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Neural and Behavioral Responses to Food Brands and Product
Combinations: A Neuromarketing Study

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Abstract

This study investigates whether the efficacy of retail strategies, particularly cross-merchandising, is reflected in early attentional allocation, as measured by the P300 neural component, and whether these neural responses are associated with typical consumer variables such as pleasantness, consumption frequency, and willingness to pay, as well as whether these variables are interrelated.

Sixty participants (49 females, 11 males, aged 20–35) viewed images from five sets, each containing a food brand, a complementary non-brand typically consumed alongside the brand, and the combination of the two, while EEG data were recorded to measure P300 amplitudes. Additionally, participants completed a questionnaire assessing consumer variables related to these products.

Within each set, P300 responses were compared across image types and correlated with the consumer variables, with additional correlations conducted across these variables.

Results showed no significant differences in P300 amplitudes between combinations and single products within each set, nor significant correlations between P300 responses and the consumer variables. Pleasantness and consumption frequency were positively correlated, whereas willingness to pay did not consistently correlate with either. Participants applied a significant monetary discount when evaluating combinations, although this did not relate to P300.

These findings suggest that early attentional salience, as indexed by the P300, does not capture consumers' evaluations of product combinations, preferences, consumption habits, or pricing decisions. Instead, such evaluations likely emerge at later cognitive stages.

By integrating neural and behavioral measures, this study contributes to the growing field of neuromarketing, providing insights into the complex interactions between early neural processes and consumer behavior in retail contexts.

Zusammenfassung

Diese Studie untersucht, ob die Wirksamkeit von Einzelhandelsstrategien, insbesondere Cross-Merchandising, in der frühen Aufmerksamkeitsallokation reflektiert wird, gemessen durch die P300-Neural-Komponente, und ob diese neuronalen Reaktionen mit typischen Verbrauchermerkmalen wie Gefallen, Konsumhäufigkeit und Zahlungsbereitschaft sowie untereinander in Beziehung stehen.

Sechzig Teilnehmer:innen (49 Frauen, 11 Männer, 20–35 Jahre alt) betrachteten Bilder aus fünf Sets, von denen jedes eine Lebensmittelmarke, eine ergänzende No-Name-Variante, die typischerweise zusammen mit der Marke konsumiert wird, und die Kombination der beiden enthielt, während EEG-Daten zur Messung der P300-Amplituden aufgezeichnet wurden. Zusätzlich füllten die Teilnehmer:innen einen Fragebogen aus, der Verbrauchermerkmale in Bezug auf diese Produkte erfasste.

Innerhalb jedes Sets wurden die P300-Reaktionen über die Bildtypen hinweg verglichen und mit den Verbrauchermerkmalen korreliert, wobei zusätzlich Korrelationen zwischen diesen Variablen durchgeführt wurden.

Die Ergebnisse zeigten keine signifikanten Unterschiede in den P300-Amplituden zwischen Kombinationen und Einzelprodukten innerhalb der Sets, ebenso wenig wie signifikante Korrelationen zwischen den P300-Reaktionen und den Verbrauchermerkmalen. Gefallen und Konsumhäufigkeit waren positiv korreliert, während die Zahlungsbereitschaft nicht konsistent mit einem der beiden zusammenhing. Die Teilnehmer:innen wendeten einen signifikanten monetären Rabatt bei der Bewertung der Kombinationen an, obwohl dies nicht mit der P300 in Zusammenhang stand.

Diese Ergebnisse deuten darauf hin, dass die frühe Aufmerksamkeitsrelevanz, gemessen durch die P300, die Bewertungen der Teilnehmer:innen von Produktkombinationen, Präferenzen, Konsumgewohnheiten oder Preisentscheidungen nicht erfasst. Solche Bewertungen treten wahrscheinlich in späteren kognitiven Stadien auf.

Durch die Integration neuronaler und verhaltensbezogener Messungen leistet diese Studie einen Beitrag zum wachsenden Feld des Neuromarketings und liefert Einblicke in die komplexen Wechselwirkungen zwischen frühen neuronalen Prozessen und dem Verbraucherverhalten im Einzelhandelskontext.

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1. Introduction

1.1 Introduction to Neuromarketing

In recent years, due to the rapid increase in the number of brands, companies have increasingly looked for new ways to stand out among the thousands of products that consumers encounter every day. Indeed, when simply visiting a supermarket, people are exposed to a vast array of options that it becomes difficult for companies to make their products noticeable and to ensure these will be chosen over alternatives (Gourville & Soman, 2005).

For this reason, today most companies are trying to understand the factors that lead consumers to pick their products rather than others. This challenge is not limited to physical stores, but is also common in advertising (Farooq & Maqbool, 2024). For example, how can a brand that sells an energy drink create an advertisement able to stand out among the many advertisements to which people are exposed every day?

In the last decades, these concerns were mainly addressed by marketers, who attempted to predict how to make their products more salient in order to be purchased by consumers. Marketers achieved this through a series of techniques, including surveys, qualitative research, and other methods aimed at understanding people's needs and preferences (Mariampolski, 2001).

However, what often happened was that even when consumers were explicitly asked about their preferences, these stated preferences did not always correspond to their actual purchasing behavior, a phenomenon often referred to as the 'say-do gap' (Sheeran, 2002; Barreiros Porto & Oliveira-Castro, 2013). In other words, marketers could understand what people said they wanted, but they could not fully predict what people would actually buy. This led marketers to consider that consumers' actions may be guided by deeper, unconscious processes, which, if understood, could better predict what actually attracts people to a specific product (Wongtada, 2018).

It is at this point that companies began to take an interest in the brain, specifically in the neural processes underlying decision-making. They realized that if they could link their theories to neuroscience and understand what happens at a non-conscious level, they would gain better insight into the mechanisms driving consumers' decisions.

For this purpose, a new field, called Neuromarketing, was born, with the aim of understanding what actually drives consumers' choices by exploring the mechanisms occurring in the brain at a non-conscious level. This term was coined by Professor A. Smidts

in 2002, representing a fusion between neuroscience and marketing (Iloka, & Onyeke, 2020). Although this term was coined more than twenty years ago, it is only in the last decade that it has begun to truly transform the field of marketing, being taken seriously as a scientific approach to understanding consumer behavior (Bhardwaj et al., 2023). Neuromarketing does not integrate only marketing and neuroscience, but also psychology, which helps explain the biases and heuristics that people use to make purchasing decisions (Arora & Jain 2020). Let us now explore how methods from neuroscience and psychology have contributed to the development of a new way of doing marketing, especially through the use of Neuroimaging.

1.2 Neuroimaging

The term “Neuroimaging” represents all the scientific, non-invasive techniques used in neuroscience to study the structure and function of the brain through direct or indirect measurement of brain activity (Ekstrand, 2022).

These techniques can be divided into two groups: structural methods (i.e., structural neuroimaging) and functional methods (i.e., functional neuroimaging).

Structural methods, such as Magnetic Resonance Imaging (MRI), are used to study the structure of the brain. They are useful to detect anatomical abnormalities or injuries. However, they do not allow the observation of the brain's responses to specific stimuli.

Functional methods, on the other hand, are used to analyse brain processes associated with cognitive and emotional responses to particular stimuli. Some common techniques include: functional Magnetic Resonance Imaging (fMRI), which is used to measure changes in blood oxygenation to infer neural activity; Electroencephalography (EEG), which provides a real-time view of the brain's electrical function; and Magnetoencephalography (MEG), which captures magnetic fields generated by neurons to map brain activity (Gui et al., 2010).

Each technique presents both strengths and weaknesses, specifically regarding temporal resolution, spatial resolution, costs, and ecological validity.

fMRI, for instance, has a high spatial resolution, allowing the identification of specific brain area activations. However, it has poor temporal resolution, as it records data only in order of seconds, which is too slow to capture rapid changes in brain activity. Therefore, its use is very limited in those studies in which researchers need to monitor cognitive processes in real time (Afrasiabi & Noroozian, 2015).

On the other hand, EEG has a very good temporal resolution, meaning that rapid neural dynamics, which occur in the order of milliseconds after the presentation of a stimulus, are

fully captured. However, EEG has a poor spatial resolution, meaning it is limited in detecting the specific area where the signal was produced (Blinowska & Durka, 2006).

In the last decades, neuroimaging techniques have started to be implemented not only in neuroscience and psychology, but also in more applied fields such as marketing, where they are used to explore the neural mechanisms underlying consumer behavior, decision-making processes, and preference formation (Morin, 2011).

In marketing, temporal resolution is highly important, as most brain processes associated with consumer behavior, such as attentional allocation and product evaluation, occur rapidly, typically outside conscious awareness. In addition, this field aims to use techniques that are non-invasive, economically sustainable, and adaptable to different experimental contexts. Overall, marketers consider highly relevant methods characterized by high temporal resolution and experimental flexibility (Khurana, 2021).

Therefore, EEG has become one of the most widely used neuroimaging techniques for analyzing consumer behavior, both because of its high capacity to capture real time brain responses, and because of its practical ease of use and compatibility with a variety of research designs employing different types of stimuli (Alsharif et al., 2022).

The study presented in this thesis adopted EEG for these reasons.

Let us now explore in detail what EEG is and how we can apply it in neuromarketing research.

1.2.1 Electroencephalography

In the brain, neurons communicate through electrical signals. When large groups of neurons fire together, their activity can be detected at the scalp.

Let us explore this in detail.

The electrical signals recorded through EEG originate from cortical pyramidal neurons, which are located mainly in the superficial layers of the cortex. They are very numerous, and are organized in a highly uniform and parallel manner. In addition, their dendrites extend perpendicular to the cortical surface (see Figure 1.1).

When pyramidal neurons generate postsynaptic potentials (i.e., changes in the postsynaptic membrane induced by neurotransmitters), they do so in a highly coordinated way, producing synchronous electrical activity. This facilitates both temporal and spatial summation when large populations of these neurons are activated at the same time. In this way, it is possible to monitor cerebral dynamics in real time as they occur (Kirschstein & Köhling, 2009).

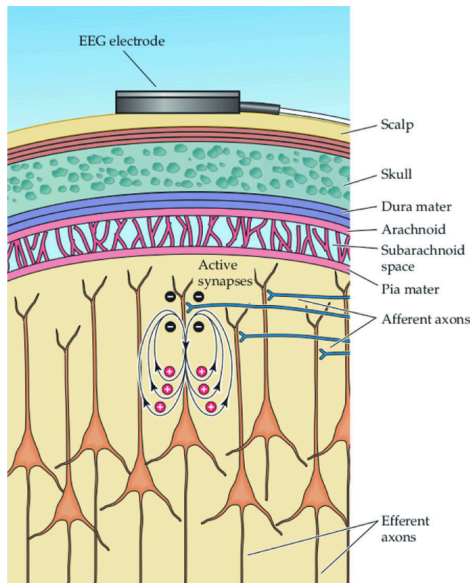


Figure 1.1 - *Pyramidal neurons* (Van Putten , 2020)

Electrical activity is detected and amplified by electrodes placed on the scalp. These are usually located according to the standardized 10–20 system, which is an internationally recognized method for positioning scalp electrodes (see Figure 1.2) (Homan et al., 1987).

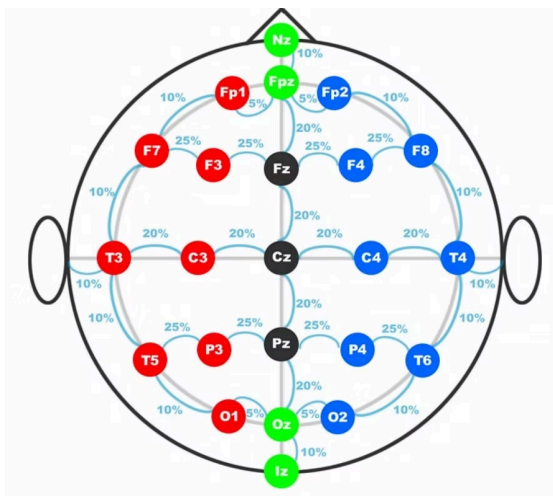


Figure 1.2 - *10-20 measurement system* (Tompkins, 2025)

However, the number of electrodes can vary depending on the EEG device used. For example, in the study presented in this thesis, an EEG with 8 electrodes was used, but there are also devices with higher or lower number of electrodes. The greater the number of electrodes, the more accurately brain activity can be mapped. The selection of the proper EEG system is generally determined by the particular research goals and the areas of the brain that need to be investigated.

Recording can be either dry or wet. When the recording is dry, no solution is placed between the electrodes and the scalp, while when the recording is wet, a saline solution is placed to ensure good contact. EEG systems that are designed for dry recording can work well without the application of any solution, but in certain situations (e.g., in participants with curly hair) gel must be applied to ensure good quality recording (Sultana et al., 2024).

As already mentioned in Section 1.2, EEG has a very high temporal resolution. In fact, unlike other functional neuroimaging techniques such as fMRI, EEG can detect neural signals in the order of milliseconds after the presentation of a stimulus. For this reason, it is particularly suitable for studying rapid cognitive responses, such as attentional changes (Höller, 2021).

However, we have also mentioned that it has poor spatial resolution, meaning that it is difficult to specifically localize the source of the signal in the brain (Srinivasan, 1999).

Furthermore, EEG recordings are very sensitive to eye movements, muscular activity, and environmental noise, with the risk of introducing artifacts and disturbing the signal (Schlögl & Pfurtscheller, 2002). However, these factors can be minimized by recording in a quiet laboratory environment and by removing artifacts during post-processing analysis (Blinowska & Durka, 2006).

Overall, EEG is safe, relatively inexpensive, and it allows repetitive measurements. It is adaptable to different laboratory settings and research designs, and it is compatible with different types of stimuli.

Let us now describe in more detail the characteristics of EEG signals.

EEG signals oscillate at different speeds, and we classify these speeds into bands. These bands are Delta (0.5 - 4 Hz), Theta (4 - 8 Hz), Alpha (8 - 12Hz), Beta (12 - 30 Hz), and Gamma (30 - 80 Hz). Each band is related to specific brain states: Delta is associated with deep sleep, Theta with light sleep, Alpha with relaxed wakefulness, Beta with active thinking, and Gamma with high-level cognition (Kandel et al., 2021).

In this study, we used EEG not to focus on specific frequency bands, but on the amplitude of electrical signals occurring at specific time intervals after stimulus presentation, known as Event-Related Potentials.

1.2.1.1 Event-Related Potentials

Event-Related Potentials (ERPs) are specific brain signals generated as a response to an event or stimulus.

We have affirmed that EEG records continuous electrical activity of the brain. ERPs represent small variations of this signal as a response to a particular stimulus. They are called Event-Related Potentials because they are potentials related to specific events (Luck, 2012).

Let us introduce how these potentials are extracted from the EEG signal.

First of all, a controlled stimulus is presented to a participant, usually visual, auditory, or motor. In neuromarketing studies, these stimuli are often images of products or advertisements.

The EEG signal is recorded continuously while the participant is exposed to this stimulus.

The raw EEG recorded signal includes information related to both spontaneous brain activity and specific responses to the stimulus. Since ERP amplitudes are very small compared to the total EEG signal, researchers must present the same stimulus multiple times and then average the results. When doing this, they define a specific time window that starts from the stimulus presentation and extends for a few hundred milliseconds, depending on the specific ERP that needs to be extracted. The process of averaging multiple recordings reduces noise and highlights the specific ERP associated with that stimulus. In other words, the averaging allows distinguishing relevant signals from random electrical fluctuations (Kuncheva & Rodríguez 2013). Averaging is one of the major steps used to extract ERPs, but not the only one; additional procedures (e.g., preprocessing, signal-cleaning, etc.) are usually applied and will be discussed in Section 2.5.1.

ERPs are characterized by two main features. Let us take, for example, the P100 and the N400, which are two ERPs components.

The letter P indicates that the polarity is positive, while the letter N indicates a negative polarity. Polarity can be either positive (P) or negative (N). After the letter, a number is presented. This number represents approximately how many milliseconds the peak of the brain response occurs after the presentation of the stimulus.

For example, P100 indicates a positive peak in the signal occurring about 100 milliseconds after the stimulus, while N400 represents a negative peak occurring at around 400 milliseconds after the stimulus. The latency (i.e., time between stimulus onset and signal peak) of each component indicates the speed of the neural process involved. For instance, P100 is associated with an immediate sensory process, while a peak occurring after 400 milliseconds reflects a slower cognitive process. In addition, each peak has a different amplitude (i.e., magnitude). The higher the amplitude, the stronger the neural response to that stimulus (McWeeny & Norton (2020); Luck et al., 1996).

In recent years, researchers have been able, through several experiments, to relate specific ERP components to particular cognitive processes. For example, the P100 component is associated with early sensory processing, while the N400 is associated with semantic processing (Kutas, & Hillyard, 1984; Herzberg et al., 2025).

In this study, we have focused our research on the P300 component.

1.2.1.1.1 P300

The P300 is one of the most well-known ERP components studied by neuroscientists (Picton, 1992). It is characterized by a positive deflection in the EEG signal that occurs approximately between 250 and 500 milliseconds (see Figure 1.3) (Polich, 2007). Since its peak latency is around 300 milliseconds, it has been called P300 (Smith et al., 1970). It is also known as P3, as it is the third major positive deflection in the sequence of late sensory ERPs recorded via EEG (Picton, 1992).

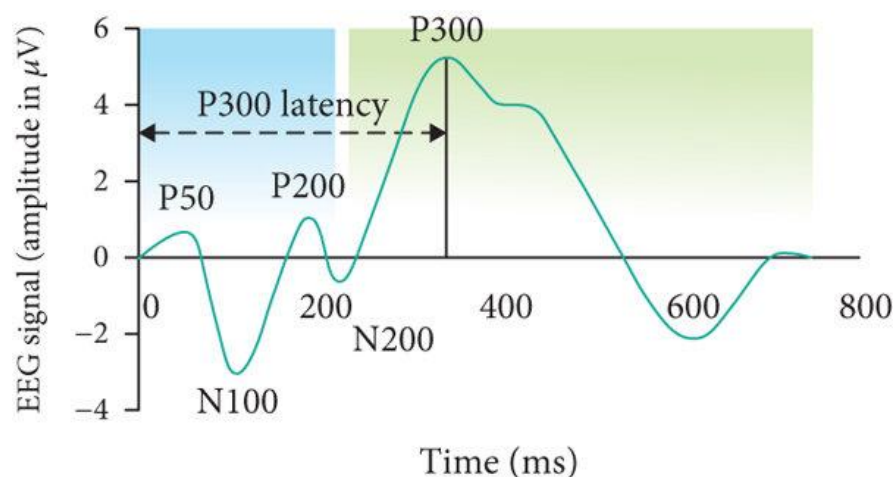


Figure 1.3 - *P300 amplitude* (Olichney et al., 2022)

The P300 does not reflect a single neural process, but rather multiple cognitive mechanisms associated with stimulus evaluation, attentional allocation, and the updating of mental context. In particular, this component emerges when a stimulus is perceived as relevant, significant, or unexpected within the context in which it is presented (Hansenne, 2000).

The P300 was discovered in 1965 by Sutton and colleagues, who observed that there was a positive component, occurring at around 300 ms after stimulus presentation, that was higher for unpredictable signals. In the experiment they designed, participants were presented with two types of stimuli, a click or a flash, and were asked to guess which stimulus would appear on each trial. Before the stimulus presentation, they received either a cue indicating which

stimulus would follow, or a cue that did not provide any information. The P300 amplitude was greater when the upcoming stimulus was not predicted by the cue (Sutton et al., 1965).

Today, the most commonly used paradigm to study the P300 is the *oddball paradigm*, in which repetitive (i.e., standard) stimuli, presented randomly, are occasionally interrupted by a rare (i.e., target) stimulus, which is the one of interest for analyzing the brain response. Standard stimuli are presented with high frequency ($\approx 80\%$), while target stimuli are presented with very low frequency ($\approx 20\%$) (Akhter, 2022).

Let us look at an example of how this paradigm is usually used in experiments.

