1635	26	34
-33	77896	11953	5560	4568	5512	4890	5572	1635	26	34
-13	77896	11953	5560	4568	5512	4890	5572	1635	26	34
-19	77896	11953	5560	4568	5512	4890	5572	1635	26	34
-73	77896	11953	5560	4568	5512	4890	5572	1635	26	34
-151	77896	11953	5560	4568	5512	4890	5572	1635	26	34
-209	77896	11953	5560	4568	5512	4890	5572	1635	26	34

up a cloud of n points in a k-dimensional space. Equation 1 can also be interpreted as a population having a covariance matrix $\sum$ or correlation for the variables involved k:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}. \quad (1)$$

Let $x_1, \ldots, x_k$ be a basis of $\Re^k$, let $M_1, M_2, \ldots M_n$ denote the k-dimensional cloud with n points, where $x_1, \ldots, x_k$ correspond to the point M_i in the $(x_{i1}, x_{i2}, \ldots, x_{ik})$ basis. Each row of the matrix X, defined in Equation 1, corresponds to the components of a point in the cloud in the coordinate system induced by this basis.

In this way, considering a different basis, $u_1, \ldots, u_k$ is a basis of $\Re^k$. In addition, take into account the coordinates $(z_{i1}, z_{i2}, \ldots, z_{ik})$ of the point M_i on this new base, to build the matrix Z of order $n \times k$, as follows:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1k} \\ z_{21} & z_{22} & \cdots & z_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nk} \end{bmatrix}. \quad (2)$$

To relate Z to X, we consider U as the step matrix from the base $x_1, \ldots, x_k$ to the new basis. The matrix U is a matrix $k \times k$ whose columns have the coordinates of the vectors $u_1, \ldots, u_k$ in the initial basis, which are linear combinations. In other words:

$$\begin{pmatrix} u_1 & = & u_{11}x_1 + u_{21}x_2 + & \cdots & +u_{k1}x_k \\ u_2 & = & u_{12}x_1 + u_{22}x_2 + & \cdots & +u_{k2}x_k \\ \vdots & & \vdots & \ddots & \vdots \\ u_k & = & u_{1k}x_1 + u_{2k}x_2 + & \cdots & +u_{kk}x_k \end{pmatrix}, \quad (3)$$

where $u_1, \ldots, u_k$ are unknown, $x_1, \ldots, x_k$ are vectors containing weights of linear combinations. We need the first principal component u_1 to explain the maximum possible variance, resulting from the linear combinations of the initial variables in $\overline{x}$.

Now, a restriction needs to be imposed on the magnitude of the elements of $\overline{u_1}$, because if not done, $var(u_1)$ will increase excessively, making it difficult to find a vector $\overline{u_1}$. It is generally assumed that the length of $\overline{u_1}$ is 1, that is, $\|u_1\| = 1$ once the solution and the optimal weight vector $\overline{u_1}$ are found. The linear combination $\overline{u_1}'\overline{x}$ is called the first principal component.

The next step is to find a second vector $\overline{u_2}$ such that the second component $u_2 = \overline{u_2}'\overline{x}$ has the following properties:

– It should explain the maximum possible variance of the remaining data (considering the constraint $\|u_2\| = 1$), and,

– It should not be correlated with the first principal component.

This procedure seeks to ensure no correlation to achieve the aim of ending up with the smallest number of linear combinations, taking into account

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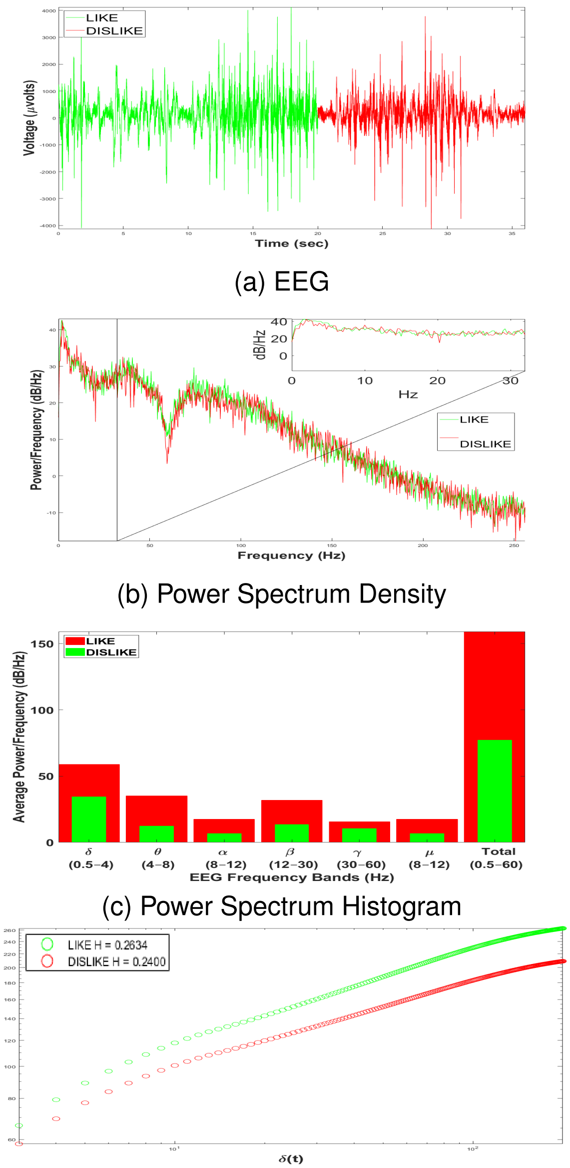

(a) EEG

(b) Power Spectrum Density

(c) Power Spectrum Histogram

(d) Self-Affine Analysis

Fig. 7. Digital processing of the EEG signal of *Panelist 1* when tasting the salty flavor of a functional product they like (in green) and dislike (in red)

the largest possible portion of the variances of the initial variables.