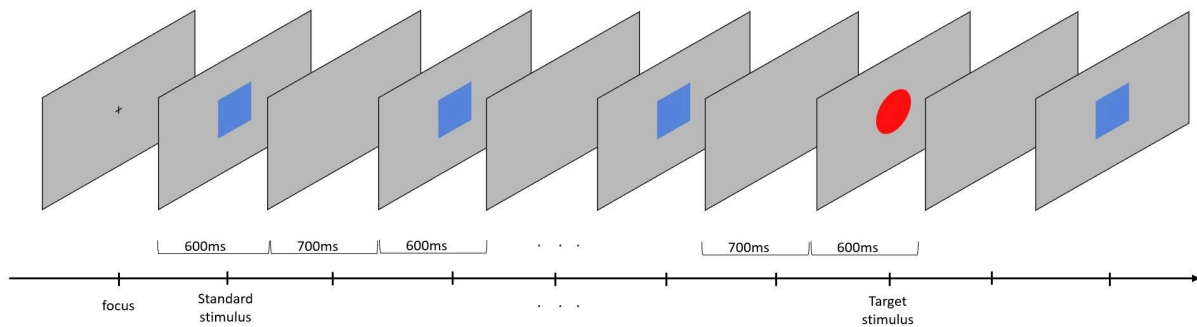


Figure 1.4 - *Oddball paradigm* (Mentalab, 2025)

In this case (see Figure 1.4), researchers aimed to analyze the brain response to the red circle (target), which is presented rarely among a larger number of presentations of the blue square (standard). In the example, each picture is presented for 100 ms, and is separated by a grey screen lasting the same time.

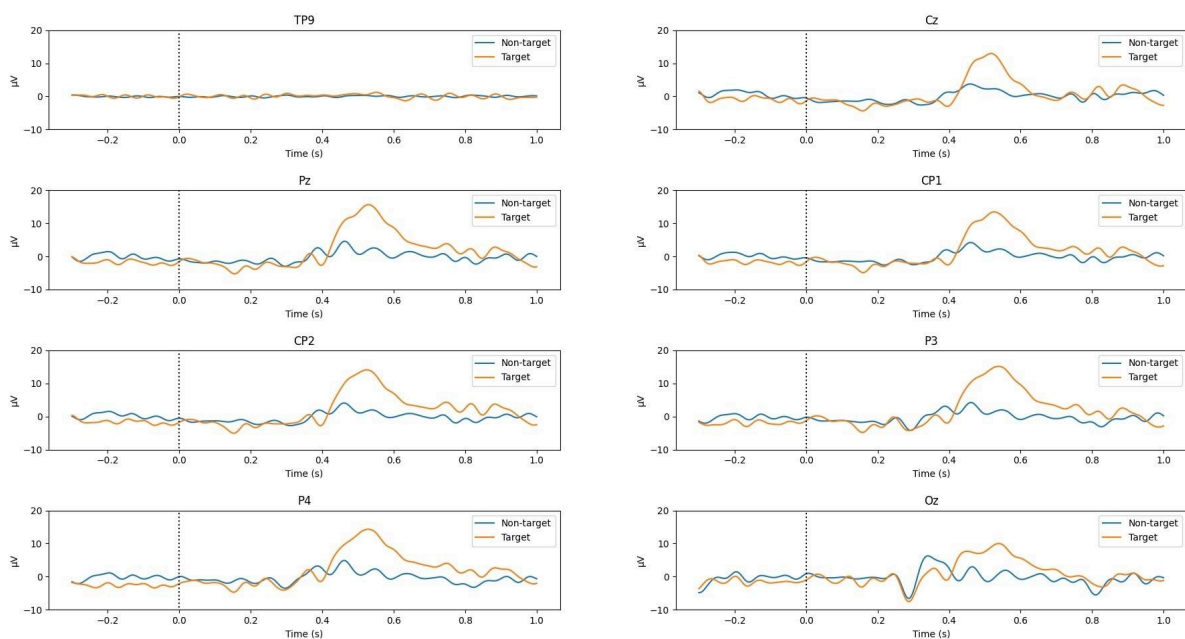


Figure 1.5 - *Waveforms produced from the P300 oddball experiment* (Mentalab, 2025)

In Figure 1.5, the results of a participant for the experiment shown in Figure 1.4 can be observed. Each graph represents a different electrode. The orange line indicates the brain signal when the target (red circle) is shown, while the blue line represents the average signal for the blue squares. A peak can be observed in the orange signal at around 400–450 ms after stimulus presentation (within the P300 time window). It is important to specify that, from a spatial perspective, P300 has generally higher amplitudes in central and parietal regions of the scalp (Anupriya et al., 2015; Picton, 1992). In Figure 4, these regions correspond to those channels starting with the letters C and P (e.g., Pz, CP2, and so on).

However, due to the limited spatial resolution of EEG, it is not possible to precisely identify a single brain area as the generator of the P300. This is one of the main limitations of this component, although it is compensated by the high temporal resolution of EEG (Picton, 1992).

Overall, the oddball paradigm is highly adaptable to different research designs: various types of stimuli can be used (visual, auditory, somatosensory), and different variables can be manipulated, such as the stimulus duration, the number of repetitions, and inter-stimulus intervals.

1.2.1.1.1 Amplitude of the P300

The P300 is generally analyzed in terms of its amplitude and latency.

Let us first explore its amplitude through a well-known model proposed by Johnson in 1986.

According to him, P300 amplitude depends on two independent factors, which combine additively. These are:

- *Subjective Probability*: how much the individual expects the stimulus to occur. It is based on the subject's personal expectations or predictions. Generally, P300 amplitude decreases when this factor increases, meaning that the signal is higher when unexpected.
- *Stimulus Meaning*: how relevant or meaningful the stimulus is for the person. It is modulated by three variables:
 - *Task complexity*: when a task is required, the harder the task, the higher the P300 amplitude. This is because a difficult task involves more extensive stimulus evaluation.
 - *Stimulus complexity*: complex visual stimuli tend to elicit larger P300 amplitudes.

- *Stimulus value*: stimuli that are important from a motivational or emotional perspective elicit higher P300 amplitudes.

These two main factors (Subjective Probability and Stimulus Meaning) are modulated by a third factor, called *Information Transmission*. This represents how effectively stimulus information is received and processed, which depends on various factors (e.g., noise, visibility, attention allocation). According to Johnson, P300 increases when information is well transmitted to the observer.

Subjective Probability and Stimulus Meaning act in an independent way: when one factor varies, it does not alter the effect of the other one on the P300 amplitude. However, changes in the amount of information conveyed by the stimulus (Information Transmission) influence both factors.

The independence between Subjective Probability and Stimulus Meaning is supported by numerous experimental studies. On the one hand, these studies show that the effect of stimulus significance on P300 amplitude remains constant regardless of how much the person expects the stimulus to occur. On the other hand, the effect of stimulus probability on P300 does not change when variations in stimulus significance occur. Finally, studies support that when the amount of information conveyed by the stimulus changes, this affects both factors (Johnson, 1986).

1.2.1.1.1.2 Latency of the P300

According to Kutas et al., (1977) The latency of the P300 does not reflect the reaction time, but rather the time required to evaluate and process the stimulus, which increases with task difficulty. Indeed, several studies have shown that P300 latency is influenced by the complexity of the target stimulus, but not by the difficulty of the required response. This supports the idea that P300 is mainly related to stimulus evaluation processes rather than to response selection or motor execution. However, in specific tasks, such as those involving stimulus–response incompatibility or complex motor choices, response selection processes may partially influence P300 latency or a subsequent component (Kutas et al., 1977).

To conclude our analysis of the P300, it is important to note that both amplitude and latency are influenced by age. Over time latency tends to increase, while amplitude tends to decrease, and initial changes are already reported in individuals aged 20–30 years. This means that from this age onward stimulus evaluation and information processing start to slow down (van Dinteren et al., 2014; Walhovd, 2008).

1.2.1.2 Unicorn Hybrid Black EEG Headset

In Section 1.2.1 we have mentioned that there are numerous EEG systems able to record the brain's electrical signals. In this section, we introduce a particular EEG headset, which we also used for our study, highlighting its main features and methodological advantages.

The Unicorn Hybrid Black (g.tec medical engineering GmbH, 2019) is an EEG headset and biosignal amplifier. It consists of 8 electrodes (i.e., channels) and is used to record the brain's electrical activity for a variety of non-medical applications (see Figure 1.6).



Figure 1.6 - *Unicorn Hybrid Black EEG headset* (g.tec medical engineering GmbH, 2019)

Recording can be performed in either dry or wet mode; in the latter case, conductive gel must be applied. Electrodes are positioned according to the international 10-20 system. These are: Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 (see Figure 1.7). The sampling rate is 250 Hz per channel, with 24-bit resolution.

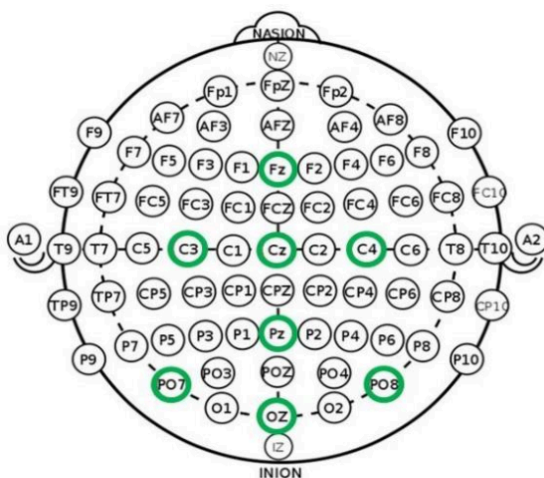


Figure 1.7 - *Location of Unicorn Hybrid Black electrodes* (Hasan et al., 2024)

As you can observe in Figure 7, electrodes are positioned over frontal (Fz), central (C3, Cz, C4), parietal (Pz), parieto-occipital (PO7, PO8), and occipital (Oz) scalp regions.

From a methodological perspective, the Unicorn Hybrid Black device provides advantages such as ease of use, reduced preparation time, mobility, and reliable signal quality, facilitating data collection and making it particularly suitable for experimental and applied research settings.

1.2.1.2.1 Blondy Check

An important neurometric system that can be used together with this EEG headset is called Blondy Check (g.tec medical engineering GmbH, 2021). This software is able to measure visual evoked potentials (VEPs), which we recall as the brain's time-locked responses to specific stimuli, in this case visual (Creed, 2019). Specifically, this system allows the recording of these responses in microvolts (μV) for further analysis.

To facilitate the understanding of the methodology used in this research, we briefly describe how the software operates.

When the Blondy Check is started (with the participant already wearing the headset), and once a good signal is reached for all electrodes, the researcher performs a *calibration phase*. To do this, the researcher generally uses default image-sets already installed in the software. This part follows the odd-ball paradigm: the participant is presented with neutral landscape images ($n = 15$), randomly intervalled by a female face (target stimulus). Each image is usually displayed for 150 ms on the screen and repeated 50 times (these numbers can be changed by the researcher according to their specific research goals). Calibration is important because it allows the software to adapt to individual neural response patterns; indeed, brain activity varies for each person (e.g., one individual may have a maximal P300 amplitude at 10 μV , while another one may have it at 15 μV).

After calibration, the researcher performs the *test phase*. This consists in presenting the same set of stimuli again, but each image is generally presented less times. This is because the aim of this phase is to obtain a percentage accuracy score. This indicates how well the system can distinguish the target from non-target stimuli using the subject's EEG responses. Accurate results are obtained when the score is higher than 80%. If this threshold is not reached at the first time, either the calibration phase or the test phase must be performed again until this score is reached.

After successful testing, the researcher can upload personalized stimuli (e.g. images developed according to the goal of the research) and present them to the participant. The

number of repetitions of each stimulus can be selected freely. Developers recommend presenting personalized images 5 times for 150 ms, but this mainly depends on the number of stimuli used. While stimuli are randomly displayed, the software records electrical activity for 1000 ms following stimulus onset for each channel. The system then averages the brain responses across the 5 repetitions and provides the mean activity for each image (g.tec., 2019). In Figure 1.8 we can observe the output generated by the system for a representative image. Each graph, corresponding to each electrode, displays the averaged signal recorded from stimulus onset (0 ms) up to 1000 ms post-stimulus.

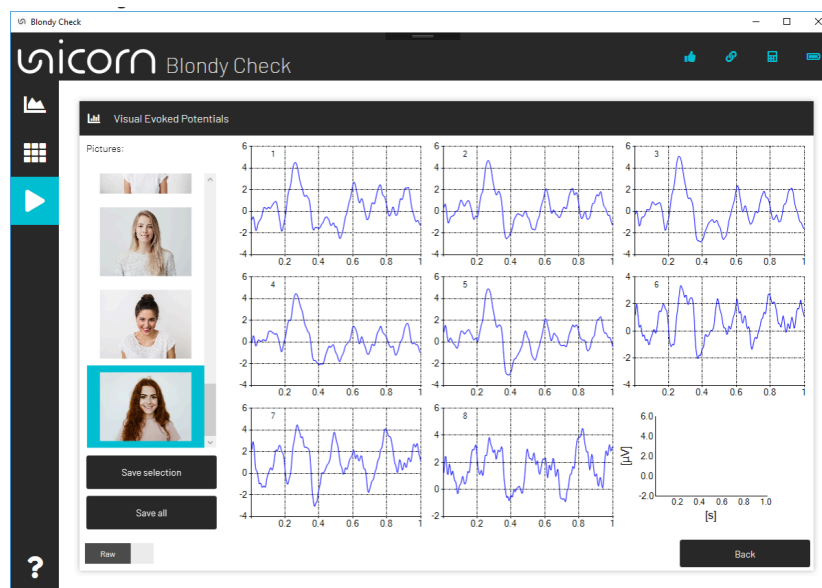


Figure 1.8 - Recorded signal of one image for each electrode (g.tec, 2019)

The software also provides CSV files containing, for each stimulus, the specific μV values recorded in a 4-second time-locked window for each electrode. This aspect will be described in detail in Section 2.5.1.

1.3 Research Rationale

In Section 1.1 we have argued that neuromarketing has developed in order to gain deeper insights into cognitive processes that cannot be fully captured through self-report measures such as questionnaires or interviews (Iloka, & Onyeke, 2020). Traditional marketing research mostly relies on declared preferences, but many decisional mechanisms occur at an implicit and early neural level (Wongtada, 2018).

We have also affirmed that attracting consumers' attention in environments characterized by high stimulus competition has become a significant challenge (Gourville & Soman, 2005). Today a variety of strategies are applied in retail settings to guide attention and influence

purchasing behavior. An example is product positioning in supermarkets, which is carefully structured, where promotional items tend to be placed at adults' eye level, while products targeted at children are positioned on lower shelves to match their visual field. Another common strategy is cross-merchandising, where complementary goods from different categories are placed in close proximity, such as pasta and sauce, or wine and cheese (Ebster & Garaus, 2015). We define complementary goods as those products that are typically consumed together and share a "joint demand", meaning the demand for one increases the demand for the other one (Avgeropoulos et al., 2015). Cross-merchandising generally aims to encourage consumers who intend to purchase one item to also consider the complementary product, given their common purpose (Ebster & Garaus, 2015; Sarantopoulos et al., 2019).

While behavioral research suggests that such strategies can influence purchasing patterns, less is known about what happens at the earliest stages of neural processing. Specifically, what occurs at a basic attentional level when complementary products are presented together? The present study addresses this question by investigating the modulation of the P300 component. We have stated that P300 is an ERP associated with attentional allocation and stimulus relevance. Our aim is to investigate whether product combinations capture greater attentional resources compared to single items presented alone.

To explore this phenomenon, we have decided to study a particular type of product combination: the *brand–non-brand combination*. Before defining this term, let us explore why investigating the role of brands is highly important in this field.

Brands play a central role in shaping consumer perception and decision-making processes. Traditionally, brands were considered a symbol of differentiation from other items of the same category, and an indicator of qualitative standards. However, research in psychology and neuroscience suggests that today brands are more than this: they operate as complex psychological constructs that activate associative networks including emotions, past experiences, expectations, and social meanings. From a psychological perspective, brands are learned signals of reliability. Over time, positive reinforcement and repeated exposure increase trust and familiarity, allowing brands to act as cognitive heuristics that simplify decision-making in contexts of high choice overload (Jahan et al., 2024).

Interestingly, brand influence often extends beyond the specific product to which it is originally known, as seen in phenomena such as brand extension and co-branding.

Brand extension is defined as the strategy to apply the brand image to a new product, often of a different category (e.g., the Virgin Group brand applied to aviation) (Aaker & Keller, 1990). Co-branding occurs when two brands collaborate to create a new product (e.g., Oreo-Milka

chocolate bar) with the goal of increasing sales and reaching new audiences. In fact, the mere presence of a recognizable brand can increase perceived value or desirability also for other products (Helmig, 2008).

Now that we have a better understanding of the role of brands in influencing consumers' perception, let us define what we mean by brand-non brand combination. In this thesis, we define this as the combination of two complementary products, one associated with a well-known brand and the other lacking a recognizable brand identity. One example is Coca-Cola and Popcorn; these goods are usually consumed together, and Coca-Cola has a high brand identity, while Popcorn is not primarily associated with a particular brand.

The aim of this study is not simply to explore how selective attention differs between single products and combinations, but specifically to investigate this change in those combinations in which the brand is paired with the non-brand. In other words, does presenting the non-branded product close to the branded product result in greater attentional allocation to the combination compared to the non-brand presented alone? And does this effect also apply to the brand, that is, does the combination attract more attention compared to the brand presented in isolation? For example, when Popcorn is displayed together with Coca-Cola, does the combination attract more attention than Popcorn alone?

A specific type of pairing could implicitly evoke a consumption context (e.g., in this case the cinema experience) that may enhance stimulus relevance at an early neural level.

We would like to clarify that, in this research, we explore these patterns exclusively within the food category.

In addition, throughout this thesis, the term *brand* (i.e., *branded product*) refers to a food item directly associated with a recognized brand. Conversely, *non-brand* (i.e., *non-branded product*) refers to a food item that is not associated with any recognizable brand. The term *combination* (i.e., *brand–non-brand combination*) refers specifically to pairings between one branded and one non-branded product. No alternative terminology will be used to describe these pairings.

This study adopts an exploratory approach. We expect that combinations may elicit greater attentional allocation (i.e., higher P300 amplitudes) compared to single items, as people may be drawn to the perception of a “complete experience” offered by the combination. Although our stimuli are inspired by retail practices, our combinations do not fully replicate physical store settings; the implications of this research extend beyond traditional retail environments. Indeed, product combinations are frequently used in advertising, both offline and online,

where complementary items are presented together to implicitly evoke specific consumption contexts or experiences (Roggeveen et al., 2023).

Given the exploratory nature of this study, we do not limit our investigation to P300 differences between single and complementary products, but we also aim to explore whether P300 amplitudes might be correlated with commonly evaluated consumer variables, such as *pleasantness* (i.e. how much consumers like a product), *consumption frequency* (i.e., how often a product is consumed), and *willingness to pay* (WTP; i.e., how much consumers would pay for a product).

Since P300 is not inherently related to these variables, we remain cautious about making formal hypotheses. Even though P300 is known to reflect attentional allocation and emotional relevance, and might therefore be associated with pleasantness, we would like to clarify that emotional relevance can also be triggered by highly negative or aversive stimuli. Indeed, what matters is the significance of the stimulus, which can be either positive or negative (Fields, 2023).

Pleasantness and consumption frequency will be analysed only for single products, as we considered it sufficient to explore a potential correlation with P300. Regarding WTP, we will analyse it both for single products and combinations. This is because, additionally to the correlations with P300 values, we also aim to explore whether participants tend to assign a higher or lower price to product combinations compared to when products are evaluated individually. Although combinations may elicit higher attention, consumers may evaluate combinations as a single unit, and thus apply a discount (Henry et al., 2023).