Once this set of $\overline{u_2}$ values is found, the linear combinations $\overline{u_2}'\overline{x}$ are called the second principal component. This process can be performed until we find k vectors $\overline{u_1}, \ldots, \overline{u_k}$ appearing on the right side of Equation 3.

By construction, the successive principal components are uncorrelated, and formally there are as many principal components as the variables studied.

Furthermore, Equation 4 can define the step matrix U, as follows:

$$U = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1k} \\ u_{21} & u_{22} & \cdots & u_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ u_{k1} & u_{k2} & \cdots & u_{kk} \end{bmatrix}. \tag{4}$$

Therefore, the relationship between Z, X and U is depicted by Equation 5 as follows:

$$X = ZU^T. \tag{5}$$

Since U is invertible, it can be deduced that:

$$X(U^T)^{-1} = Z. \tag{6}$$

If the vectors $u_1, \ldots, u_k$ form an orthonormal basis, the matrix U satisfies the relation $U^T U = I$, and therefore $\left(U^T\right)^{-1} = U$ In summary, Principal Component Analysis is a powerful and versatile statistical technique that has a wide range of applications in research and data analysis.

By allowing the reduction of data complexity and the identification of hidden patterns and structures, PCA is an essential tool in the exploration and analysis of large data sets.

2.4 Acquisition of EEG Signal

An EEG signal is the measurement of electricity flowing during synaptic excitation of dendrites in pyramidal neurons of the cerebral cortex. When neurons are activated, electricity is produced inside the dendrites, generating a magnetic and electric field that is measured with EEG systems.

The human head contains different layers (the brain, skull and scalp) to attenuate the signal and add external and internal noise, thus only a large group of active neurons can emit a potential that can be measured or recorded using surface electrodes [31].

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The electrical activity of the brain can be captured on the scalp, at the base of the skull with the brain exposed, or in deep brain locations. The electrodes that acquire the signal can be superficial, basal, or surgical. For EEG, superficial electrodes are used [32].

Generally, for the acquisition and recording of the brain's electrical activity in BCI systems, surface electrodes are used on the scalp. There are several ways to accommodate them, called acquisition systems or simply arrays, e.g., Illionis, Montreal Aird, Lennox, etc., but the most used for research purposes, and certainly in this study, is the International 10-20 Positioning System [4].

The 10-20 International System is a standardized protocol based on longitudinal anatomical references of the inion and nasion and transverse earlobes, ensuring that electrodes are placed in the same areas, regardless of head size. Furthermore, this system is named after its use of 10% or 20% of the anatomically specified distances to place the electrodes as shown in Figure 1 from the Nasion to the Inion and from the earlobes [14], indicating that it is the center.

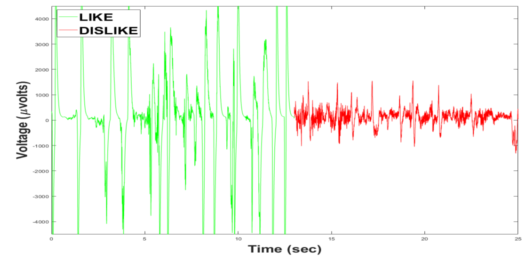
This work uses the ThinkGear TGAM1, an EEG device that collects neural signals and inputs them into the ThinkGear chip to process the signal into a sequence of usable data and filter any interference digitally. Raw brain signals are amplified and processed to provide concise contributions to the device.

The device considered as the interface between the brain and the computer is the NeuroSky ThinkGear module, Figure 2, since it meets the requirement of being a noninvasive method while also having a reliability rate of 98%. The electrode is placed in position F_{p1} [22, 35].

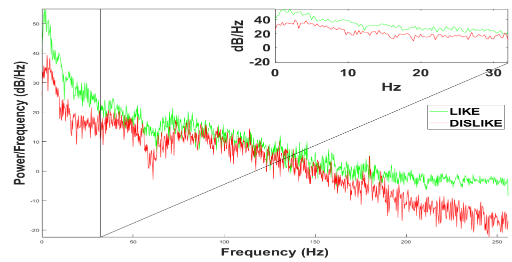
2.5 Experimental Methodology

In this section we describe the methodology used to measure the brain response of the panelists while tasting eight samples of functional products containing the four-basic taste sensations: sour, bitter, salty, and sweet.

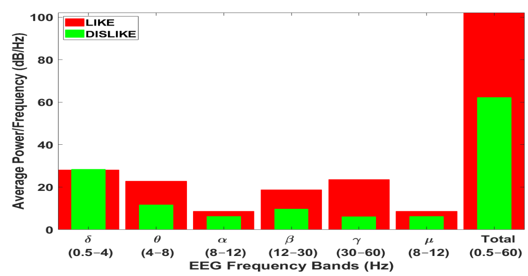
A laptop model Machenike T58 and the COLAB platform with Phyton code were used to record the data.