Lastly, to provide a complete picture, we will also analyze correlations between the three consumer variables themselves. In general, pleasantness is positively correlated with consumption frequency, although this relationship is not straightforward, as several other factors (e.g., motivational states, availability, and situational constraints) may influence it (Yoon & Meyvis, 2024). Regarding WTP, Seppä et al. (2015) showed that it increases with higher levels of pleasantness and consumption frequency. We remind that these relationships should be interpreted as associative patterns rather than causal effects, as other variables, depending on the context, may also influence WTP.

We decided to adopt a mixed approach, including both neurometric and behavioral measures, as the aim is to conduct an exploratory study in which we can analyze and correlate both types of data. In other words, we considered both unconscious and conscious variables to provide a more complete picture of brain mechanisms when both single items and brand–non-brand combinations are processed.

1.4 Research Questions

Now that we have defined the research rationale, let us summarise our research questions:

1. Do combinations elicit higher P300 than brands presented alone?
2. Do combinations elicit higher P300 than non-brands presented alone?
3. Do P300 amplitudes correlate with participants' reported pleasantness, consumption frequency, and willingness to pay?
4. Is pleasantness positively correlated with consumption frequency?
5. Is willingness to pay positively correlated with both pleasantness and consumption frequency?
6. Is willingness to pay for the combination lower than the sum of the individual products presented separately?
7. Is the magnitude of the discount (i.e., the difference between the willingness to pay for the combination and the sum of the individual products presented separately) correlated with the P300 amplitude elicited by the combination?

In this thesis, research questions will be referred to as RQ1, RQ2, RQ3, etc., according to their respective numbers.

1.5 Hypotheses

Below are listed the hypotheses corresponding to each research question:

1. Combinations will elicit higher P300 amplitudes than brands presented alone.
2. Combinations will elicit higher P300 amplitudes than non-brands presented alone.
3. The relationship between P300 amplitudes and the behavioral measures will be explored without a specific directional hypothesis.
4. Reported pleasantness will be positively correlated with consumption frequency.
5. Willingness to pay will be positively correlated with both pleasantness and consumption frequency.
6. Willingness to pay for the combination will be lower than the sum of the individual products presented separately.
7. The relationship between P300 amplitudes for the combination and the magnitudes of the discounts for the combination will be explored without a specific directional hypothesis.

2. Method

2.1 Participants

A total of 60 participants (49 women, 11 men) took part in the study. This number allowed sufficient statistical power to test our hypotheses. Subjects were tested in a single session, and all collected data were included in the final analysis.

Participants were healthy adults between 20 and 35 years. We applied this age restriction for different reasons. First, it allowed us to minimize age-related variability in the P300 component and maintain greater cognitive homogeneity across subjects. Second, since in this study we used brands that targeted a primary consumer segment within this age range, this restriction increased the likelihood that participants were consumers of these products.

Subjects were required to have no history of neurological or psychiatric disorders (including epilepsy or seizures), and no current use of psychoactive medications, as these factors could distort EEG signal. In addition, they were required to have a normal or corrected vision, in order to ensure a proper perception of the images. All inclusion and exclusion criteria were discussed with participants before the experiment. No restrictions were applied to gender or nationality, as the selected brands were internationally well-known and we did not aim to compare responses between genders, or to restrict the sample to a specific group.

In addition, no high level of education was required for this study; however, participants needed basic numeracy skills to perform simple price estimations, and knowledge of basic English in order to complete the questionnaire after the EEG recording.

Subjects were recruited following a non-probabilistic convenience sampling approach, primarily among students at the University of Ljubljana. Limitations of this sampling method were acknowledged, and inferences were made cautiously with respect to the general population (see Section 4.6). Recruitment was carried out through social media platforms and personal invitations, and experiments were conducted at the Faculty of Natural Sciences and Engineering.

All participants gave their consent to participation by signing an informed consent form, which included every detail about the research procedure, their rights in case of withdrawal, and anonymization procedure, in accordance with the ethical standards of the Declaration of Helsinki and the General Data Protection Regulation (GDPR) (see Appendix B). The study received ethical approval from the Faculty of Education of the University of Ljubljana.

Participation was entirely voluntary, so no monetary or material compensation was provided.

2.2 Materials

2.2.1 Stimuli

A total of 15 images were designed. Specifically, three types of stimuli were developed:

- 5 images of brands presented alone
- 5 images of non-brands presented alone
- 5 images of brand-non-brand combinations

In order to create these stimuli, we first selected five internationally well-known brands: Coca-Cola, Pringles, Starbucks, Oreo, and Nutella. Each of these brands was then paired with a complementary non-branded product (i.e., a food or drink that is typically consumed with the brand, but can also be consumed independently). Based on these pairings, after developing the images of the brands, we designed the 5 images of the non-brands alone and the 5 pictures of the corresponding combinations.

Below are listed the 5 sets we created (15 pictures in total), including respectively the brand, the non-brand and the combination of the two:

1. *Coca-Cola Set*: Coca-Cola, Popcorn, and Coca-Cola-Popcorn
2. *Pringles Set*: Pringles, Cocktail, Pringles-Cocktail
3. *Starbucks Set*: Starbucks, Muffin, Starbucks-Muffin
4. *Oreo Set*: Oreo, Milk, Oreo-Milk
5. *Nutella Set*: Nutella, Bread, Nutella-Bread

To give an example, below are shown the images of both the Coca-Cola Set (Figures 2.1, 2.2, 2.3) and the Nutella Set (Figures 2.4, 2.5, 2.6). The complete set of stimuli is provided in the Appendix A.



Figure 2.1 - *Coca-Cola*



Figure 2.2 - *Popcorn*



Figure 2.3 - *Combination*



Figure 2.4 - *Nutella*



Figure 2.5 - *Bread*



Figure 2.6 - *Combination*

All pictures were developed with Google Gemini 2.5 Pro (Google, 2025), which is an AI platform, and subsequently refined using Canva (2025), a web-based graphic design platform. We cared about maintaining consistent proportions, colors and luminosity across all pictures. In addition, we ensured all images had the same size, with the items centered, and displayed on a uniform light-grey background. These criteria were important to ensure that observed effects were driven only by the content of the images, and not by additional design factors.

2.2.2 Questionnaire

A questionnaire was developed to collect data about the three consumer variables.

As mentioned in Section 1.3, these were:

- *Pleasantness*: how much participants liked the product.
- *Consumption frequency*: how often they consumed the product.
- *Willingness to Pay (WTP)*: the amount participants were willing to pay for the product (or combination) presented in the image.

All 60 participants completed the questionnaire. Two versions of it were developed: the first 30 participants completed *Version 1*, while the other half completed *Version 2*.

Both versions were developed using QuestionPro (2025), a cloud-based survey and research platform that allows the creation and distribution of surveys for both academic studies and market research.

In both Version 1 and Version 2, the questionnaire was organized into five blocks, each corresponding to a specific set. All blocks were presented in a randomized order to avoid potential order biases. However, within each block, all questions were presented in the same fixed order, to avoid potential confusions for participants, as well as to facilitate their responses.

In addition, in both versions each block was divided into three sections. All sections consisted of 2 questions.

Let us define in detail the structure of each block for the two versions.

2.2.2.1 Version 1

2.2.2.1.1 Section 1 - Willingness to Pay

For each set (i.e., block), participants were first shown the picture of the non-branded product and were asked to assume that the item had a specific price. Based on this information, subjects were asked to indicate:

1. how much they would be willing to pay for the brand alone (first question)
2. how much they would be willing to pay for the combination (second question)

For example, in the Coca-Cola Set, participants were first shown Popcorn priced €3.59, and then they were asked to enter how much they would be willing to pay for the Coca-Cola alone and for the Coca-Cola-Popcorn combination. For all items, the corresponding images were presented when participants were asked to indicate the price.

The specific prices of non-brands were selected after a careful analysis of average prices in Slovenia and other countries, to ensure that the values were realistic for everyone. In addition, we selected prices that included cents, to encourage subjects to deliberate more on their answers and to avoid simple summation strategies for the combinations.

2.2.2.1.2 Section 2 - Pleasantness

In the second section of each block, subjects rated both the branded and the non-branded item on a 5-point Likert scale, according to how much they liked them (1 = I don't like it at all; 2 = I don't like it; 3 = Neutral, 4 = I like it , 5 = I like it very much).

2.2.2.1.3 Section 3 - Consumption Frequency

In the third section of each block, subjects rated both the branded and the non-branded item on a 5-point Likert scale, according to how often they consumed them (1 = Never; 2= Less than once a month; 3 = Monthly; 4 = Weekly; 5 = Daily)

To sum up, in each of the five blocks (each corresponding to a set) of Version 1, participants were asked:

- two questions about how much they would pay for the brand and for the combination, given the non-brand price
- two questions indicating how much they liked the brand and the non-brand
- two questions indicating how often they consumed the brand and the non-brand

2.2.2.2 Version 2

The second version of the questionnaire was identical to the first version for Sections 2 and 3, corresponding to Pleasantness and Consumption frequency.

The only difference was in Section 1, related to WTP. Instead of showing participants the cost of the unbranded product, this time they were shown the price of the brand, and they were asked to indicate:

1. how much they would be willing to pay for the non-brand alone (first question)
2. how much they would be willing to pay for the combination (second question; the same of Version 1)

Therefore, the only difference between the two versions was that, in Version 1, participants were asked to indicate how much they would pay for the brand given the price of the non-brand, while in Version 2, they were asked to indicate how much they would pay for the non-brand given the price of the brand.

We decided to create two versions to allow the analysis of willingness to pay for both branded and non-branded products, while minimizing potential biases. In fact, asking participants to estimate WTP for all products within a single version without a reference price was considered risky, as no information about quantities (e.g., grams or volume) was provided. This could have made price estimation difficult and inconsistent across participants.

Therefore, the two versions were created to include an “anchoring” price for each one: the non-brand for Version 1 and the brand for Version 2. This facilitated more realistic evaluations and reduced cognitive load.

In addition, this approach allowed for a more reliable assessment of individual differences in willingness to pay and their relationship with P300 amplitudes measured via EEG.

2.2.3 EEG Equipment

As already mentioned in Section 1.2.1.2, the Unicorn Hybrid Black headset was used in combination with the Blondy Check software for P300 recording. The 15 images used for the EEG recording were implemented and presented in random order after the calibration and testing phases (see Section 1.2.1.2.1 for details about the general EEG recording procedure with Blondy Check).

2.3 Experimental Design

The study employed a single-condition design, as it did not include experimental manipulations. All participants viewed the same set of images while EEG activity was continuously recorded. Thus, the procedure was identical for all participants.

Two questionnaire versions were used exclusively to obtain different WTP measures (branded vs. non-branded products) and did not constitute separate experimental conditions, as no comparisons between questionnaire versions were performed in the analyses.

Measures of pleasantness and consumption habits were identical across all participants.

2.4 Procedure

Let us now describe the procedure we followed for each participant.

Before starting the experiment, the participant was asked to sign the informed consent form, containing general information about the purpose of the study and the participant's rights in case of withdrawal (see Appendix B). Before signing, the researcher ensured that all inclusion and exclusion criteria for the experiment were met.

The participant was then asked to sit in front of a monitor connected to the laptop running the Blondy Check program. The monitor was used to enhance the visibility of the stimuli.

Next, the researcher placed the EEG headset on the participant's scalp, ensuring that all the electrodes were correctly positioned. After this, the headset was turned on and the signal quality of each electrode was checked to ensure a good signal. In case the signal was poor, the researcher applied conductive gel where necessary to obtain better connection.

Once a good quality connection was established, the calibration procedure was started using the default picture set in the program, followed by the testing phase (see Section 1.2.1.2.1 for details about the calibration and the test phase).

After successful calibration and testing, the researcher ran the presentation of the 15 food images, each shown 5 times for 150 ms in random order.

During all phases, the participant was asked to simply look at the pictures and focus just on the task, avoiding thinking about anything in particular. In addition, they were asked to minimize any movement, as the EEG signals are highly sensitive to motion.

Once the EEG recording was completed, the researcher saved the raw EEG signal data for each image. Finally, the headset was turned off and removed, and the subject was given the questionnaire to complete. After the questionnaire was completed the session was concluded. The experiment lasted approximately 30-40 minutes.

2.5 Data Analysis

In the following sections we will explore how we extracted P300 amplitudes from the raw EEG signal and how we analysed them, including consumer variables.

2.5.1 P300 Extraction

In order to extract P300 values we developed a Python code integrating our expertise with generative artificial intelligence (AI) support. Specifically, ChatGPT (GPT-4o, OpenAI, 2025) was used as a computational assistance tool to facilitate the translation of our analytical objectives into an executable Python-based pipeline.

As mentioned in Section 2.4, for each stimulus presentation, EEG signal was recorded across the eight electrodes for a period of 1000 ms following stimulus onset. Through the BlondyCheck system, all data were saved in tabular format, one table for each stimulus (the software already averaged the EEG signal across the 5 repetitions for each image), resulting in 15 tables for each participant. Within each table, columns corresponded to EEG channels and rows represented signal time points. Signals were sampled at regular 4-ms intervals, resulting in 250 time-resolved EEG samples spanning a 1000-ms post-stimulus epoch for each image. Given this structure, our aim was to extract a single representative ERP (P300) value for each stimulus. To do this, we needed to average the signal across all channels to obtain a single 1000-ms epoch, and then find the peak (i.e., highest amplitude) within the P300 time window (250-500 ms).

In order to translate our conceptual analysis steps into programmatic procedures, we used AI as a computational support tool to guide the structuring, implementation, and automation of the analysis in Python.

We will now describe all the processes we implemented in Python with the assistance of AI. As mentioned, these processes were applied to each table, representing one image, meaning the procedure was repeated 15 times for each participant, to extract 15 P300 values.

First of all, we imported in Python the CVS file containing the table. Then, we cleaned data to remove invalid or non-numeric entries, ensuring that only valid numerical samples were maintained for analysis.

The Blondy Check system recorded EEG data at a sampling frequency of 250 Hz, meaning that 250 samples were collected every second. Since we recorded for 1 second (1000 ms) after stimulus onset, this resulted in 250 time points (4 ms each), each one corresponding to a specific μV (microvolt) value. This information was used to construct the time vector, to ensure precise identification of specific time windows. After this, all channels were selected to obtain the average signal at each time point. Conceptually, at each point the code averaged the corresponding μV value from all channels to obtain a single representative value (i.e., a new 1000-ms averaged epoch). We decided to include all channels in the analysis due to the limited number of electrodes, the potential presence of noise, and the fact that the P300 is characterized by a relatively broad scalp distribution rather than a strictly localized topography.

After the averaging, we applied a digital band-pass filter from 1 to 30 Hz to the resulting signal. Hertz (Hz) indicates how many times a signal oscillates per second (Encyclopedia Britannica, n.d.); very slow oscillations (<1 Hz) and very fast oscillations (>30 Hz) were attenuated, while the frequency range relevant for the P300 component was preserved. We chose an upper limit of 30 Hz because higher frequencies typically reflect muscle activity or technical noise rather than neural activity. In this way, the filter smoothed out unwanted fluctuations, producing a cleaner and more continuous signal, without changing the temporal resolution of 4 ms per data point.

Next, we applied a baseline correction. This process removes small pre-response fluctuations in the EEG signal, ensuring that post-stimulus peaks reflect true neural responses. In simple words, baseline correction sets the starting level of the response to zero.

To do this, we used the first 100 ms after stimulus onset as a reference interval, as the P300 response has not occurred yet in this period. Specifically, we calculated the mean of the first 25 time points (0–100 ms) and we subtracted it from each of the 250 time points of the epoch. Subsequently, we applied a quality-control criterion by computing the peak-to-peak amplitude (i.e., the difference between the maximum and minimum voltage) of the entire epoch. If peak-to-peak amplitude exceeded 150 μV , the epoch was automatically rejected. This step removes trials with unusually high or noisy signals that could distort the measure. In addition, since small timing variations can occur during the preprocessing steps just

described, all values were then resampled to a common temporal grid of 250 points covering the 1000 ms epoch.

At this point we applied baseline normalization (z-score standardisation). This process was important to allow comparisons between participants, for example when correlating P300 μV values with consumer variables. Specifically, we computed the standard deviation (SD) of the baseline interval (0-100 ms), and we divided each data point of the baseline-corrected epoch by this value. This transforms μV values into units (z-scores) of baseline variability, making them comparable across participants. Therefore, for analysis within individuals (RQ1, RQ2), we used baseline-corrected values, while for analysis between individuals (RQ3, RQ7) we used normalized values.

Finally, we segmented the P300 time window (250-500 milliseconds) from the epoch, and we extracted the peak amplitude and its corresponding latency within this window.

Below is an example of the graph produced at the end of the pipeline for one stimulus (see Figure 2.7). The blue line shows the averaged signal amplitude (y-axis) as a function of time (x-axis). In this case, within the P300 time window, we observe a peak (orange dot) at 320 ms, corresponding to 11.46 μV . This value is the one used for within-participant analyses.

Although not shown here, the pipeline also produces an additional graph, identical to the one just illustrated, displaying the z-score instead of the μV value. It is important to note that this graph also shows the N400 peak and the label SEM (Standard Error of the Mean). This is because the code we developed is flexible and can be adapted also for the analysis of multiple stimuli together and for the N400 component. However, since the aim of this thesis is only to extract the P300 amplitude from one image at a time, we only described the steps relevant to this analysis. We clarify this to explain why these additional labels appear in the graph.

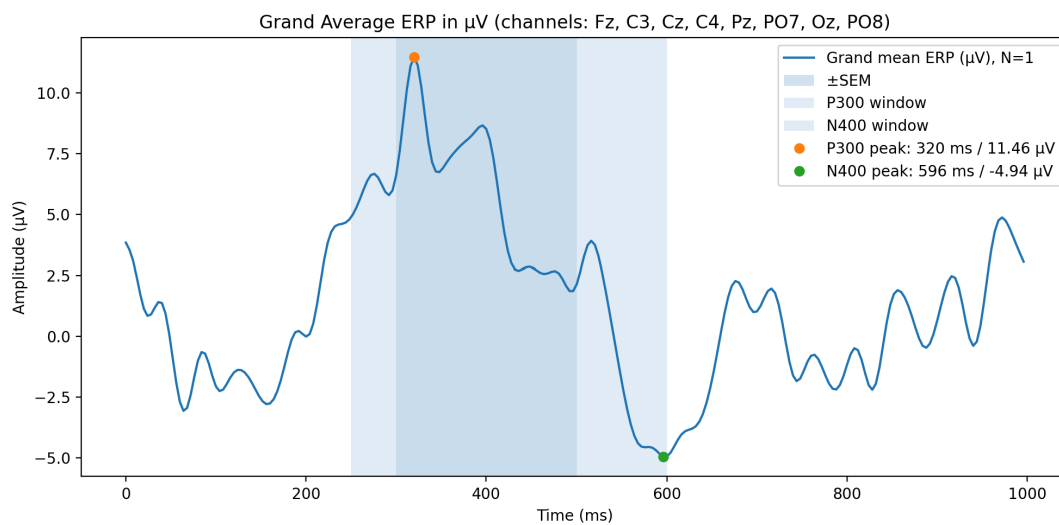


Figure 2.7 - Averaged EEG signal and P300 peak

2.5.2 Binomial Tests

To answer RQ1 and RQ2, in each set, for each participant, we created a ranking of the three items based on their P300 values.

Subsequently, we counted how many participants had a higher P300 value for the combination than for the brand (and vice versa), and applied a binomial test in R to assess whether the difference between the two groups was statistically significant (RQ1).

We repeated the same procedure for comparisons involving non-brands (RQ2).

2.5.3 Correlations

In order to answer RQ3, RQ4, RQ5, and RQ7, Pearson and Spearman correlation tests were computed in R across participants for each set.

Specifically, to answer RQ3, we calculated correlations between:

- P300 z-scores and pleasantness for the brand (all participants; Spearman)
- P300 z-scores and pleasantness for the non-brand (all participants; Spearman)
- P300 z-scores and consumption frequency for the brand (all participants; Spearman)
- P300 z-scores and consumption frequency for the non-brand (all participants; Spearman)
- P300 z-scores and WTP for the brand (participants 1–30; Pearson)
- P300 z-scores and WTP for the non-brand (participants 31–60; Pearson)
- P300 z-scores and WTP for the combination (all participants; Pearson)

To answer RQ4, we calculated correlations between:

- Pleasantness and consumption frequency for the brand (all participants; Spearman)
- Pleasantness and consumption frequency for the non-brand (all participants; Spearman)

To answer RQ5, we calculated correlations between:

- WTP and pleasantness for the brand (participants 1–30; Spearman)
- WTP and pleasantness for the non-brand (participants 31–60; Spearman)
- WTP and consumption frequency for the brand (participants 1–30; Spearman)
- WTP and consumption frequency for the non-brand (participants 31–60; Spearman)

Finally, to answer RQ7, we calculated the correlation between:

- P300 z-scores for the combinations and magnitudes of the discounts (i.e., the difference between the willingness to pay for the combination and the sum of the individual products presented separately) (all participants; Pearson)

Pearson correlations were applied when both variables were continuous (e.g., P300 and WTP), while Spearman correlations were applied when at least one of the variables was ordinal (e.g., pleasantness and consumption frequency)

Regarding RQ7, we have affirmed that the magnitude of the discount was calculated as the difference between the WTP assigned to the combination and the sum of the individual products presented separately.

For the first 30 participants, this sum represented the WTP assigned to the brand plus the given price of the anchor (non-brand). For the last 30 participants, this sum represented the WTP assigned to the non-brand plus the given price of the anchor (brand). In both cases, the magnitude of the discount was obtained by subtracting this sum from the WTP assigned to the combination.

A positive value indicated that participants were willing to pay more for the combination than the sum of the individual products, while a negative value indicated that participants valued the combination less than the sum of its parts, reflecting a perceived discount.

The magnitudes of the discounts were then correlated with P300 z-scores for the combinations.

2.5.4 One-Sample t-Tests

In order to evaluate whether the magnitudes of the discounts applied to the combination were significantly different from zero (RQ6), we conducted one-sample t-tests in R.

3. Results

In the following pages we illustrate the results for each set. The significance level was set at $\alpha = 0.05$ for all analyses. All images shown were generated in R.

3.1 Coca-Cola Set

RQ1. Do combinations elicit higher P300 than brands presented alone?

Results showed that 31 out of 60 participants had a higher amplitude for the combination of Coca-Cola and Popcorn compared to Coca-Cola presented alone, while 29 participants had a higher amplitude for the brand alone compared to the combination.

We conducted a binomial test to examine whether the two proportions differed from chance ($p = .897$), indicating no significant difference between them.

RQ2. Do combinations elicit higher P300 than non-brands presented alone?

Results indicated that 28 out of 60 participants had a higher amplitude for the combination of Coca-Cola and Popcorn compared to Popcorn presented alone, while 32 participants had a higher amplitude for the non-brand alone compared to the combination.

The binomial test we applied to examine whether the two proportions differed from chance indicated no significant difference between them ($p = .699$).

RQ3. Do P300 amplitudes correlate with participants' reported pleasantness, consumption frequency, and willingness to pay?

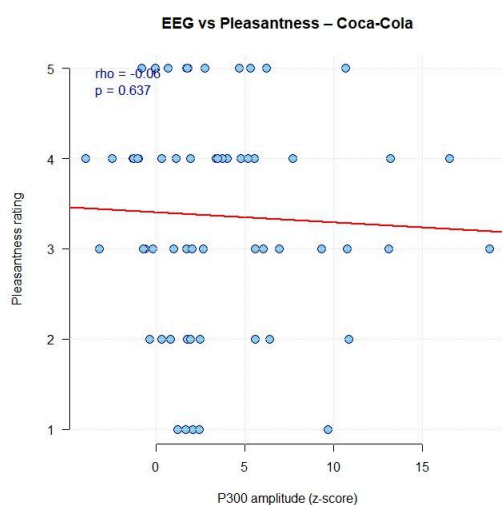


Figure 3.1.1 EEG vs Pleasantness (brand)

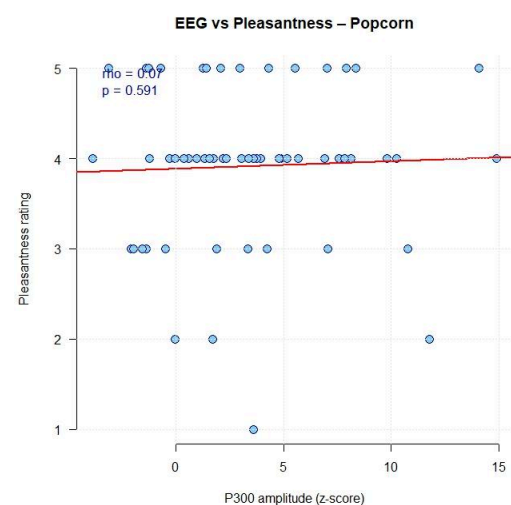


Figure 3.1.2 EEG vs Pleasantness (non-brand)

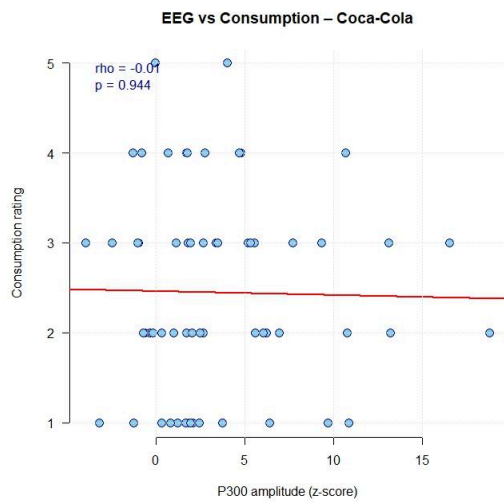


Figure 3.1.3 EEG vs Consumption (brand)

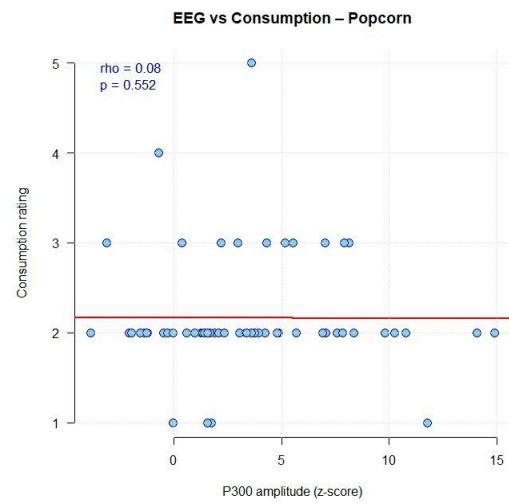


Figure 3.1.4 EEG vs Consumption (non-brand)

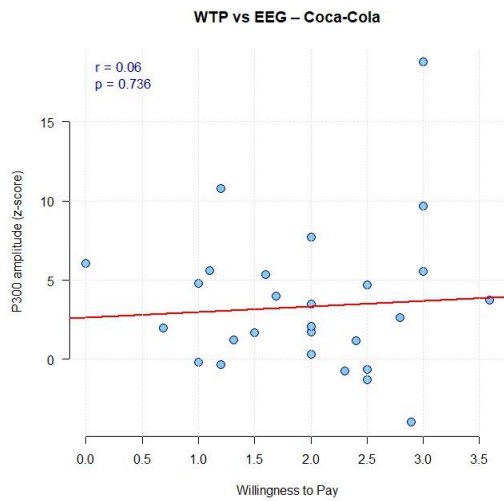


Figure 3.1.5 WTP vs EEG (brand)

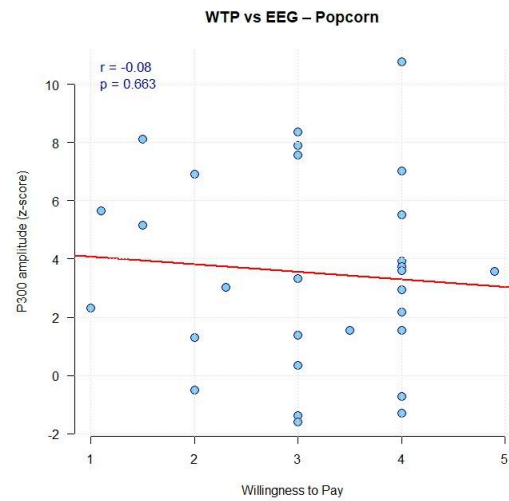


Figure 3.1.6 WTP vs EEG (non-brand)

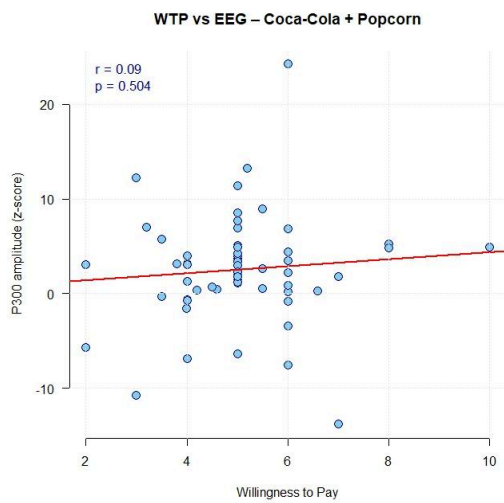


Figure 3.1.7 WTP vs EEG (combination)

- P300 amplitudes did not significantly correlate with reported pleasantness for either Coca-Cola ($p = .637$) or Popcorn ($p = .591$) (Figures 3.1.1 and 3.1.2).
- P300 amplitudes did not significantly correlate with reported consumption frequency for either Coca-Cola ($p = .944$) or Popcorn ($p = .552$) (Figures 3.1.3 and 3.1.4).
- P300 amplitudes did not significantly correlate with reported WTP for Coca-Cola ($p = .736$), Popcorn ($p = .663$), or the combination ($p = .504$) (Figures 3.1.5, 3.1.6, 3.1.7).

RQ4. Is pleasantness positively correlated with consumption frequency?

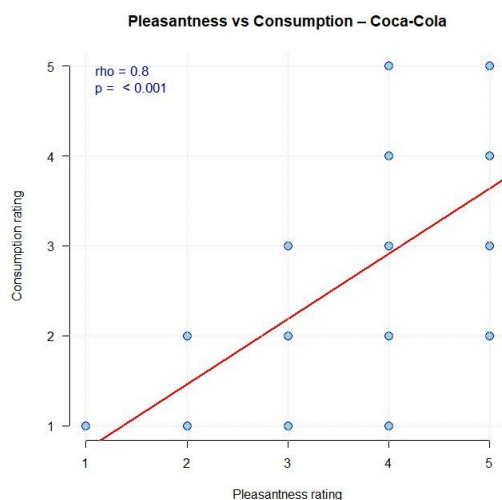


Figure 3.1.8 *Pleasantness vs Consum.(brand)*

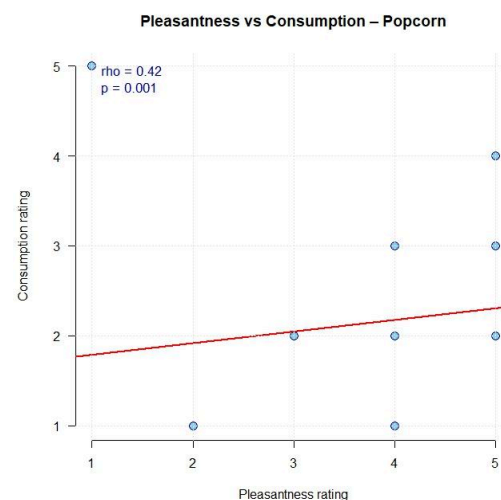


Figure 3.1.9 *Pleasantness vs Consum. (non-brand)*

Pleasantness is significantly positively correlated with consumption frequency for both Coca-Cola ($\rho = 0.8$; $p < .001$) and Popcorn ($\rho = 0.42$; $p = .001$) (Figures 3.1.8 and 3.1.9).

RQ5. Is willingness to pay positively correlated with pleasantness and consumption?

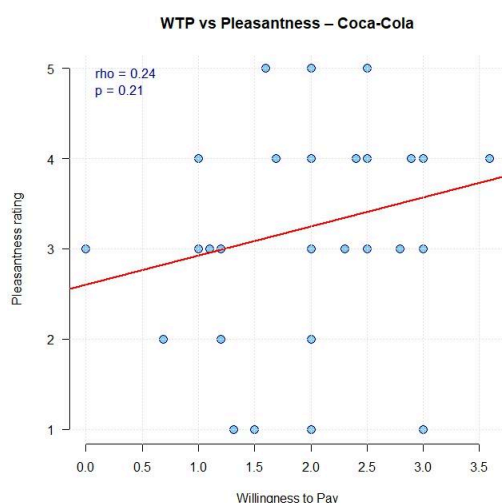


Figure 3.1.10 *WTP vs Pleasantness (brand)*

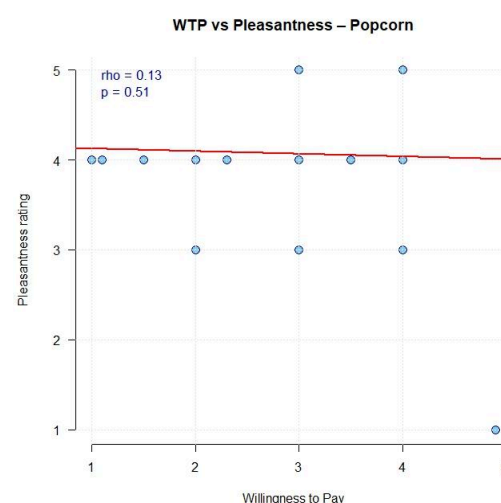


Figure 3.1.11 *WTP vs Pleasantness (non-brand)*

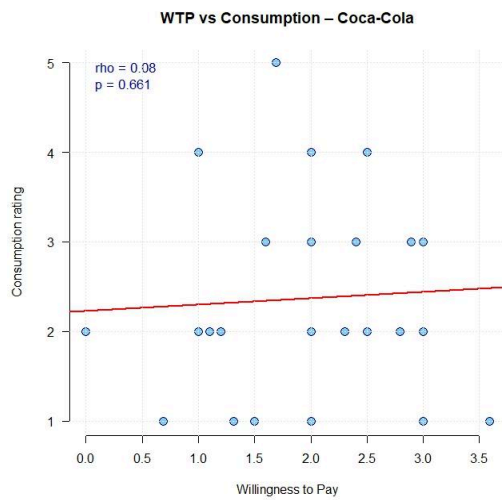


Figure 3.1.12 *WTP vs Consumption (brand)*

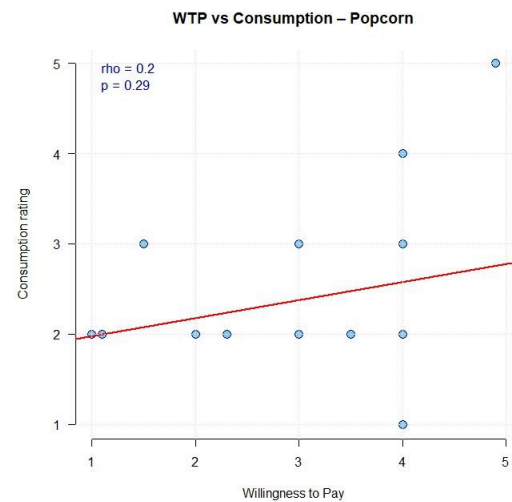


Figure 3.1.13 *WTP vs Consumption (non-brand)*

- WTP did not significantly correlate with reported pleasantness for either Coca-Cola ($p = .210$) or Popcorn ($p = .510$) (Figures 3.1.10 and 3.1.11).
- WTP did not significantly correlate with reported consumption frequency for either Coca-Cola ($p = .661$) or Popcorn ($p = .290$) (Figures 3.1.12 and 3.1.13).

RQ6. Is willingness to pay for the combination lower than the sum of the individual products presented separately?

The one-sample t-test indicated that subjects assigned a discount of € -0.400 to the combination, which was significantly different from zero ($p = .001$).

RQ7. Is the magnitude of the discount correlated with the P300 amplitude elicited by the combination?

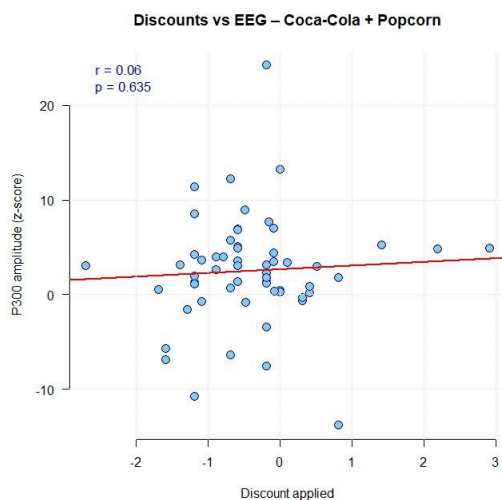


Figure 3.1.14 *Discounts (or surcharges) vs EEG (combination)*

Results showed that discounts (or surcharges) applied to the combination did not significantly correlate with P300 amplitudes elicited by the combination ($p = .635$) (Figure 3.1.14).

3.2 Pringles Set

RQ1. Do combinations elicit higher P300 than brands presented alone?

Results showed that 31 participants had a higher amplitude for the combination of Pringles and Cocktail compared to Pringles presented alone, while 29 participants had a higher amplitude for the brand alone compared to the combination.

The binomial test indicated no significant difference between the two groups ($p = .897$)

RQ2. Do combinations elicit higher P300 than non-brands presented alone?

Results indicated that 26 participants had a higher amplitude for the combination of Pringles and Cocktail compared to Cocktail presented alone, while 34 participants had a higher amplitude for the non-brand alone compared to the combination.

The binomial test showed no significant difference between the two groups ($p = .366$).

RQ3. Do P300 amplitudes correlate with participants' reported pleasantness, consumption frequency, and willingness to pay?