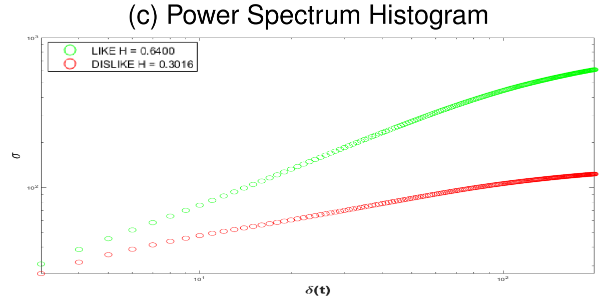
(a) EEG



(b) Power Spectrum Density



(c) Power Spectrum Histogram



(d) Self-Affine Analysis

Fig. 8. Digital processing of the EEG signal of *Panelist 11* when tasting the salty flavor of a functional product they like (in green) and dislike (in red)

We applied EEG as a neuroscientific technique in Phase 1 of an ongoing study on the use of neuromarketing to understand consumer behavior.

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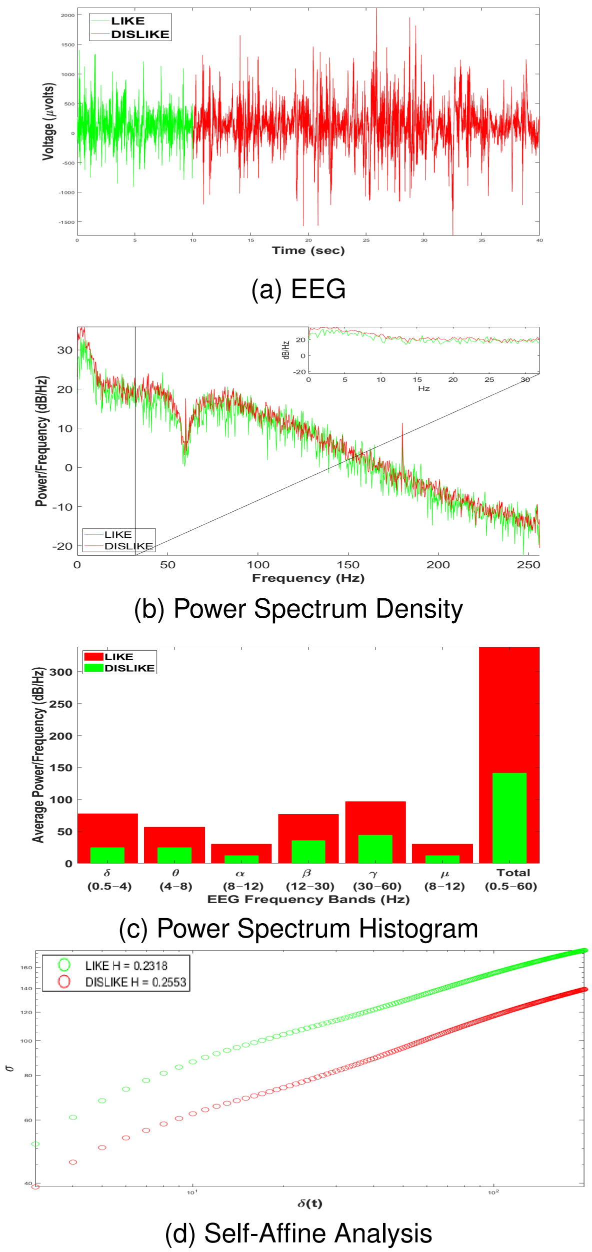

Fig. 9. Digital processing of EEG signal from *Panelist 2* when tasting the bitter taste of a functional product they like (in green) and dislike (in red)

This phase started with the preparation of the panelists to acquire the first data, pointing out the preference of the consumer for functional products. This article focuses on the results obtained in Phase 1, and the viability of continuing the research will be considered.

Phase 1 was divided into four subphases related to the sense of taste: i) the collection of the panelists' preference beliefs, ii) brain measurement through EEG, iii) verification of information, and iv) determination of the waves having a connection. These data will allow the process to be replicated on a larger scale in the research. Once Phase 1 is completed, the next Phase 2 related to the combination of the basic taste senses will proceed.

Sixteen people were recruited into a panel service, where they expressed their taste preferences and dislikes on a response application when tasting a functional food for the first time. For each panelist, two samples of each basic taste sensation were provided and they were asked to indicate whether they liked or disliked each sample. The responses of the panelists were compared with the EEG data, leaving a gap between each sample to taste an unsalted cookie and a water sip to remove any taste detected by the panelist before, Figure 3.

The panelists aged 20 to 29 years (median = 25). Prior consent was obtained from all panelists. 43. 7% of the 16 panelists were women and 56.3% men. Brain activity was measured using an EEG and the facial expressions of the panelists were recorded while tasting the samples as a test for the next phase.

Our outcomes were studied to assess the relationship between the panelists' responses and the measurements of brain activity. These results can provide valuable information to the food industry to create products that meet consumer preferences.

3 Results

To develop a Neuromarketing-based system for providing information about preferences regarding taste and visual senses, and thus to generate consumer behavior Neuromarketing strategies, we conducted tests focused on sensory Neuromarketing and emotional Neuromarketing.

Starting with sensory neuromarketing, EEG was used to acquire data on sensory perception of

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taste, as part of an ongoing research project. Access to the panelists' data was obtained that consumed functional products to analyze their brain activity and determine whether they liked the product or not.

Once this is concluded, a comparison of information can be made from emotions provoked in consumers to determine their purchasing behavior. For this study, data are acquired from the prefrontal cortex to generate information at the moment of decision making.

However, ongoing research is in its initial stage, so for this article the information was delimited to sensory neuromarketing using EEG as a tool.

3.1 EEG Data Base

The electroencephalographic sample database consists of 124 samples that vary in time but contain between nine thousand and fifteen thousand samples, equivalent to 18-30 seconds.

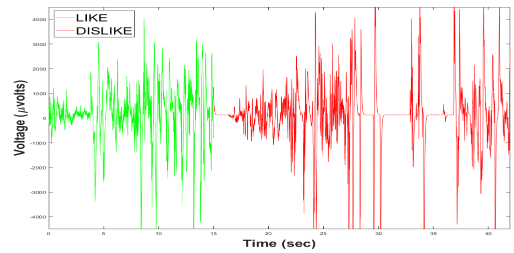
Table 1 shows a sample of 10 values of brain activity, from raw signals and preprocessed signals such as Delta, Theta, Low Alpha, High Alpha, Low Beta, High Beta, Low Gamma, and High Gamma frequency-bands (Figure 4), along with the subject's percentage of Attention (Atte) and Meditation (Med) during the test (Figure 5). The TGAM1 EEG sensor sampling rate is 512 samples per second only for the *RAW* time series, while the rest of the time series is one sample per second.

3.2 Analysis of Principal Components

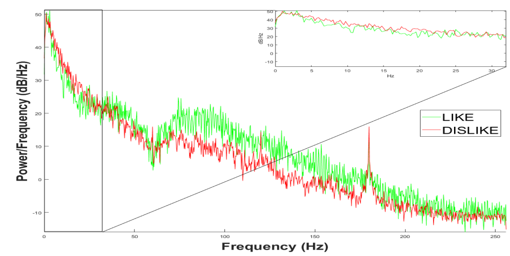
To be successful in Principal Component Analysis, we separate the samples. All separated samples are divided according to brain activity when the functional product was liked or disliked.

The divided samples are compressed into a file called *flavour.zip* and uploaded to a Google Drive folder, Figure 6. For this example, we use the EEG_DCNN folder, and the following instructions are used for decompression inside the site:

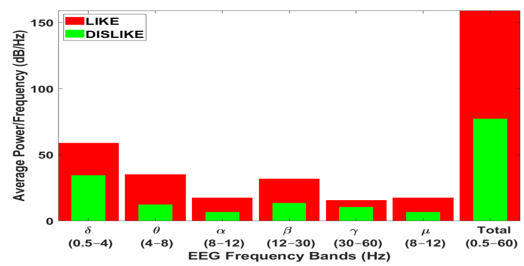
```
import zipfile
import os
path = '/content/drive/MyDrive/EEG_DCNN/flavor.zip'

with zipfile.ZipFile(path, 'r') as zip_ref:
    zip_ref.extractall()
```



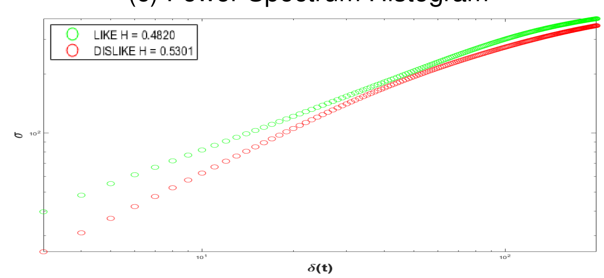
(a) EEG



(b) Power Spectrum Density



(c) Power Spectrum Histogram



(d) Self-Affine Analysis

Fig. 10. Digital processing of EEG signal from *Panelist 7* when tasting the bitter taste of a functional product they like (in green) and dislike (in red)

To store all samples, it is necessary to read and store them in a list, highlighting the inclusion of *RAW* data as follows:

```
def ReadExcelEEG(emotion):
```

Table 2. Analysis of Principal Components (PC) based on brain activity of functional products that the panelists liked

Signal	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
RAW	6.80E-06	4.13E-06	-0.000002	0.000031	0.00001	0.000097	-0.000071	-0.000014	-1	1.97E-05	-1.44E-04
Delta	9.75E-01	-2.23E-01	-0.018887	-0.001283	0.001717	-0.001517	0.003372	0.001105	0.000005	-5.39E-07	-2.74E-07
Theta	2.03E-01	9.18E-01	-0.33982	-0.018001	-0.008793	0.003576	0.004992	-0.008894	0.000005	7.19E-06	3.68E-07
LowAlpha	6.60E-02	2.34E-01	0.70082	-0.639781	0.198031	0.02778	-0.018687	-0.005683	-0.000013	-2.87E-05	-6.24E-06
HighAlpha	4.26E-02	1.41E-01	0.411845	0.250827	-0.844714	-0.001628	-0.179445	-0.010104	0.000013	-4.81E-05	8.14E-06
LowBeta	3.30E-02	1.16E-01	0.297863	0.492086	0.302997	0.681927	0.020008	0.3121	0.000079	1.36E-04	-1.06E-05
HighBeta	2.53E-02	8.46E-02	0.22783	0.389171	0.31785	-0.187136	-0.313347	-0.744715	0.00003	-1.34E-05	6.04E-05
LowGamma	2.24E-02	8.62E-02	0.199954	0.295649	0.232617	-0.675076	-0.175851	0.569138	-0.000049	-1.08E-04	-2.54E-05
HighGamma	1.73E-02	7.12E-02	0.206858	0.215474	-0.014639	-0.208419	0.915371	-0.154467	-0.000077	-2.13E-08	-2.00E-05
Atte	8.92E-07	1.29E-06	0.000018	-0.000015	-0.00003	-0.000112	-0.000049	-0.000038	0.000119	6.83E-01	-7.30E-01
Med	9.42E-07	8.51E-07	0.000019	-0.000035	-0.000036	-0.000124	-0.000002	0.000047	-0.000084	7.30E-01	6.83E-01

```
all_data = pd.DataFrame()
for j in FilesEmotions:
   path=os.path.join('/content/flavor',j,emotion,'eeg')
   print(path)
   for file in os.listdir(path):
     ts_path=os.path.join(path,file)
     TimeSeriesData = pd.read_excel(ts_path)
     all_data = pd.concat([all_data, TimeSeriesData],
                          ignore_index=True)
return all_data
```

Then, a function is generated to find the *loadings* from one to eleven dimensions, i.e., Delta, Theta, Low Alpha, High Alpha, Low Beta, High Beta, Low Gamma, and High Gamma frequency-bands, along with the subject's percentage of Attention (Atte) and Meditation (Med).