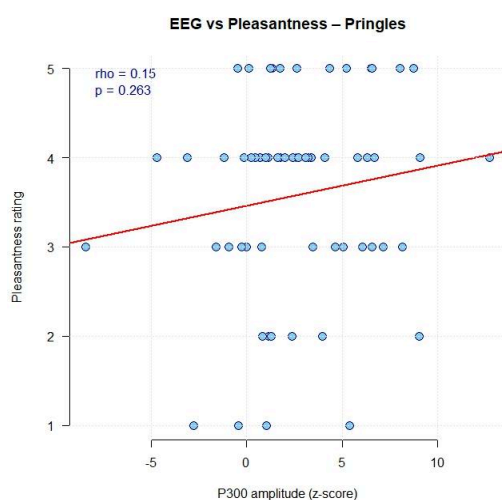


Figure 3.2.1 EEG vs Pleasantness (brand)

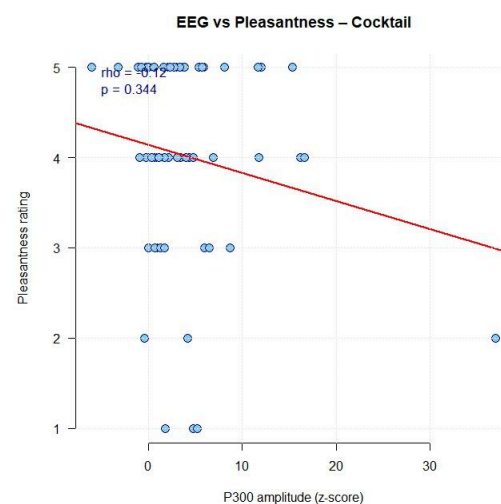


Figure 3.2.2 EEG vs Pleasantness (non-brand)

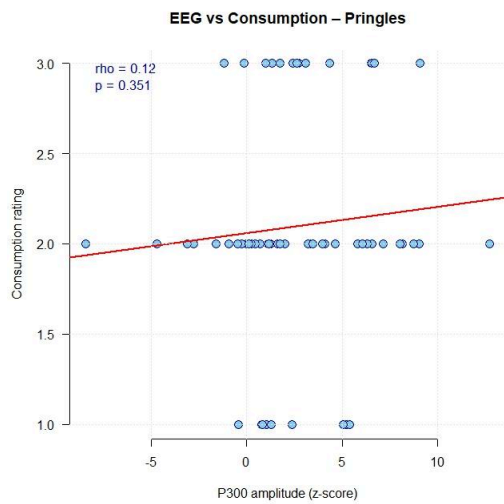


Figure 3.2.3 EEG vs Consumption (brand)

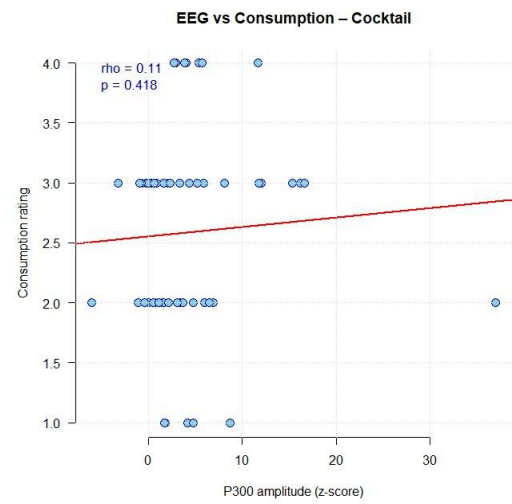


Figure 3.2.4 EEG vs Consumption (non-brand)

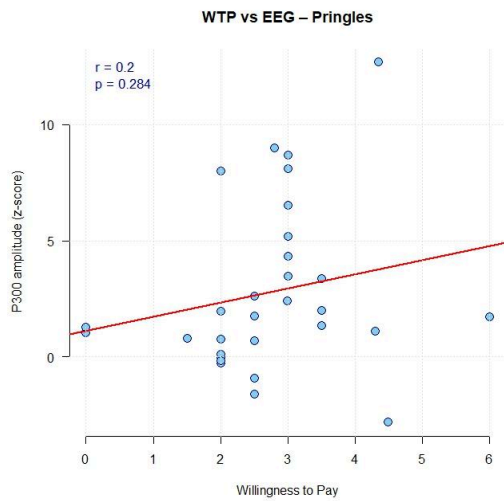


Figure 3.2.5 WTP vs EEG (brand)

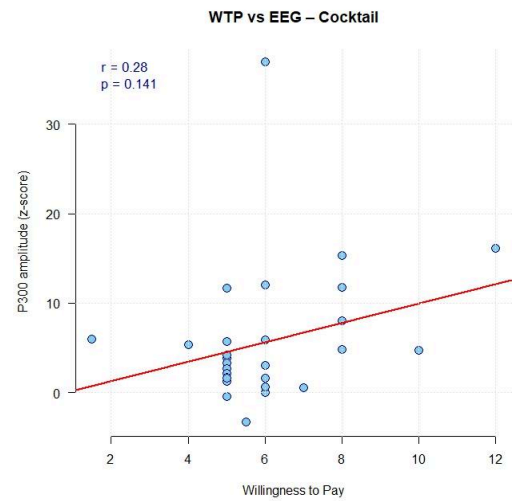


Figure 3.2.6 WTP vs EEG (non-brand)

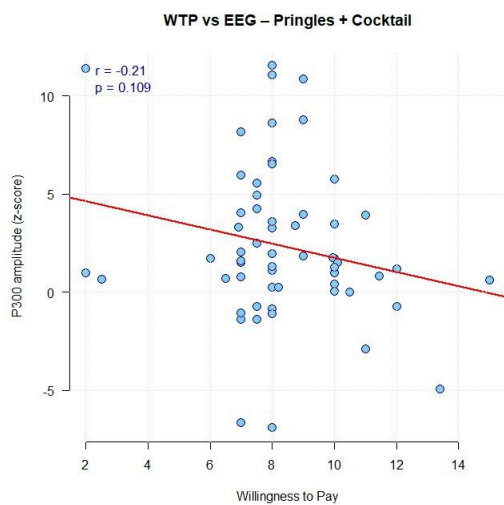


Figure 3.2.7 WTP vs EEG (combination)

- P300 amplitudes did not significantly correlate with reported pleasantness for either Pringles ($p = .263$) or Cocktail ($p = .344$) (Figures 3.2.1 and 3.2.2).
- P300 amplitudes did not significantly correlate with reported consumption frequency for either Pringles ($p = .351$) or Cocktail ($p = .418$) (Figures 3.2.3 and 3.2.4).
- P300 amplitudes did not significantly correlate with reported WTP for Pringles ($p = .284$), Cocktail ($p = .141$), or the combination ($p = .109$) (Figures 3.2.5, 3.2.6, 3.2.7).

RQ4. Is pleasantness positively correlated with consumption frequency?

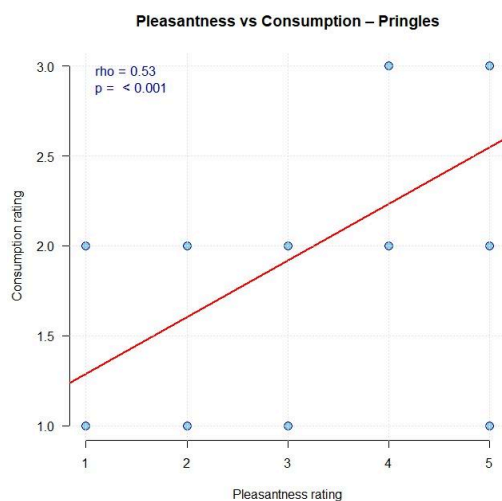


Figure 3.2.8 *Pleasantness vs Consum. (brand)*

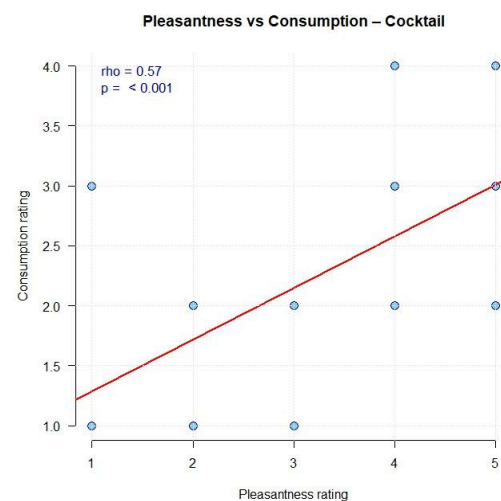


Figure 3.2.9 *Pleasantness vs Consum. (non-brand)*

Pleasantness was significantly positively correlated with consumption frequency for both Pringles ($\rho = 0.53$; $p < .001$) and Cocktail ($\rho = 0.57$; $p < .001$) (Figures 3.2.8 and 3.2.9).

RQ5. Is willingness to pay positively correlated with both pleasantness and consumption?

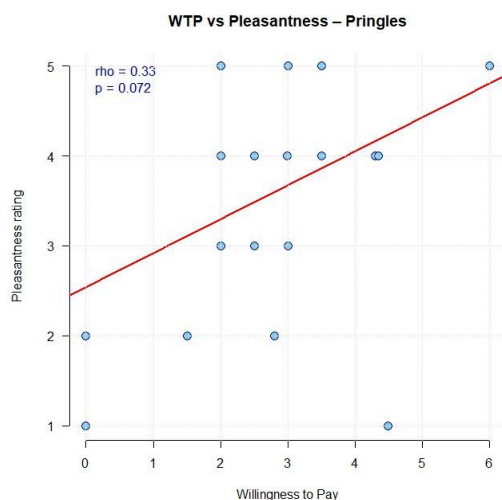


Figure 3.2.10 *WTP vs Pleasantness (brand)*

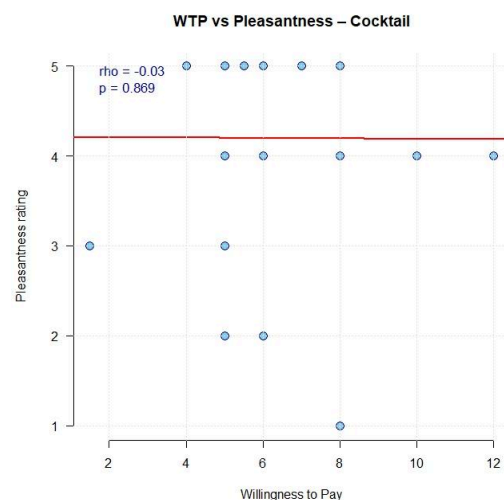


Figure 3.2.11 *WTP vs Pleasantness (non-brand)*

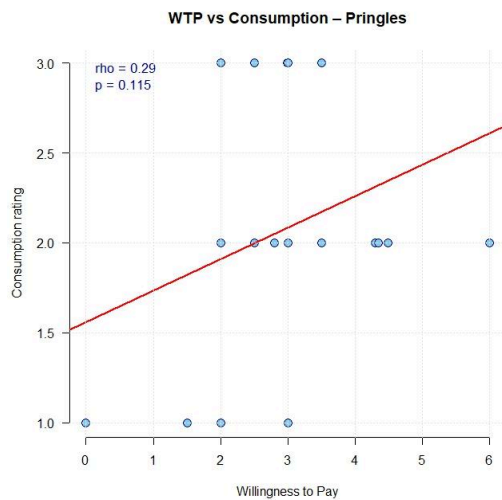


Figure 3.2.12 *WTP vs Consumption (brand)*

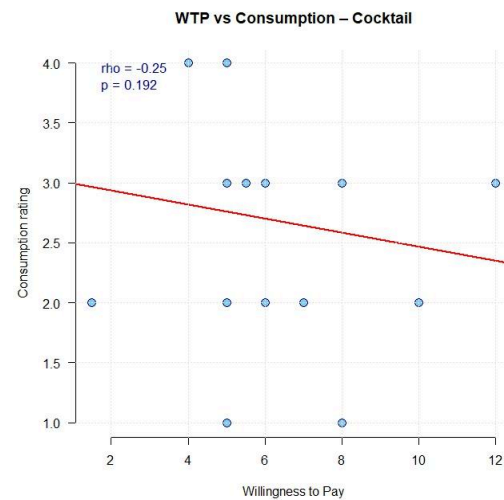


Figure 3.2.13 *WTP vs Consumption (non-brand)*

- WTP did not significantly correlate with reported pleasantness for either Pringles ($p = .072$) or Cocktail ($p = .869$) (Figures 3.2.10 and 3.2.11).
- WTP did not significantly correlate with reported consumption frequency for either Pringles ($p = .115$) or Cocktail ($p = .192$) (Figures 3.2.12 and 3.2.13).

RQ6. Is willingness to pay for the combination lower than the sum of the individual products presented separately?

The one-sample t-test indicated that subjects assigned a discount of € -1.207 to the combination, which was significantly different from zero ($p < .001$).

RQ7. Is the magnitude of the discount correlated with the P300 amplitude elicited by the combination?

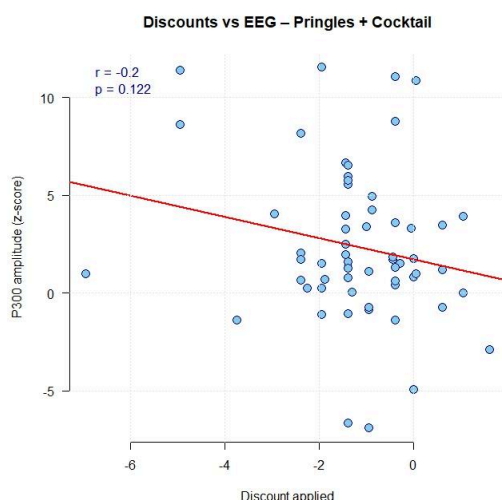


Figure 3.2.14 *Discounts (or surcharges) vs EEG (combination)*

Results showed that discounts (or surcharges) applied to the combination did not significantly correlate with P300 amplitudes elicited by the combination ($p = .122$) (Figure 3.2.14).

3.3 Starbucks Set

RQ1. Do combinations elicit higher P300 than brands presented alone?

Results showed that 32 participants had a higher amplitude for the combination of Starbucks and Muffin compared to Starbucks presented alone, while 28 participants had a higher amplitude for the brand alone compared to the combination.

The binomial test indicated no significant difference between the two groups ($p = .699$).

RQ2. Do combinations elicit higher P300 than non-brands presented alone?

Results indicated that 23 participants had a higher amplitude for the combination of Starbucks and Muffin compared to the Muffin presented alone, while 37 participants had a higher amplitude for the non-brand alone compared to the combination.

The binomial test showed no significant difference between the two groups ($p = .092$).

RQ3. Do P300 amplitudes correlate with participants' reported pleasantness, consumption frequency, and willingness to pay?

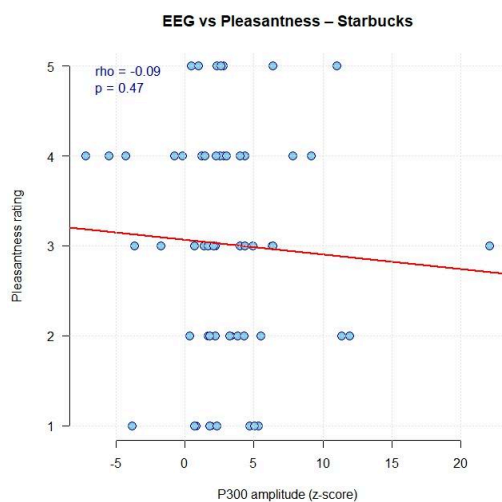


Figure 3.3.1 EEG vs Pleasantness (brand)

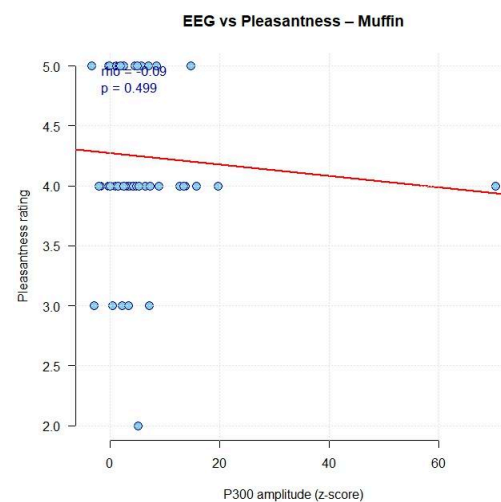


Figure 3.3.2 EEG vs Pleasantness (non-brand)

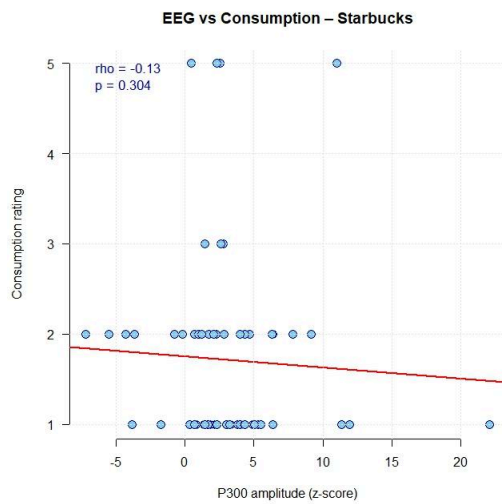


Figure 3.3.3 EEG vs Consumption (brand)

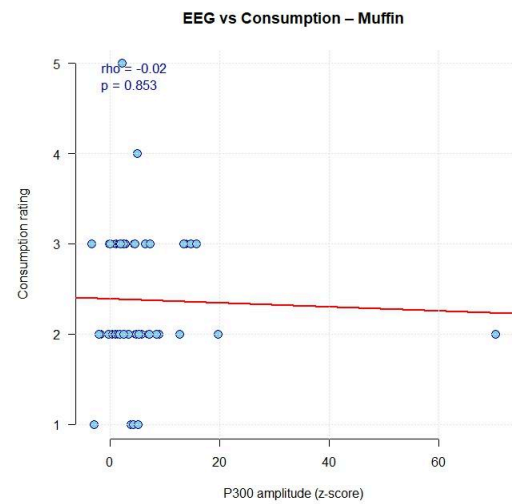


Figure 3.3.4 EEG vs Consumption (non-brand)

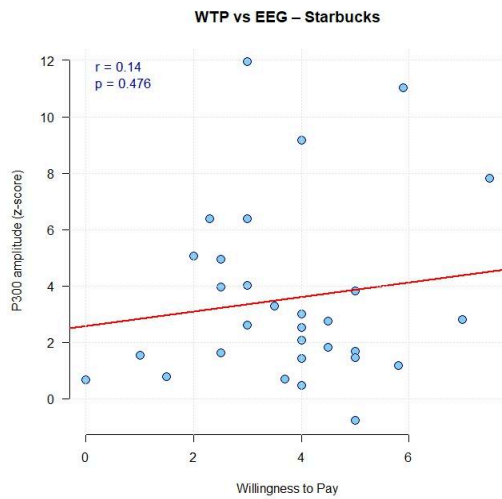


Figure 3.3.5 WTP vs EEG (brand)

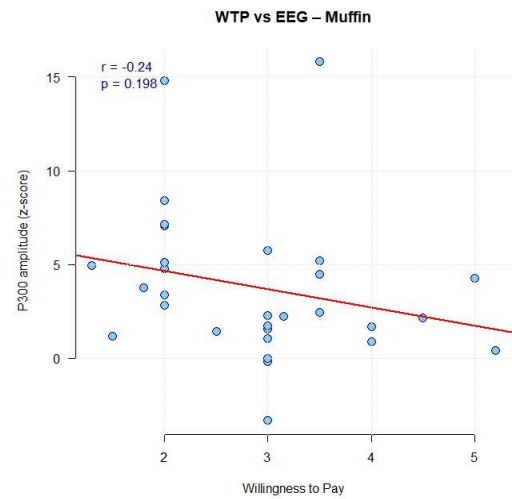


Figure 3.3.6 WTP vs EEG (non-brand)

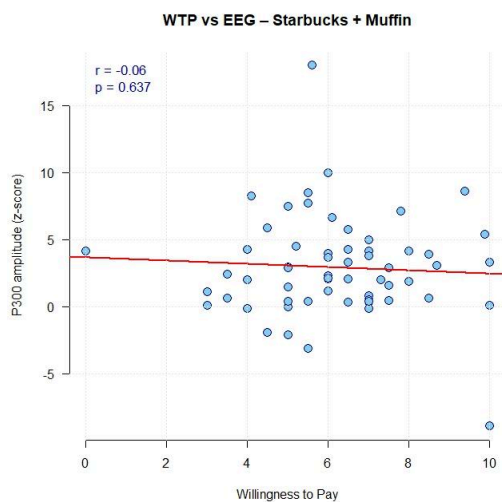


Figure 3.3.7 WTP vs EEG (combination)

- P300 amplitudes did not significantly correlate with reported pleasantness for either Starbucks ($p = .470$) or Muffin ($p = .499$) (Figures 3.3.1 and 3.3.2).
- P300 amplitudes did not significantly correlate with reported consumption frequency for either Starbucks ($p = .304$) or Muffin ($p = .853$) (Figures 3.3.3 and 3.3.4).
- P300 amplitudes did not significantly correlate with reported WTP for Starbucks ($p = .476$), Muffin ($p = .198$), or the combination ($p = .637$) (Figures 3.3.5, 3.3.6, 3.3.7).

RQ4. Is pleasantness positively correlated with consumption frequency?