To do this, the data is first standardized and the principal components of n dimensional, and their respective *loadings* are calculated using these data as follows:

```
def PcaEeg (all_data,NoComponents):
  signals = ['RAW',"Delta", "Theta", "LowAlpha",
             "HighAlpha", "LowBeta","HighBeta", "LowGamma",
             "HighGamma",'Atte','Med']
  cols=signals[0:NoComponents]
  data = all_data.loc[:, cols].values
  data_standardized = (data - data.mean()) / data.std()

  pca = PCA(n_components=NoComponents)
  principalComponents = pca.fit_transform(data_standardized)
  principalDf = pd.DataFrame(data = principalComponents,
                           columns = cols)

  loadings = pd.DataFrame(pca.components_.T, index=cols,
                        columns = cols)
  display(loadings)

  fig, ax = plt.subplots(figsize=(12, 10))
  sns.heatmap(loadings, annot=True, cmap='coolwarm', ax=ax)
  plt.show()
  return loadings
```

To compare two components, the following function is performed, generating a scatter plot to compare the *loadings* of the electroencephalographic signals. The function is performed as follows:

```
def PlotPCA2D (loadings,ComponentA,ComponentB):
  signals = ['RAW',"Delta", "Theta", "LowAlpha",
             "HighAlpha", "LowBeta", "HighBeta",
             "LowGamma", "HighGamma",'Atte','Med']
  fig, ax = plt.subplots()
  display(pd.to_numeric(loadings.iloc[:, ComponentA],
                        errors='coerce'))
  ax.scatter(pd.to_numeric(loadings.iloc[:, ComponentA],
                           errors='coerce'),
             pd.to_numeric(loadings.iloc[:, ComponentB],
                           errors='coerce'))

  plt.xlabel('Principal Component '+ str(ComponentA+1))
  plt.ylabel('Principal Component '+ str(ComponentB+1))
  for i, name in enumerate(signals):
          ax.annotate(name, (pd.to_numeric(
              loadings.iloc[i,ComponentA],errors='coerce'),
                             pd.to_numeric(
                                 loadings.iloc[i, ComponentB]
                                 errors='coerce')))
  plt.show()
  return
```

4 Discussion

The discussion and validation of the present proposal will revolve around two main axes:

– Digital Signal Processing, using Power Spectral Density, supported by Self-Affine Analysis, and,

– Principal Component Analysis.

Table 3. Analysis of Principal Components (PC) based on brain activity of functional products that the panelists disliked

Signal	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
RAW	-3.059E-06	0.000008	-0.000005	-0.000012	-0.000023	0.000047	0.000009	-0.000017	-0.9999999	-0.0002554	-0.000214
Delta	0.9707286	-0.238494	-0.025515	-0.012427	0.000332	0.000066	0.000667	0.000839	-4.5748E-06	-1.0582E-06	-0.000002
Theta	0.21731	0.920679	-0.316519	-0.0461	-0.051301	-0.000008	0.007435	-0.011419	1.0293E-05	-2.3029E-07	0.000001
LowAlpha	0.0634106	0.211751	0.74002	-0.625721	0.056942	-0.083361	0.00652	0.041835	-9.0624E-07	4.7995E-06	0.000015
HighAlpha	0.0529627	0.137497	0.468302	0.509515	-0.654905	0.228594	-0.112308	-0.074887	1.8214E-05	1.3601E-05	0.000031
LowBeta	0.03975888	0.111597	0.251102	0.459768	0.267051	-0.750039	0.263947	-0.089352	-4.3336E-05	-2.83E-05	-0.000041
HighBeta	0.02916058	0.089915	0.144119	0.25163	0.429858	0.057633	-0.765726	0.364062	-2.3064E-05	-7.0168E-05	-0.000102
LowGamma	0.02765483	0.083036	0.177627	0.180802	0.510148	0.484666	0.118818	-0.64717	2.0146E-05	6.8152E-05	0.000082
HighGamma	0.02098957	0.065528	0.129821	0.197978	0.221086	0.374184	0.563175	0.658147	3.6358E-06	0.00011799	0.000003
Atte	1.8478E-06	0.000002	0.000001	0.000024	0.000034	0.000007	0.000018	0.000073	-2.0072E-06	-0.6368149	0.771017
Med	-5.0104E-08	0.000007	0.000025	-0.000008	-0.000009	0.00012	0.00014	-0.000047	0.00033292	-0.7710167	-0.636815

Table 4. Overall Analysis of Principal Components (PC) based on brain activity of functional products

Signal	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
RAW	9.86E-06	-0.000004	0.000004	0.000043	0.000033	0.000051	-0.00008	0.000003	-3.86E-08	2.75E-04	0.00007
Delta	4.00E-03	0.015934	0.006628	0.011144	0.001385	-0.001582	0.002705	0.000266	9.88E-06	5.19E-07	0.000002
Theta	-1.43E-02	-0.002644	-0.0233	0.028099	0.042507	0.003584	-0.002444	0.002526	-5.14E-06	7.42E-06	-0.000001
LowAlpha	2.55E-03	0.022368	-0.0392	-0.01406	0.141088	0.111142	-0.025207	-0.047518	-1.25E-05	-3.35E-05	-0.000021
HighAlpha	-1.04E-02	0.00325	-0.056457	-0.258687	-0.189809	-0.230222	-0.067137	0.064783	-5.53E-06	-6.17E-05	-0.000022
LowBeta	-6.80E-03	0.004181	0.046761	0.032318	0.035946	1.431966	-0.243939	0.401452	1.22E-04	1.64E-04	0.000031
HighBeta	-3.83E-03	-0.005289	0.083711	0.137541	-0.112008	-0.244769	0.452379	-1.108777	5.27E-05	5.68E-05	0.000162
LowGamma	-5.21E-03	0.003141	0.022327	0.114847	-0.277531	-1.159743	-0.294668	1.216307	-6.96E-05	-1.76E-04	-0.000107
HighGamma	-3.74E-03	0.00565	0.077037	0.017496	-0.235725	-0.582603	0.352195	-0.812614	-8.05E-05	-1.18E-04	-0.000023
Atte	-9.56E-07	-0.000001	0.000017	-0.000039	-0.000064	-0.000119	-0.000067	-0.00011	1.21E-04	1.32E+00	-1.501508
Med	9.921E-07	-0.000006	-0.000006	-0.000027	-0.000027	-0.000244	-0.000142	0.000094	-0.00041688	1.501507	1.319737

4.1 Digital Signal Processing

The Digital Signal Processing involves the use of two tools in the literature, namely Power Spectral Density [40, 36, 29] and Self-Affine Analysis [24, 37, 3, 33].

In this subsection, we aim to understand the nature of EEG time series so that they are analyzed in both frequency and time domains from panelists' brain activity in order to estimate the sample variability over time.

Due to the large number of samples and panelists, we conducted two experiments:

– Two panelists were selected based on liking and disliking salty taste, as shown in Figures 7 and 8.

– Two panelists were selected based on liking and dislike of the bitter taste, as shown in Figures 9 and 10.

It is worth to note that in all cases the subscripts in Figures 7, 8, 9, and 10 denote the following:

(a) The RAW EEG signal of the panelists is shown when they taste a functional product they like (in green) and dislike (in red).

(b) The Power Spectrum Density of the panelists' EEG signal is shown when they taste a functional product they like (in green) and dislike (in red).

(c) The Power Spectrum Histogram of the panelists' EEG signal is shown when they taste a functional product they like (in green) and dislike (in red).

(d) The Self-Affine Analysis of the panelists' EEG signal is shown when they taste a functional product they like (in green) and dislike (in red).

All these four experiments show some common elements, for example:

– In all Figures 7(b), 8(b), 9(b), and 10(b); there is a nearly complete attenuation at 60 Hz because a Notch filter was applied to eliminate the power line noise, and the range is up to 256 Hz due to the sampling rate of the TGAM1 EEG sensor, which is 512 samples per second.

– In all Figures 7(c), 8(c), 9(c), and 10(c); there is greater brain activity in a panelist when they taste a functional product they like compared to when they don't like it.

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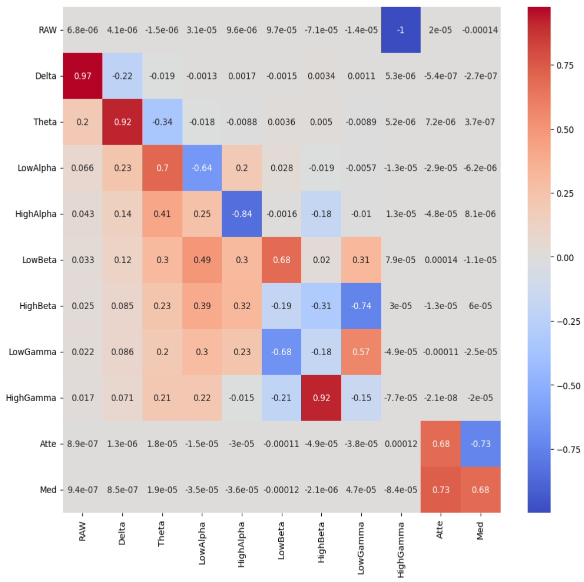

Fig. 11. Analysis of Principal Components 6 and 8 when the panelists like the functional product

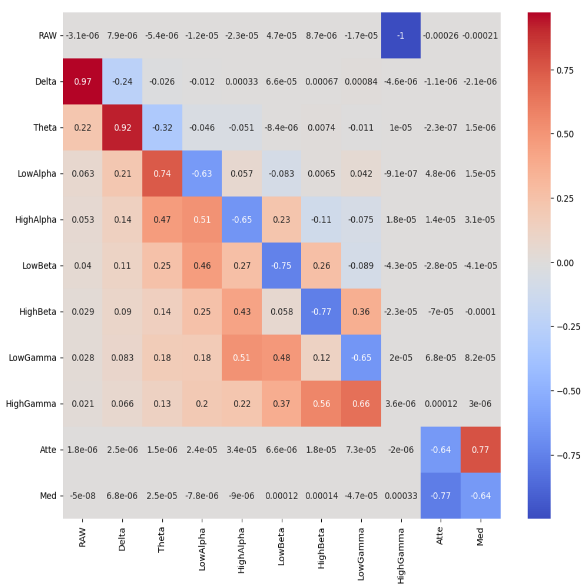

Fig. 12. Analysis of Principal Components 6 and 8 when the panelists don't like the functional product

– In all Figures 7(d), 8(d), 9(d), and 10(d); we observe an antipersistent behavior because the value of the exponent of Hurst is $H < 0.5$, that is, if the voltage during the tasting is increasing, it is more probable that the following voltage value is lower than the value of the last voltage, and vice versa. It can explain why panelists' brain activity has greater variability when they taste a functional product they like compared to when they don't like it.