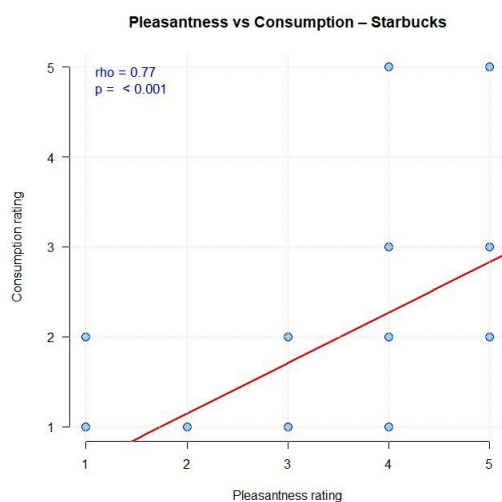


Figure 3.3.8 Pleasantness vs Consum. (brand)

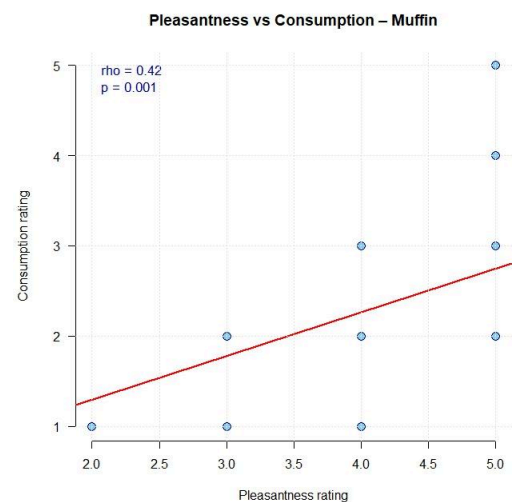


Figure 3.3.9 Pleasantness vs Consum. (non-brand)

Pleasantness was significantly positively correlated with consumption frequency for both Starbucks ($\rho = 0.77$; $p < .001$) and Muffin ($\rho = 0.42$; $p = .001$) (Figures 3.3.8 and 3.3.9).

RQ5. Is willingness to pay positively correlated with both pleasantness and consumption?

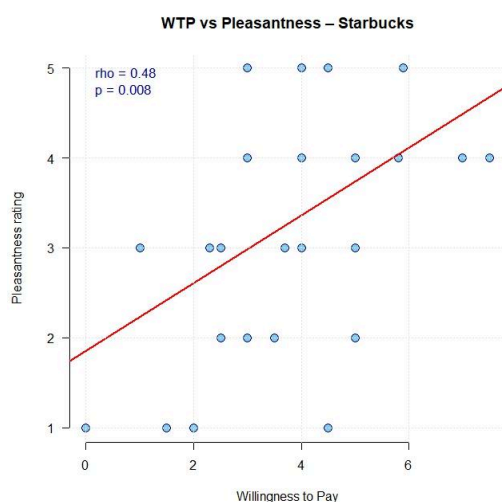


Figure 3.3.10 WTP vs Pleasantness (brand)

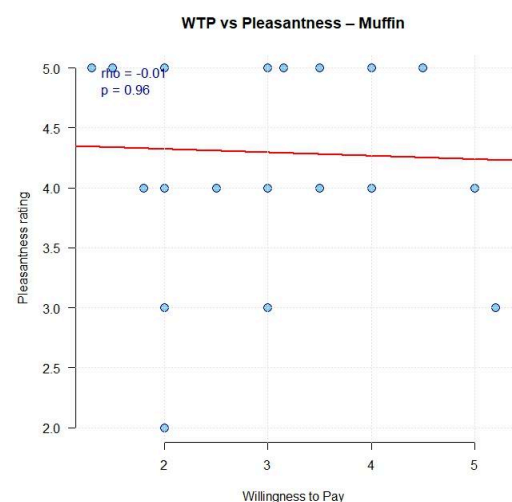


Figure 3.3.11 WTP vs Pleasantness (non-brand)

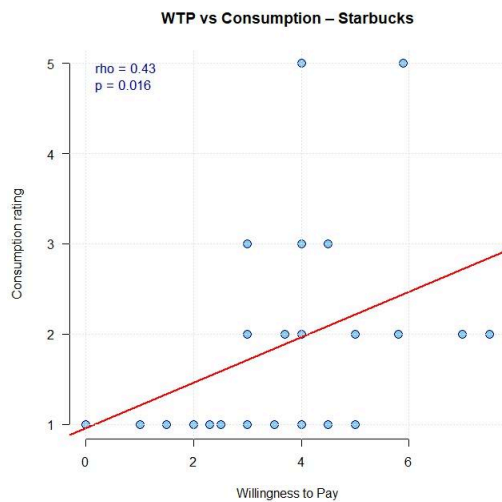


Figure 3.3.12 *WTP vs Consumption (brand)*

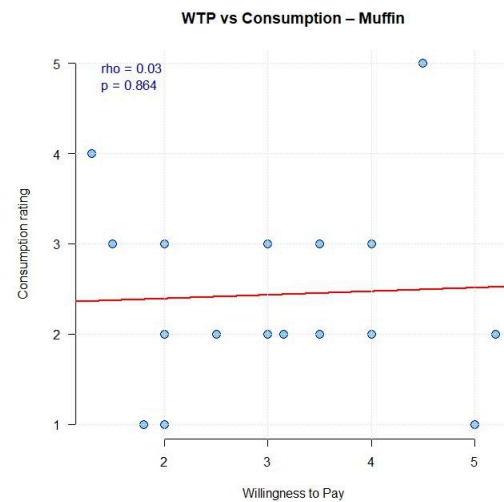


Figure 3.3.13 *WTP vs Consumption (non-brand)*

- WTP was significantly positively correlated with pleasantness for Starbucks ($\rho = 0.48$; $p = .008$), but not significantly correlated for Muffin ($p = .960$) (Figures 3.3.10 and 3.3.11).
- WTP was significantly positively correlated with consumption for Starbucks ($\rho = 0.43$; $p = .016$), but not significantly correlated for Muffin ($p = .864$) (Figures 3.3.12 and 3.3.13).

RQ6. Is willingness to pay for the combination lower than the sum of the individual products presented separately?

The one-sample t-test indicated that subjects assigned a discount of € -0.532 to the combination, which was significantly different from zero ($p < .001$).

RQ7. Is the magnitude of the discount correlated with the P300 amplitude elicited by the combination?

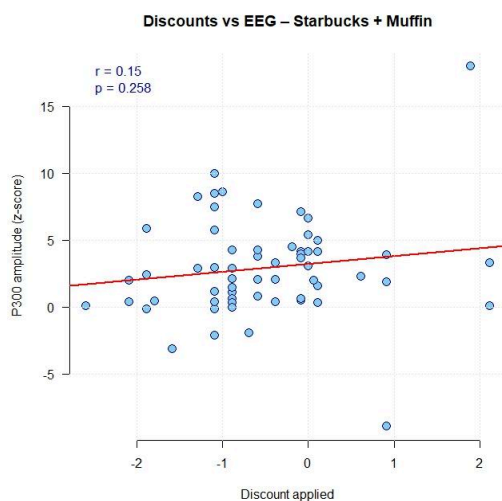


Figure 3.3.14 *Discounts (or surcharges) vs EEG (combination)*

Results showed that discounts (or surcharges) applied to the combination did not significantly correlate with P300 amplitudes elicited by the combination ($p = .258$) (Figure 3.3.14).

3.4 Oreo Set

RQ1. Do combinations elicit higher P300 than brands presented alone?

Results showed that 25 participants had a higher amplitude for the combination of Oreo and Milk compared to Oreo presented alone, while 35 participants had a higher amplitude for the brand alone compared to the combination.

The binomial test indicated no significant difference between the two groups ($p = .245$).

RQ2. Do combinations elicit higher P300 than non-brands presented alone?

Results indicated that 32 participants had a higher amplitude for the combination of Oreo and Milk compared to Milk presented alone, while 28 participants had a higher amplitude for the non-brand alone compared to the combination.

The binomial test showed no significant difference between the two groups ($p = .699$).

RQ3. Do P300 amplitudes correlate with participants' reported pleasantness, consumption frequency, and willingness to pay?

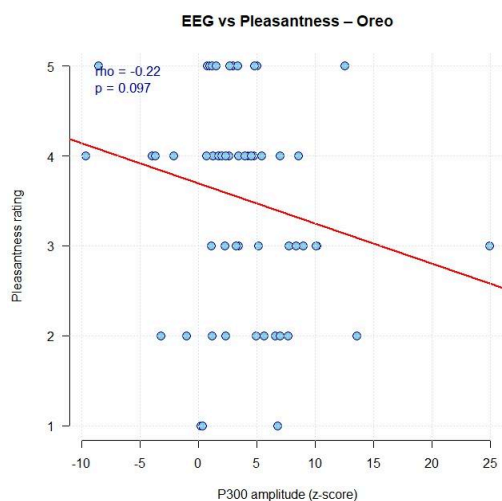


Figure 3.4.1 EEG vs Pleasantness (brand)

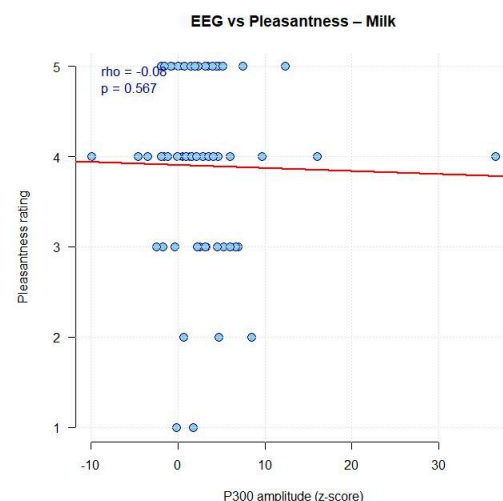


Figure 3.4.2 EEG vs Pleasantness (non-brand)

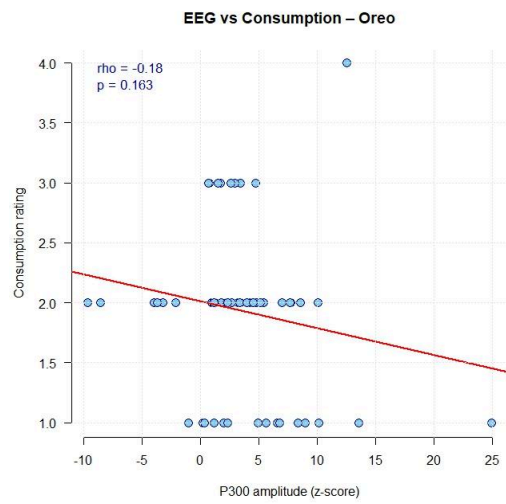


Figure 3.4.3 EEG vs Consumption (brand)

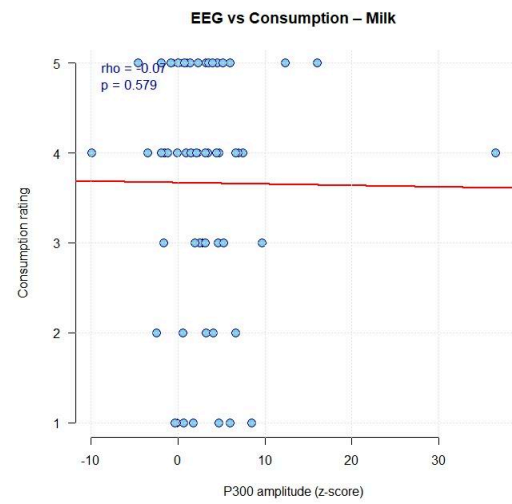


Figure 3.4.4 EEG vs Consumption (non-brand)

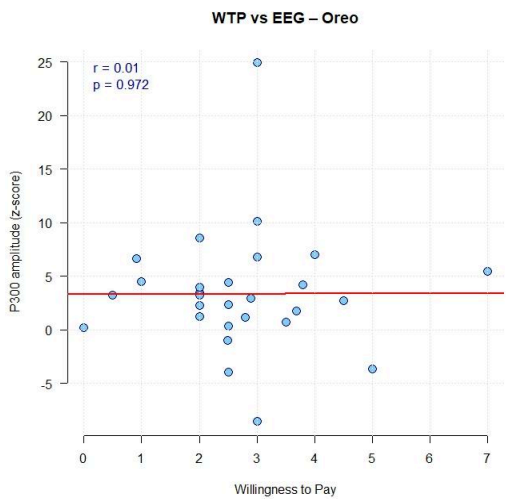


Figure 3.4.5 WTP vs EEG (brand)

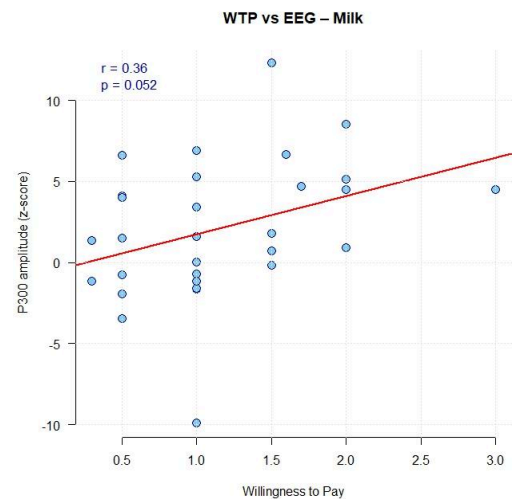


Figure 3.4.6 WTP vs EEG (non-brand)

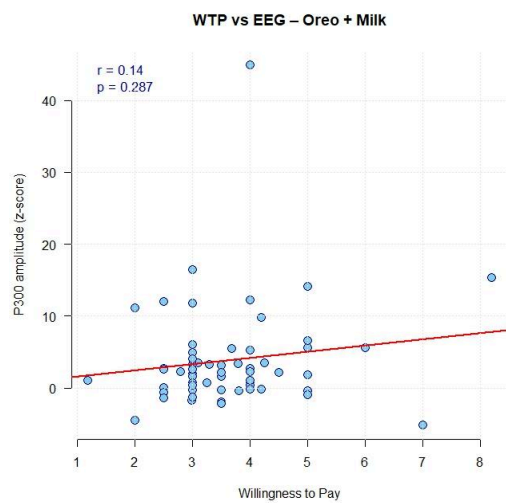


Figure 3.4.7 WTP vs EEG (combination)

- P300 amplitudes did not significantly correlate with reported pleasantness for either Oreo ($p = .097$) or Milk ($p = .567$) (Figures 3.4.1 and 3.4.2).
- P300 amplitudes did not significantly correlate with reported consumption frequency for either the Oreo ($p = .163$) or Milk ($p = .579$) (Figures 3.4.3 and 3.4.4).
- P300 amplitudes did not significantly correlate with reported WTP for Oreo ($p = .972$), Milk ($p = .052$), or the combination ($p = .287$) (Figures 3.4.5, 3.4.6, 3.4.7).

RQ4. Is pleasantness positively correlated with consumption frequency?

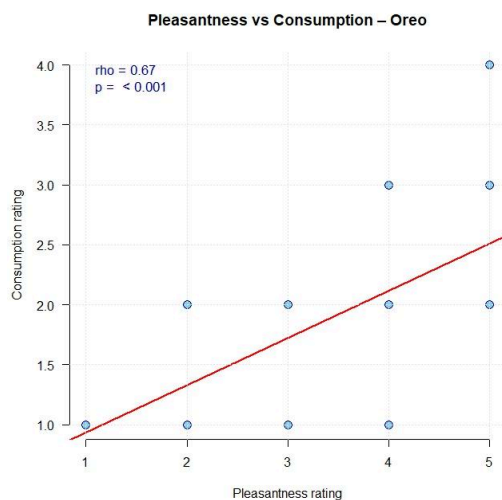


Figure 3.4.8 *Pleasantness vs Consum.(brand)*

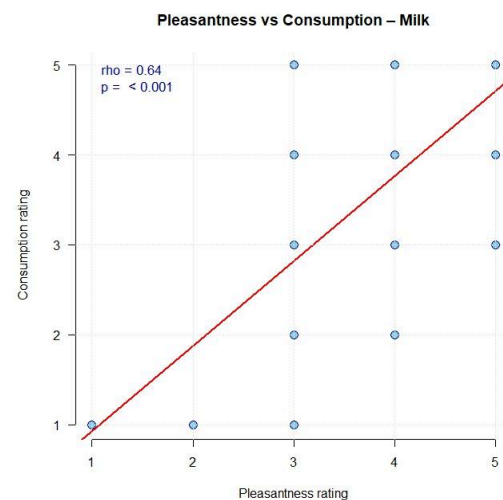


Figure 3.4.9 *Pleasantness vs Consum. (non-brand)*

Pleasantness was significantly positively correlated with consumption frequency for both Oreo ($\rho = 0.67$; $p < .001$) and Milk ($\rho = 0.64$; $p < .001$) (Figures 3.4.8 and 3.4.9).

RQ5. Is willingness to pay positively correlated with both pleasantness and consumption?

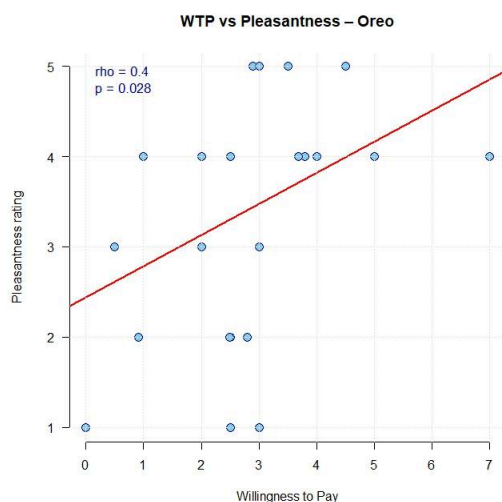


Figure 3.4.10 *WTP vs Pleasantness (brand)*

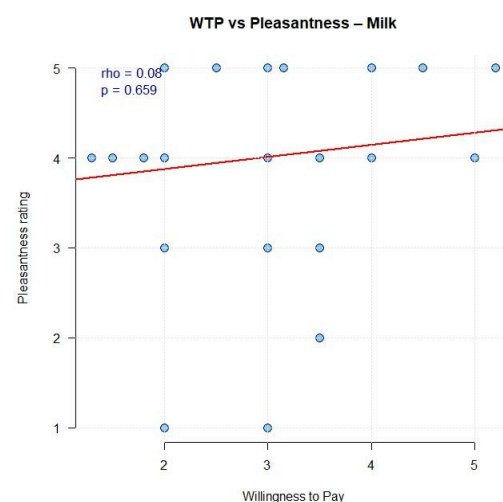


Figure 3.4.11 *WTP vs Pleasantness (non-brand)*

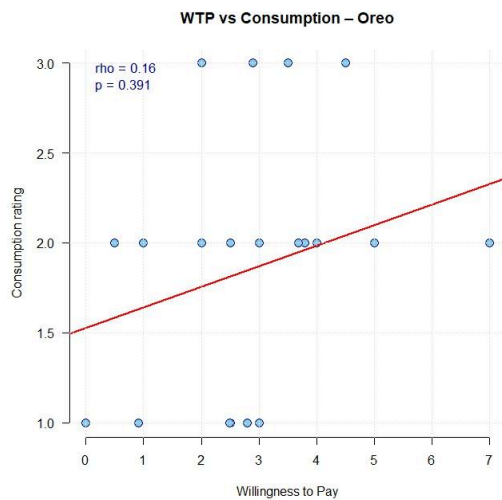


Figure 3.4.12 *WTP vs Consumption (brand)*

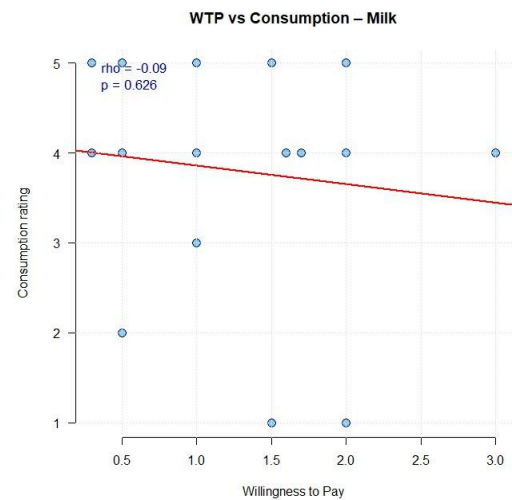


Figure 3.4.13 *WTP vs Consumption (non-brand)*

- WTP was significantly positively correlated with pleasantness for Oreo ($\rho = 0.40$; $p = .028$), but not significantly correlated for Milk ($p = .659$) (Figures 3.4.10, 3.4.11).
- WTP did not significantly correlate with reported consumption frequency for either Oreo ($p = .391$) or Milk ($p = .626$) (Figures 3.4.12 and 3.4.13).