Due to our findings proving the existence of a difference in the panelists' brain activity when they eat a functional food that they like and dislike, we can now establish what are the main frequency bands (δ, θ, α, β or γ;) influencing a panelist's decision-making.

4.2 Principal Component Analysis

The present study was conducted for assessing the brain activity of 16 individuals via EEG tests. A total of 124 EEG tests were collected, recorded and analyzed to identify possible patterns of brain activity associated with certain stimuli.

Furthermore, the acceptance of 8 different samples of functional products was evaluated by a group of the 16 panelists. In this regard, a total of 1 291 photographs of the tasted samples were analyzed, which were liked or disliked by the subjects or panelists surveyed.

In addition, 1 330 facial expressions were evaluated to demonstrate whether the taste sample was liked or disliked. Our results suggest a relationship between brain activity and the perception of the evaluated functional products.

The first step is to read all the brain activity samples from the panelist and place them in a list in Python. On the one hand, Principal Component Analysis is performed on only the samples that were liked by the panelists. Table 2 and Figure 11 show the results of the eleven dimensions or components in this work.

On the other hand, the same analysis was performed on samples that were not liked by the panelists, and the results of this are found in Table 3 and Figure 12.

When comparing images in Figures 11 and 12, supported by Tables 2 and 3, certain signals in specific Principal Components can be observed to clearly behave positively when the panelist likes a functional product and negatively when they do

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not. Based on this, the following four Principal Components can be highlighted:

– In Component 6, the Low Beta signal has a value of 0.68 when panelists like the product and -0.75 when they do not.

– In Component 8, the Low Gamma signal has a value of 0.57 when the panelists like the product and -0.65 when they do not.

– In Component 10, the percentage of panelists' Attention has a value of 0.68 when they like the product and -0.64 when they do not.

– In Component 11, the percentage of panelists' meditation has a value of 0.68 when they like the product and -0.64 when they do not.

When contrasting the value of the *loadings*, we can observe that few of them have a value greater than one, and that these outcomes are consistent with the low beta and low gamma frequency bands and with the Attention and Meditation percentages of the panelists. Therefore, in this contrast we subtract the *loadings* obtained when panelists like and dislike the product. These observations can be seen in Table 4 and Figure 13.

Now, when we isolate the principal components 6 and 8 for analysis of the interaction with other frequency bands, we can observe in Figures 14, 15 and 16 that the only relevant bands are Low Beta and Low Gamma. Similarly, in Components 10 and 11, Figures 17, 18 and 19, the Attention and Meditation percentages of the participants are the only relevant factors, while all frequency bands are close to zero.

Based on the above outcomes, we suggest a clear relationship between brain activity and the perception of the evaluated functional products.

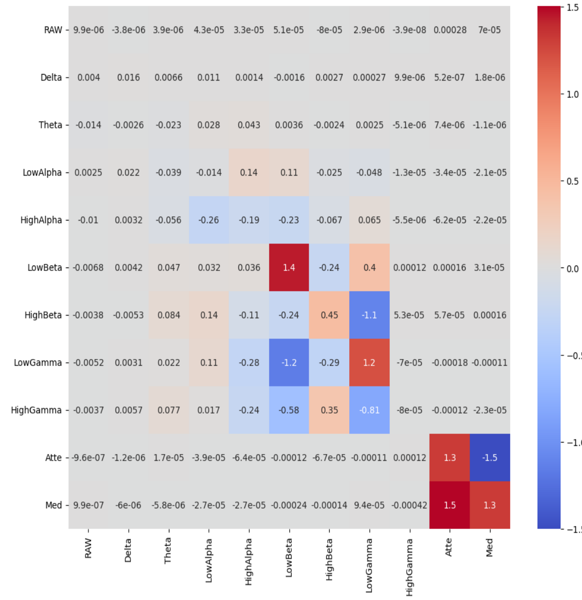

Fig. 13. Overall Analysis of Principal Components 6 and 8 when the panelists test functional products

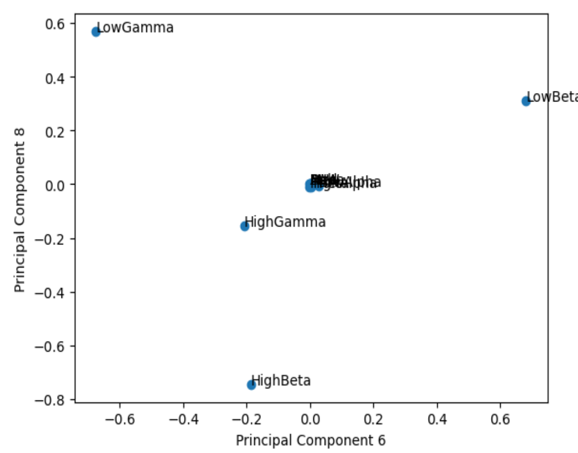

Fig. 14. Analysis of Principal Components 6 and 8 when the panelists like the functional product

5 Conclusions

Our study provides strong evidence that brain activity can be used to determine food preferences in panelists. Analysis of this study helped identify that EEG can be an effective tool for evaluating taste preferences in consumers.

By analyzing EEG signals, we were able to accurately identify whether a participant liked or disliked a particular food sample. In this way, we found that the low beta and low gamma frequency bands along with the Attention and Meditation percentages of the panelists are the main factors in decision making.

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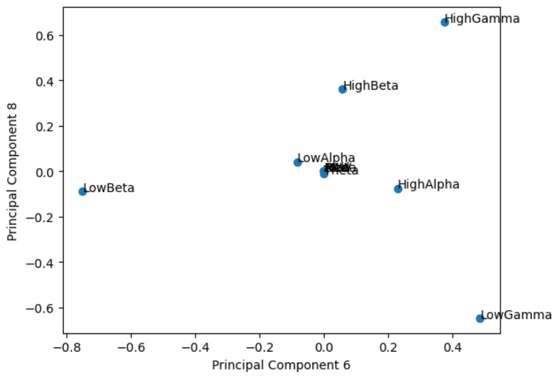

Fig. 15. Analysis of Principal Components 6 and 8 when the panelists don't like the functional product

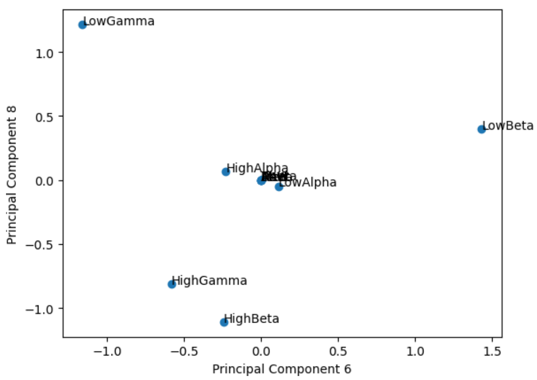

Fig. 16. Overall Analysis of Principal Components 6 and 8 when the panelists test functional products

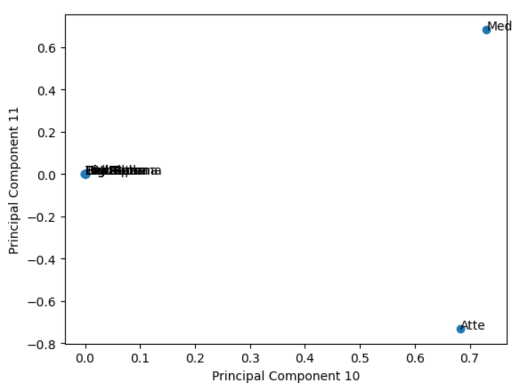

Fig. 17. Analysis of Principal Components 10 and 11 when the panelists like the functional product

This information is relevant to the food industry sector as it can provide valuable insight to companies producing or commercializing functional foods, with the intention of making their products more attractive and tailored to their target audience.

On the one hand, by analyzing the brain's electrical signals in response to different taste stimuli, researchers can determine what flavors are more attractive to each person, enabling the generation of taste combinations that are more appealing to the consumer.

The digital image processing tools, Power Spectral Density, and Self-Affine Analysis demonstrate that there is a difference in the panelists' brain activity when they eat functional foods that they like and dislike. Thus, it is clearly established that Low Beta and Low Gamma frequency bands influence a panelist's decision-making process.

However, our results suggest that facial expressions may be an important factor to consider when evaluating food preferences, as they provide valuable information that complements the EEG data. Therefore, they will be considered as part of Phase 2 of this investigation.

Regarding future work, it is recommended to further explore the relationship between brain activity and food preferences, with larger and more diverse samples.

Additionally, the incorporation of other methods of physiological measurement, such as eye tracking, may provide additional insight into the decision-making process around food choices, as information provided by the sense of sight can be identified in the same brain area as the one studied in this research.

Finally, it is suggested to investigate the possible applications of this research in the food industry, by developing personalized nutrition plans based on individuals' patterns of brain activity, aiming to provide a beneficial diet plan that helps modify the diets of the Mexican population and contributes to reducing the indicators of obesity and overweight.

Based on the findings, it is intended to continue the research with the aim of being able to develop a deep Convolutional Neural Network that allows for a greater analysis of brain activity in decision-making.

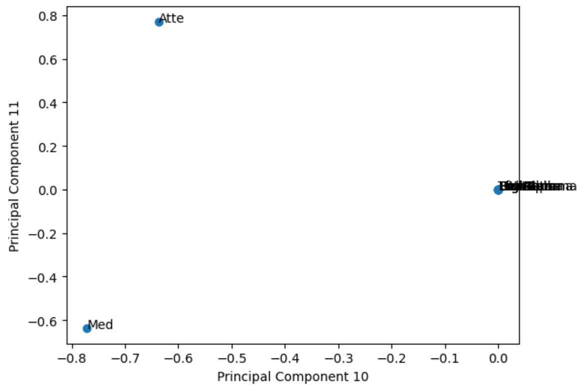

Fig. 18. Analysis of Principal Components 10 and 11 when the panelists don't like the functional product

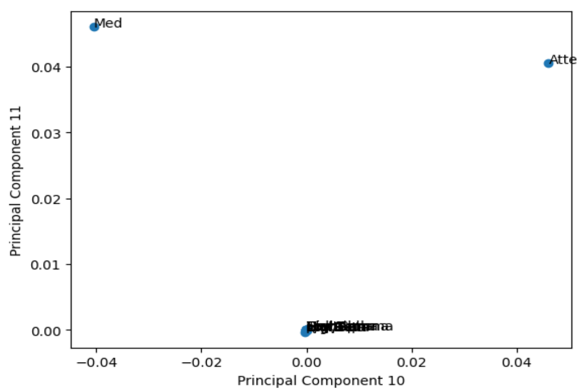

Fig. 19. Overall Analysis of Principal Components 10 and 11 when the panelists test functional products

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Corresponding author is Ana Lilia Coria-Páez.