RQ6. Is willingness to pay for the combination lower than the sum of the individual products presented separately?

The one-sample t-test indicated that subjects assigned a discount of € -0.286 to the combination, which was significantly different from zero ($p < .001$).

RQ7. Is the magnitude of the discount correlated with the P300 amplitude elicited by the combination?

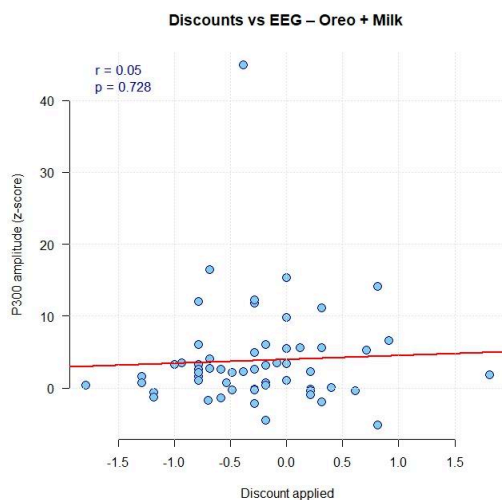


Figure 3.4.14 *Discounts (or surcharges) vs EEG (combination)*

Results showed that discounts (or surcharges) applied to the combination did not significantly correlate with P300 amplitudes elicited by the combination ($p = .728$) (Figure 3.4.14).

3.5 Nutella Set

RQ1. Do combinations elicit higher P300 than brands presented alone?

Results showed that 30 participants had a higher amplitude for the combination of Nutella and Bread compared to Nutella presented alone, while the other half had a higher amplitude for the brand alone compared to the combination. Therefore, the two proportions did not differ from chance.

RQ2. Do combinations elicit higher P300 than non-brands presented alone?

Results indicated that 30 participants had a higher amplitude for the combination of Nutella and Bread compared to Bread presented alone, while the other half had a higher amplitude for the non-brand alone compared to the combination. Therefore, the two proportions did not differ from chance.

RQ3. Do P300 amplitudes correlate with participants' reported pleasantness, consumption frequency, and willingness to pay?

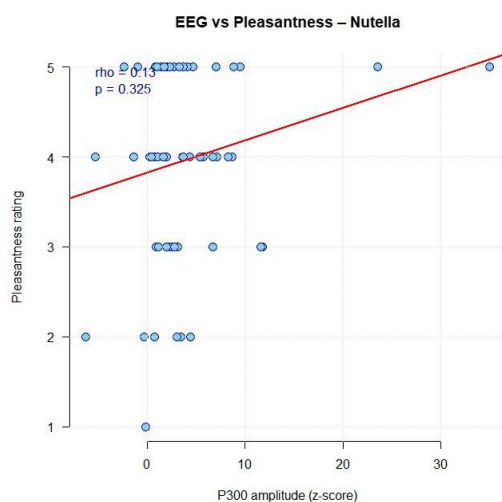


Figure 3.5.1 EEG vs Pleasantness (brand)

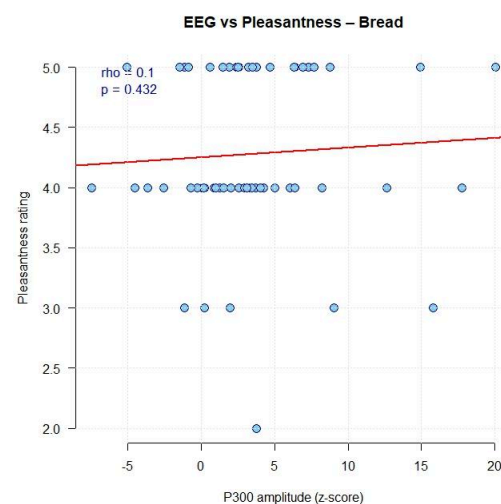


Figure 3.5.2 EEG vs Pleasantness (non-brand)

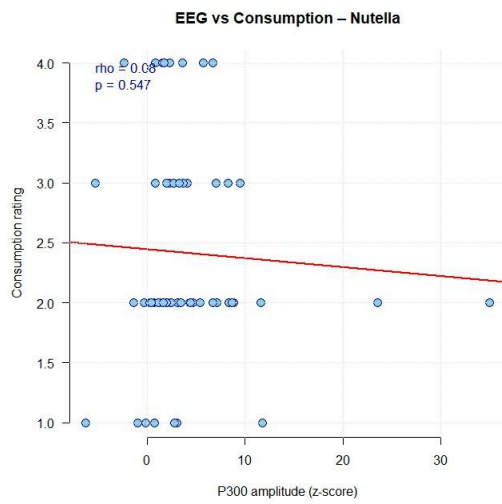


Figure 3.5.3 EEG vs Consumption (brand)

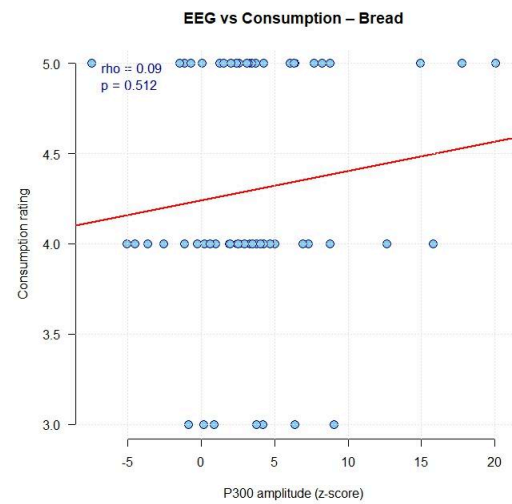


Figure 3.5.4 EEG vs Consumption (non-brand)

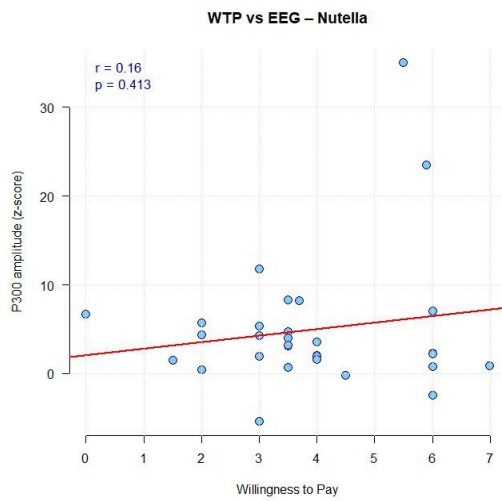


Figure 3.5.5 WTP vs EEG (brand)

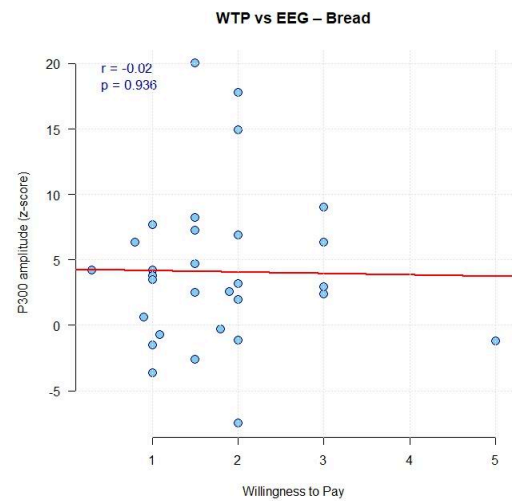


Figure 3.5.6 WTP vs EEG (non-brand)

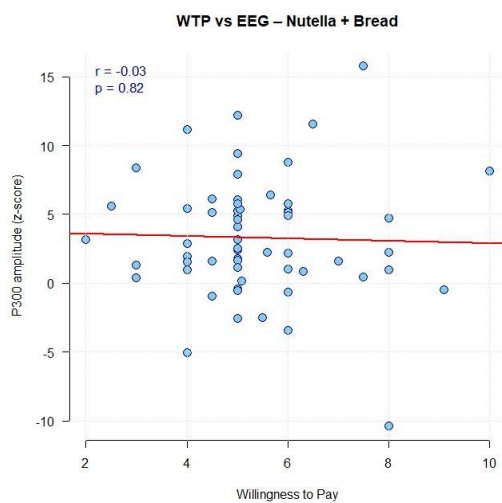


Figure 3.5.7 WTP vs EEG (combination)

- P300 amplitudes did not significantly correlate with reported pleasantness for either Nutella ($p = .325$) or Bread ($p = .432$) (Figures 3.5.1 and 3.5.2).
- P300 amplitudes did not significantly correlate with reported consumption frequency for either Nutella ($p = .547$) or Bread ($p = .512$) (Figures 3.5.3 and 3.5.4).
- P300 amplitudes did not significantly correlate with reported WTP for Nutella ($p = .413$), Bread ($p = .936$), or the combination ($p = .820$) (Figures 3.5.5, 3.5.6, 3.5.7).

RQ4. Is pleasantness positively correlated with consumption frequency?

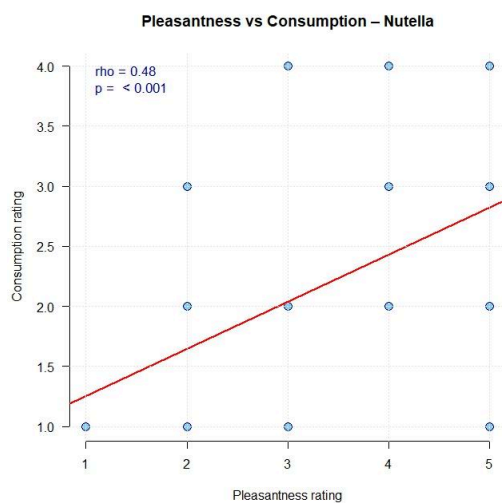


Figure 3.5.8 *Pleasantness vs Consum. (brand)*



Figure 3.5.9 *Pleasantness vs Consum. (non-brand)*

Pleasantness was significantly positively correlated with consumption frequency for both Nutella ($\rho = 0.48$; $p < .001$) and Bread ($\rho = 0.27$; $p = .040$) (Figures 3.5.8 and 3.5.9).

RQ5. Is willingness to pay positively correlated with both pleasantness and consumption?

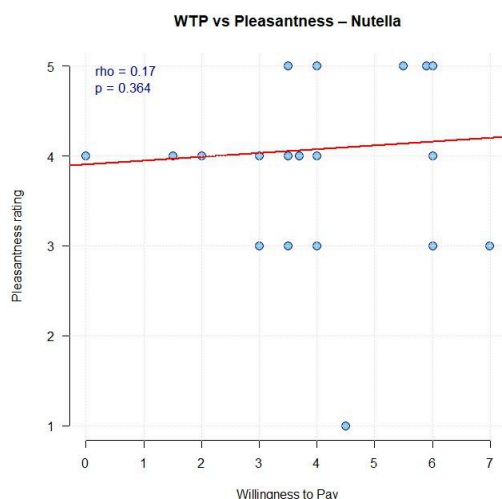


Figure 3.5.10 *WTP vs Pleasantness (brand)*

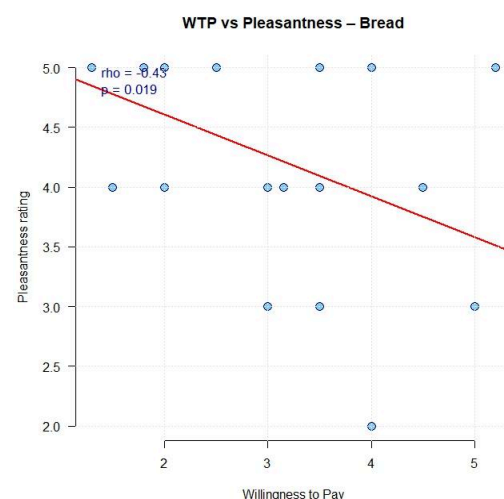


Figure 3.5.11 *WTP vs Pleasantness (non-brand)*

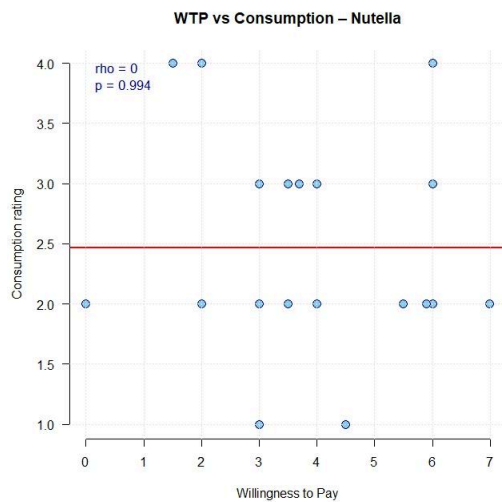


Figure 3.5.12 *WTP vs Consumption (brand)*

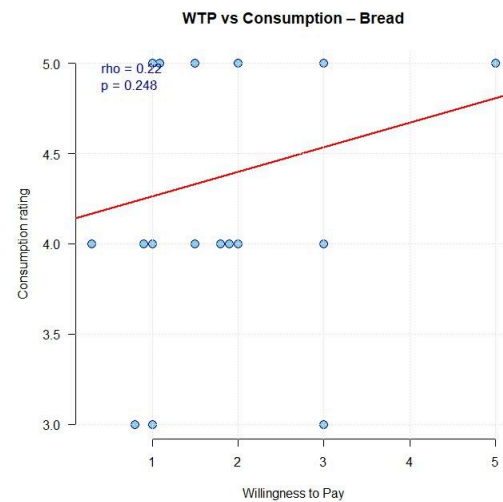


Figure 3.5.13 *WTP vs Consumption (non-brand)*

- WTP was significantly negatively correlated with pleasantness for Bread ($\rho = -0.43$; $p = .019$), but not correlated for Nutella ($p = .364$) (Figures 3.5.10, 3.5.11).
- WTP did not significantly correlate with reported consumption frequency for either Nutella ($p = .994$) or Bread ($p = .248$) (Figures 3.5.12 and 3.5.13).

RQ6. Is willingness to pay for the combination lower than the sum of the individual products presented separately?

The one-sample t-test indicated that subjects assigned a discount of € -0.580 to the combination, which was significantly different from zero ($p < .001$).

RQ7. Is the magnitude of the discount correlated with the P300 amplitude elicited by the combination?

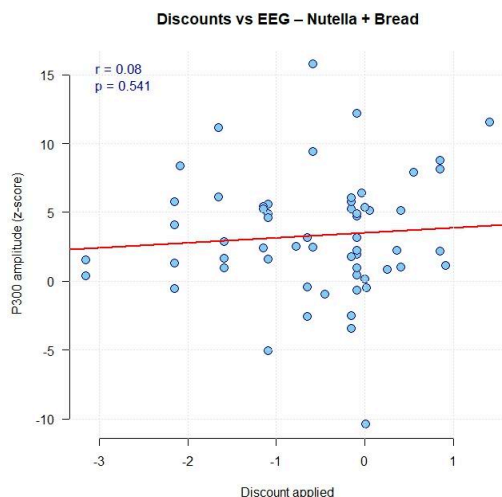


Figure 3.5.14 *Discounts (or surcharges) vs EEG (combination)*

Results showed that discounts (or surcharges) applied to the combination did not significantly correlate with P300 amplitudes elicited by the combination ($p = .541$) (Figure 3.5.14).

4. Discussion

4.1 RQ1 & RQ2

With the first research question we have explored whether the brand-non-brand combination was more salient for participants than the brand alone. Results showed no significant difference between the two, meaning that subjects did not find one more salient than the other. However, even if not significant, we observed a slight pattern of higher P300 amplitudes for the combination in three sets, although this effect cannot be distinguished from chance.

With the second research question we instead investigated differences in P300 amplitudes between the combination and the non-brand. Again, results indicated no significant difference between the two across sets. A slight pattern emerged in the opposite direction, with the non-brand sometimes eliciting higher P300 amplitudes than the combination, although this pattern was again far from significance.

From these first two results we can infer that attentional allocation was not systematically related to a specific type of image within each set. Participants showed higher P300 amplitudes to different types of stimuli, and no consistent pattern emerged across sets.

Our aim in this first part of the study was to explore what happens at the earliest level of neural processing when consumers evaluate complementary products and single items. In Section 1.3 we have explored how cross-merchandising strategies are used in retail settings to encourage consumers to purchase two products when they are placed close to each other and share the same consumption purpose (Sarantopoulos et al., 2019).

Our aim was to examine the earliest stages of neural processing to determine whether attentional allocation and early salience play a role in the mechanisms underlying the efficacy of this strategy.

Findings suggest that the effectiveness of cross-merchandising is not driven by differences in early attentional allocation, as no differences in P300 amplitudes were observed between the three types of products. This indicates that the underlying mechanisms of this strategy are unlikely to operate at early stages of stimulus processing, and may instead involve later cognitive or evaluative processes.

A similar argument applies to brands: although they are typically associated with familiarity, trust, and symbolic meaning (Jahan et al., 2024), and might therefore be more salient for consumers, these associations may not be reflected in early attentional responses, as images

containing the complementary brand did not elicit greater attentional responses than those not containing it.

In the present experiment, we were primarily capturing the perceptual salience of the images. At very early stages of processing, stimuli may attract attention because of perceptual features such as color or visual composition rather than because of the symbolic meaning associated with the brand or the combination. For example, Coca-Cola may attract attention because of its distinctive red color, without necessarily triggering the broader symbolic associations linked to the brand.

Although the P300 component was selected because its amplitude increases with emotionally and motivationally relevant stimuli (Johnson, 1986), in the context of consumer behavior this early neural response may not fully capture the processes that lead consumers to prefer a complementary combination over a single product. For instance, associating the combination of Coca-Cola and Popcorn with the “cinema” experience may require more conscious or contextual evaluation, which likely occurs at later stages of neural processing.

4.2 RQ3

With the third research question we aimed to understand whether P300 amplitudes were correlated with pleasantness, consumption frequency, and willingness to pay.

Let us discuss these relationships separately in the following sections.

4.2.1 P300 vs Pleasantness

Regarding the correlation between P300 amplitudes (z-scores) and pleasantness, computed only for single products, Spearman correlation tests did not reveal significant results across all sets, meaning that EEG scores were not associated with participants’ reported pleasantness ratings. In addition, no particular pattern emerged: for some products the correlation tended to be slightly positive, while for others it was negative, even though none of these tendencies reached statistical significance.

Since RQ3 was exploratory, we did not have specific expectations about a possible correlation. Based on our findings, we cannot conclude that P300 amplitudes are correlated with pleasantness, suggesting that this neural component is not a reliable indicator of consumer liking.

This result can be interpreted in two ways. First, as discussed in Section 1.3, P300 increases not only for stimuli that people like, but also for those that are evaluated negatively, as they

are both salient (Fields, 2023). Therefore, the presence of both positive and negative tendencies across products may reflect the fact that attentional salience does not necessarily correspond to hedonic evaluation.

Second, in Section 4.1 we have stated that our findings may suggest that early neural processing does not capture those variables typically associated with consumer evaluation; these aspects likely emerge during later and more deliberative stages of processing. Consequently, P300 responses may reflect the immediate attentional relevance of a stimulus rather than the broader set of factors that influence consumer preferences. How much people like a product may depend on memories, personal experiences, or contextual associations, which are not necessarily reflected in the P300 component.

4.2.2 P300 vs Consumption Frequency

Regarding the correlation between P300 amplitudes (z-scores) and consumption frequency, computed only for single products, results showed no significant associations between the two. This means that P300 values did not predict whether participants reported consuming a product more or less frequently.

In Section 4.2.1 we highlighted that this research question was exploratory, as scientific literature in this field does not suggest that greater attentional allocation should necessarily predict consumption behavior. However, since pleasantness and consumption frequency are often positively correlated in consumer research (Yoon & Meyvis, 2024), we considered it relevant to explore not only possible associations with pleasantness, but also whether early neural salience might indirectly relate to consumption habits.

Given that results did not indicate a relationship between P300 and pleasantness, it is not surprising that no correlation with consumption frequency was observed. These findings are consistent with the interpretation proposed in Section 4.1: early neural responses captured by the P300, associated with attentional salience, may be relatively independent from more deliberative consumer variables that depend on broader behavioral and experiential factors.

4.2.3 P300 vs Willingness to Pay

A similar pattern emerged for willingness to pay. As discussed in Section 1.3, this variable is often positively related to pleasantness and consumption frequency, although this relationship should be interpreted cautiously due to numerous additional factors involved (Seppä et al., 2015). In this case we again did not find significant correlations between P300 amplitudes (z-scores) and willingness to pay. This indicates that attentional salience is not a direct

indicator of how much participants would be willing to pay for a single product or a combination. Specifically, our findings suggest that early neural indicators of attentional salience do not directly translate into economic valuation processes, which likely emerge at later stages of cognitive processing.

This result is not surprising considering that willingness to pay is influenced by many variables, including perceived quality, personal preferences, purchasing habits, and contextual factors (Seppä et al., 2015). Since we did not observe significant relationships between P300 and either pleasantness or consumption frequency, it is reasonable that also this neural measure did not predict WTP.

Overall, these results reinforce the interpretation that early attentional processes measured through P300 are not sufficient to explain more complex consumer evaluations such as product liking, habitual consumption, or economic valuation.

4.3 RQ4 & RQ5

With the fourth and fifth research questions we aimed to understand whether consumer variables were correlated with each other. We remind that in this case correlations were computed only for single items.

Let us discuss these relationships separately in the following sections.

4.3.1 Pleasantness vs Consumption Frequency

Regarding the relationship between reported pleasantness and consumption frequency, results showed positive correlations between the two, and these were always statistically significant. This means that the more participants liked a product, the more frequently they tended to consume it.

Spearman's rho ranged between 0.27 and 0.80 across all items; some correlations were particularly strong while others were weaker, but all remained positive.

These results align with our expectations and with previous research, which states that people tend to consume products more frequently when they like them more (Yoon & Meyvis, 2024).

However, even though we found significant results for all items, it is important to note that this relationship may not always be so straightforward. In some cases, consumers may strongly like certain products but still consume them less frequently, due to other factors. For example, when food is perceived as unhealthy or high in calories, it may be liked a lot but

intentionally consumed less often for health concerns (Paakki et al., 2022). Therefore, other variables such as dietary habits, or subjective situational factors may influence this relationship.

In this study, however, we consistently observed a positive correlation between pleasantness and consumption frequency across all items. This suggests that, for the products we included in this experiment, individual differences in dietary considerations may not have substantially altered this relationship.

4.3.2 Willingness to Pay vs Pleasantness

Regarding the correlation between willingness to pay and reported pleasantness, this relationship appears to be more complex than the previous one. In fact, in Section 1.3 we have stated that several variables can influence willingness to pay, so this relationship may vary depending on the product and the context (Seppä et al., 2015).

In this study, most correlations were not statistically significant. However, we found significant results for three items: Starbucks ($\rho = 0.48$; $p = .008$), Oreo ($\rho = 0.40$; $p = .028$), and Bread ($\rho = -0.43$; $p = .019$).

Regarding Starbucks and Oreo, the correlations were positive, meaning that the more participants liked these products, the more they were willing to pay for them. Therefore, in this case the pattern aligns with the idea that higher product appreciation can increase its perceived value.

However, we found the opposite pattern for Bread, characterized by a significant negative correlation. The more subjects liked this product, the less they were willing to pay for it. One possible explanation is that, since Bread is a basic/everyday product, consumers may expect relatively low prices regardless of how much they like it, but this needs further investigation.

For all of the other products, correlations were mostly positive but not significant.

Overall, results suggest that while pleasantness can influence WTP, the relationship is not consistent across all products and may depend on product characteristics or consumer expectations.

4.3.3 Willingness to Pay vs Consumption Frequency

Regarding the relationship between willingness to pay and consumption frequency, we found a similar pattern to the one just discussed in Section 4.3.2. In this case, there was only one significant correlation, which was positive and observed for Starbucks ($\rho = 0.48$; $p = .008$).

Participants who reported consuming Starbucks more frequently were also willing to pay more for it.

As regards the other items, correlations were not statistically significant, although most of them were positive. This suggests that there may be a tendency for people who consume a product more frequently to be willing to pay more for it, but this relationship appears relatively weak.

Different factors may explain this result. For instance, people who frequently consume a product may sometimes expect lower prices, discounts, or promotions when buying it (Zhang et al., 2018). In other cases, consumers may choose to buy certain products more often specifically because they are relatively inexpensive (Sturm & Datar, 2011).

Therefore, WTP may depend on a broader set of factors beyond consumption habits (e.g., perceived product value, price expectations, brand perception, and personal purchasing strategies), which could be further investigated in future research.

4.4 RQ6

With the sixth research question we aimed to understand whether participants applied a discount (or a surcharge) when evaluating the combination, compared to the sum of the single products.

Results indicate that for each set participants evaluated the combination applying a discount that was significantly different from zero, meaning they expected to pay less when purchasing the combination.

This result was expected, as discussed in Section 1.3. In fact, when evaluating a bundle, consumers often expect a price advantage compared to purchasing the items separately (Nguyen et al., 2009; Henry et al., 2023). In other words, the idea of accepting to purchase two products together is typically associated with the expectation of receiving a discount.

The discounts applied ranged between € 0.29 (for the Oreo Set) and € 1.21 (for the Pringles Set).

We did not further investigate the reasons why some combinations received higher discounts than others. However, one possible explanation may be related to the initial price of the items included in the set. For example, the Pringles Set included the product that received the highest individual price evaluation (Cocktail), while the Oreo Set included the product with the lowest individual price evaluation (Milk).

Based on this, we think that when the base price of the items increases, participants may expect a proportionally larger discount when the products are offered as a combination. This aspect could be further explored in future studies.

4.5 RQ7

As regards the last research question, we aimed to explore whether there was a correlation between P300 amplitudes (z-scores) for the combinations and the respective discounts applied to them.

This question was purely exploratory, and we did not have specific expectations about a possible association. Results showed no significant correlations across all sets.

In addition, even when analysing the overall pattern, we could not identify a clear positive or negative tendency, as the correlation coefficients were mostly close to zero.

Referring back to the discussion presented in Section 4.2, related to the relationship between P300 amplitudes and consumer variables, these findings again suggest that attentional allocation may not play a role in monetary evaluations. Instead, these evaluations may occur at later stages of neural processing and may not depend on early responses captured by the P300 component.

From the results of this research question we can therefore infer that P300 amplitudes are not able to predict the extent to which participants apply a specific discount.

Other neural components may still play a role in this evaluation, but this remains an open question for future research (see Section 4.7).

4.6 Conceptual Processing Model

In Figure 4.1, a conceptual model is presented to clarify the different stages of consumer processing. The model highlights which associations are supported by the results and which are not.

In the previous paragraphs, we showed that image types were able to elicit a P300 response, which can be considered as reflecting first-stage cognitive processing; we note that the stimulus elicits the response, although this does not significantly differ across image types.

We also observe a second-stage processing, in which we analyse whether the P300 response has a direct effect on consumer variables. In this case, this effect is not supported. Consumer variables can sometimes be interrelated, but they are not necessarily influenced by early attentional processing.

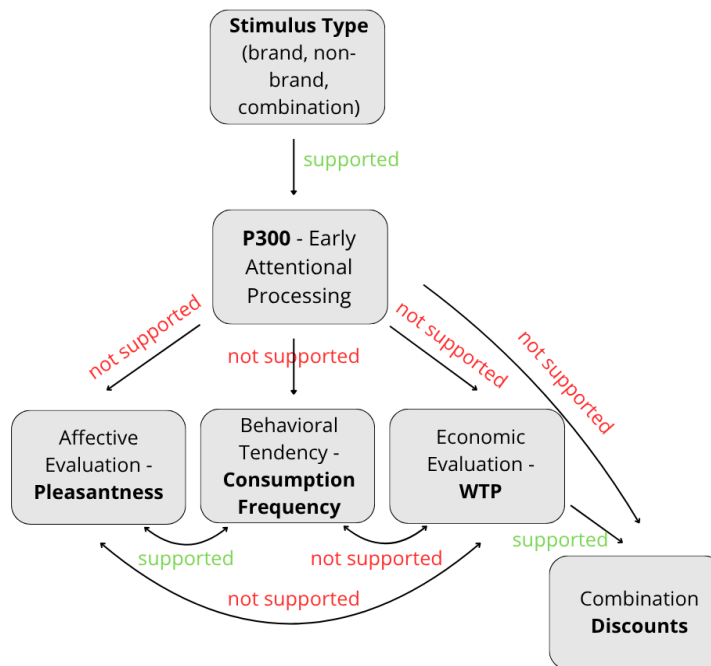


Figure 4.1 - *Conceptual Processing Model*

Overall, this model aims to better integrate and clarify, in a single framework, the contributions of our findings to the understanding of the role of early attentional processing in consumer cognition. This model also helps to understand the limits of the P300 neural component as a neuromarketing tool: while it is highly informative of attentional processes, it is not informative about higher-level evaluative processes, suggesting that other neural metrics should be used to investigate what drives consumer evaluations.

To conclude, this framework highlights how attentional processes are distinct from later evaluative mechanisms in consumer cognition.

4.7 Limitations

Let us now expose a few limitations that should be considered in this study.

First of all, more women than men took part in the experiment, specifically 49 women and 11 men. This was not planned at the beginning, but since we were not interested in making comparisons between the two genders, we did not ensure having a balanced sample. In fact, the study followed a non-probabilistic convenience sampling approach, so simply more women agreed to participate in the experiment. Of course, due to this imbalance, we cannot generalize the findings to both genders.

In addition, only young participants (20–35 years old) took part in the study, so we also cannot generalize the results to all age groups. This aspect is relevant because the way people respond to stimuli and the characteristics of the P300 may vary across the age ranges. As discussed in Section 1.2.1.1.2, P300 amplitude tends to decrease as age increases (van Dinteren et al., 2014).

Another limitation regards the procedure used when participants were asked to indicate the price they would be willing to pay for a product. In this case, we indicated the price of the complementary product as an anchor to facilitate their reasoning and make price evaluations more consistent across participants. Although we carefully evaluated each time which price to indicate as the anchor, based on the Slovenian market price, this can still represent a limitation, especially considering that some participants were international students who may expect different prices.

Another aspect to consider is the inclusion of Starbucks in the experiment, where participants were asked to indicate how much they liked and consumed this brand. We note this because there is no physical Starbucks store in Ljubljana. However, some supermarkets sell Starbucks products, such as coffee capsules, that can be used to prepare coffee at home. For this reason, we decided to include it anyway, even though this may not fully reproduce the experience of purchasing coffee at a physical store. Another reason for including it is that we expected international students to participate, and they were likely to have experience with Starbucks products. Those who did not consume it simply reported “never” when asked about their consumption frequency.

Another limitation concerns the fact that participants’ evaluations were based only on the visual presentation of the products. Since our aim was to mimic real product presentations, we could not indicate the exact grams or quantity of each item, therefore participants were asked to base their evaluations only on what they could see. We think that in some cases this might have made their evaluations more difficult. This is also one of the reasons why providing an anchor price was important: in the absence of information about the products’ weight, this provided participants with a reference point for their evaluations.

However, this limitation was partially controlled by the fact that all participants ultimately based their evaluations on the same information.

In addition, we should acknowledge the general limitation related to the use of questionnaires, in particular the social desirability bias, where participants may provide responses they believe align with researchers’ expectations (or with social norms) rather than their genuine opinions (King & Bruner, 2000).

We would also like to point out a limitation related to the EEG measurement itself. Since the experiment was conducted in a laboratory setting, we cannot directly generalize EEG responses to real purchasing contexts, such as physical stores. At the same time, conducting an EEG experiment in a real store would be extremely difficult, due to the high noise and the many distracting factors present in such environments. Therefore, a trade-off between experimental control and ecological validity was necessary.

We also acknowledge a limitation related to participants' lack of familiarity with experimental settings in general. In fact, in the context of an experiment that is new and unusual for participants, the presented stimuli may all appear equally interesting or salient simply because the situation itself is novel.

In the next section we will discuss how future research could address some of these aspects.

4.8 Future Research

Future research could explore potential differences between genders and across different age groups, to analyse whether our findings remain consistent across these groups. In addition, researchers could examine the nationality of participants and investigate whether different cultural backgrounds lead to different responses across groups.

Furthermore, future research could investigate whether there are differences between the three types of images (within each set) using other tools, such as eye-tracking. This device is often used in studies conducted in physical retail environments. Participants would be asked to observe the three types of products (brand, non-brand, combination), and results would be analysed using heat maps, which visually represent the areas on which gaze fixations are most concentrated (Wedel & Pieters, 2008).

In addition, further studies could explore other consumer variables, such as familiarity with the product, trust in the item, or perceived quality, and analyse whether these variables show significant correlations with the P300 component.

Not only the P300 can be investigated; other neural measures can also be considered, such as the Frontal Alpha Asymmetry (FAA), which reflects the tendency to approach or avoid a stimulus (Fitzgerald, 2024). FAA could be explored to analyze potential differences between images in terms of approach and avoidance tendencies, and its correlation with consumer variables could be investigated to examine potential associations with pleasantness, consumption frequency, and WTP. By studying other neural components, researchers could explore whether different patterns of correlation emerge with consumer-related variables.

A similar line of investigation would be to directly compare different neural and physiological measures. For example, P300 responses could be correlated with eye-tracking data, to evaluate whether the images eliciting the highest P300 amplitudes are also those receiving the greatest visual attention. Similarly, P300 could be examined in relation to electrodermal activity (EDA), a measure of skin conductance reflecting emotional arousal (Caruelle et al., 2019), to assess whether images eliciting higher P300 responses also evoke greater arousal. Finally, eye-tracking data could be compared with EDA to analyse whether the most visually attended images are also those associated with higher arousal.

Furthermore, future research could investigate not only food products, but also other types of complementary goods (e.g., toothpaste and toothbrush, shampoo and shower gel, etc.).

Finally, in Section 4.6 we have mentioned that one limitation concerns the fact that different images might appear equally novel to participants due to their unfamiliarity with experimental contexts. Future studies could therefore explore one set at a time, repeating the presentation of the images several times, to analyse whether this condition leads to more pronounced differences in P300 responses.

4.9 Theoretical and Practical Implications

Our results highlight the importance of integrating implicit neural measures with explicit behavioral measures, which is the core aim of neuromarketing, to examine their association and determine whether early neural activity is reflected in behavioral responses. Specifically, the theoretical contribution of our study lies in examining whether attentional salience is a key driver of specific consumer behaviors.

First of all, our findings contribute to the understanding that the effectiveness of the cross-merchandising strategy in influencing purchasing behavior is not reflected in differences in attentional allocation between combinations and single products, suggesting that its impact may be driven by other underlying factors. Evaluations that consumers perform when observing products are likely part of processes occurring at later stages, as we found that at an early neural level consumers do not consistently perceive complementary combinations as more salient than single products.

In addition, our study contributes to understanding the relationship between P300 and consumer variables. According to our findings, early attentional processes are not associated with variables such as pleasantness, consumption frequency, and willingness to pay, suggesting that attentional processes alone are not sufficient to explain higher-order consumer evaluations.

However, our research indicates that consumer variables can sometimes be correlated, as observed for pleasantness and consumption frequency, but not always, as in the case of their correlation with WTP, highlighting the complexity of these mechanisms and the potential influence of other factors. This suggests a closer interdependence among consumer variables themselves, meaning that one consumption-related behavior can influence another, whereas this pattern is not observed for P300, which does not appear to directly relate to behavioral outcomes.

Lastly, we observed that participants generally expect a discount when evaluating product combinations, although the magnitude of the discount does not correlate with differences in attentional allocation to the combinations. This further suggests that discount expectations are driven by higher-order cognitive processes rather than early attentional mechanisms.

Overall, this study advances the theoretical understanding that early attentional processes do not directly influence specific consumer behaviors and are likely complemented by more complex cognitive processes, which warrant further investigation.

From a practical perspective, our results are relevant for retailers seeking to understand how neural measures and consumer variables relate, and for conducting this type of research in a field that remains relatively novel.

At the same time, marketers can recognize that when designing advertisements or promotions, consumer evaluations are not driven solely by early attentional salience, but involve more complex considerations that influence purchasing decisions.

Overall, effective marketing strategies should account not only for initial attention capture, but also for the broader cognitive and contextual processes that shape consumer preferences and decision-making.

5. Conclusion

With the study presented in this thesis, we aimed to investigate whether strategies used by retailers, particularly cross-merchandising, have a basis at the early neural level, and whether neural responses are associated with typical consumer variables, such as pleasantness, consumption frequency, and willingness to pay, as well as whether these variables are interrelated.

The primary goal was to examine a well-known neural component, the P300, to observe differences within each set between the brand, the non-brand, and the combination, and to assess whether P300 amplitudes were correlated with the aforementioned consumer variables. Overall, the results did not show significant differences in P300 responses between combinations and single products within each set. Additionally, P300 amplitudes were not significantly correlated with the consumer variables. Furthermore, results indicated that pleasantness and consumption frequency were significantly positively correlated, while their correlations with willingness to pay were mostly non-significant. Finally, participants applied a discount significantly different from zero when evaluating combinations compared to single items, although this discount did not show any correlation with P300.

Taken together, these findings suggest that evaluations related to product combinations, consumer preferences, pricing, and consumption habits do not rely on early attentional allocation, but may instead emerge at later stages of cognitive processing.

By integrating neuroscience and marketing, this study contributes to the growing literature on consumer neuroscience and neuromarketing, providing further insight into the complex processes underlying consumer neural responses in retail contexts.

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Appendix A

Below are all the images used in the study, organized by set.

SET 1: COCA-COLA



SET 2: PRINGLES



SET 3: STARBUCKS



SET 4: OREO



SET 5: NUTELLA



Appendix B

Below is presented the informed consent form, provided to each participant before starting the experiment.

Informed Consent Form

Title of the research: Neural and Behavioral Responses to Food Brands and Product Combinations: A Neuromarketing Study

Purpose of the study

You are invited to take part in a study investigating how people perceive and evaluate products when they are presented alone or together with familiar brands. The aim is to understand how brand familiarity influences behavioral responses and brain activity patterns.

Procedure

If you agree to participate, you will complete a short computer-based task while your brain activity is recorded using a non-invasive EEG headset (Unicorn Hybrid Black - 8 channels: <https://www.gtec.at/product/unicorn-hybrid-black/>)

During the task, you will view images of foods and brands and will be asked to simply observe them. After the task, you will complete a short questionnaire to rate each image on general subjective perception factors.

The session will last approximately 40-45 minutes in total, including setup time.

Risks and benefits

The EEG is completely safe and non-invasive. There are no known risks associated with participation. You may experience minimal discomfort from wearing the EEG cap or mild fatigue due to concentration. You will not receive any direct personal benefits, but your participation will contribute to research on decision-making and consumer perception.

Voluntary participation

Participation in this study is entirely voluntary, therefore you will not receive financial compensation. You may refuse to participate or withdraw your consent at any time without giving any reason and without any consequences.

- During the study: If you decide to withdraw during the study, data collection will stop immediately, and all data collected up to that point, including identifying and demographic information, will be permanently deleted. You will be informed that your data have been removed, and we thank you for your participation.
- After the study: If you choose to withdraw when your data are still identifiable, all collected data will be permanently deleted.
- Anonymized or de-identified data: If your data have already been anonymized, we will remove any information that could identify you. However, aggregated and fully de-identified data will remain in the study, as it is no longer possible to link them to you individually.

To exercise your right to withdraw, please contact the responsible researcher.

Confidentiality and data protection

All data collected will remain strictly confidential and will be stored securely in anonymized form. No identifying information will appear in any report or publication. Data will be used solely for academic and scientific purposes in accordance with the GDPR and university ethical standards.

Consent

I have read and understood the information above. I have had the opportunity to ask questions and received satisfactory answers. I voluntarily agree to participate in this study.

Participant's full name: _____

Participant's Signature: _____

Date: _____

Principal Investigator's signature: _____