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Understanding the Effects of Front-of-Pack Labels on Food Liking and Wanting: An EEG Study

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Abstract

Front-of-pack labels (FoPLs) have been proposed as an easy-to-implement intervention tool to encourage individuals to consume healthier diets. While various such labels exist, the literature shows that the most effective ones are color-coded interpretive labels, allowing for direct interpretation of the healthiness of the food item, thus making healthier food choices easier. While there are many factors influencing food choices, food liking (hedonic valuation) and wanting (motivational drive) are two of the most important ones. This thesis aims to understand if, and how, FoPLs modulate food liking and wanting.

Participants were asked to rate liking and wanting of high- and low-calorie processed and unprocessed foods after being exposed to one of three label conditions (dark green "A", yellow "C", dark red "E") immediately before seeing the food item. Behavioral and EEG, data were collected to investigate the possible modulation in behavior and brain activity following FoPL exposure. Additionally, liking and wanting ratings were correlated with the participant scores on the Teruel Orthorexia Scale (TOS), where the sample was split into two groups based on the sample median - healthy orthorexia and orthorexia nervosa.

Results from the behavioral part of the experiment suggest that high-calorie foods were more liked and wanted compared to low-calorie foods in all label conditions. Additionally, processed foods were more liked compared to unprocessed foods, across label conditions. When considering the effects of each specific label ("A", "C", or "E") a clear pattern emerged - foods labelled with the dark green "A" were more liked and more wanted than foods labelled with the other two labels. When considering liking and wanting in the context of the TOS group, high-calorie foods were significantly more liked and wanted than low-calorie ones only in the healthy

orthorexia group. The qualitative visual analyses of the ERP data reveal smaller peaks in the label "C" condition compared to the other two conditions.

The significant increase in liking and wanting following a dark green "A" label are in favor of the effectiveness of FoPLs in encouraging consumption of healthier food products. These results are also in line with the idea that color carries psychological meaning - in this case, green stimulates approach behaviors. On the other hand, looking at the differences in brain processing following a "C" label compared to "A" or "E" could stem from possible cognitive re-appraisal of an ambiguous stimulus. In this case, the yellow "C" represents a medium score without a clear-cut significance, thus lower brain activation could reflect less automatic and more effortful evaluation of the food items.

In conclusion, following the results from this study, FoPLs appear to modulate food liking and wanting, as well as brain activity. However, more research is necessary in order to get a more complete idea of how FoPLs fit in with other factors influencing food choices - e.g., affordability.

Keywords: Front-of-Pack Labels, Liking, Wanting, EEG, TOS, Calories, Processing

Introduction

The aim of this thesis is to investigate the effects of FoPLs on food liking and wanting by employing a behavioral task. Additionally, EEG data were gathered to better understand the underlying brain mechanisms underlying food choices. Chapter 1 provides background information on the determinants of food choices, spanning from biological and neurophysiological to social and economic factors, as well as individual preferences. Additionally, descriptions of food liking and wanting, as well as electroencephalography are provided. The end of the chapter describes in depth the controversy surrounding a universal implementation of FoPLs in the European Union (EU). With the aim to bring some clarity into the debate on the effectiveness of FoPLs, an experiment was devised in which participants had to rate liking and wanting of foods after being presented with one of three categories of a color-coded interpretive FoPL. Chapter 2 goes into the methodology of the current experiment. Details of the pilot phase, determining the feasibility of the design, as well as details about the main experiment are presented. Chapter 3 presents the behavioral and neurophysiological results of the study. Furthermore, in Chapter 4 the results are discussed and interpreted. Final commentary of FoPLs is provided, as well as potential future directions for exploration following this study. Finally, Chapter 5 provides the conclusions from this thesis.

Chapter 1. Understanding the Importance of Food

Food is an integral part of our daily lives. In today's context of industrialization and convenience, food has undergone extensive changes, both in terms of manufacturing processes, and in terms of importance and meaning for the individual. Over the past decades, the food industry has rapidly evolved to offer products that are easier to prepare and consume, as well as market them in an effective manner to buyers, driving up consumption and, ultimately, revenue. In line with these efforts, newer fields, such as consumer neuroscience, have emerged and are quickly changing the landscape of marketing and consumption (Niedziela & Ambroze, 2021). These fields are aimed at optimizing the way food is produced, marketed and distributed with their ultimate aim being an increase in purchases and loyal consumers. Complementary to consumer neuroscience, the field of nutritional neuroscience has been exponentially developing. Its focus lies in understanding how people make food-related decisions, what brain areas and networks underlie everyday eating behavior, as well as how one's health and mental being are influenced by food.

Diet influences long-term health outcomes and is an important part of the promotion of a better, more health-conscious lifestyle (Fanelli et al., 2020). Today, especially in the Western world, food is abundant and people consume many more packaged, highly processed food items compared to whole foods (Yi et al., 2025). Such a diet, rich in highly processed foods is typically poor in some key nutrients, such as fiber, vitamins and minerals (Fuhrman, 2018). Thanks to the literature, it is possible to state that such a lack of crucial nutrients is linked to a variety of adverse health outcomes. In this regard, many noncommunicable diseases (NCDs) can be traced back to poor diet, such as cardiovascular diseases (Mente et al., 2023), metabolic disorders, and obesity (Fanelli et al., 2020; Rakhra et al., 2021). Specifically, overweight and obesity are the direct consequence of a poorly balanced diet that includes too many calories with respect to energy expenditure (Berthoud et al., 2017; World Health Organization (WHO), 2025). Indeed, an obesity epidemic has been recognized in the 21st century (Kanter et al., 2018) with the prevalence of obesity increasing more than twofold from 1990 to 2022 (WHO, 2025). A big portion of the blame has been put on ultra-processed food (UPF). UPFs have undergone substantial industrial processing which is typically impossible to achieve in a regular kitchen, contain negligible amounts of whole foods, and are created with the goal to increase profits and little regard for proper nutrition (Monteiro et al., 2025). Since UPFs are specifically designed to bring in more money to the corporation by increasing consumption, much effort is put into making them as palatable (enjoyable) as possible. Ultra-processed foods are now considered to be one of the main drivers of the obesity epidemic worldwide, largely due to their high caloric content and otherwise poor nutritional profile (Swinburn et al., 2011; The Lancet, 2025).

Beyond that, the WHO has also expressed concerns that this rise in the consumption of highly processed foods puts many low- and middle-income countries at what has been called the double burden of malnutrition (WHO, 2025). Malnutrition is defined by the WHO as "deficiencies, excesses, or imbalances in a person's intake of energy and/or nutrients" (WHO, 2024). There are three main types of malnutrition recognized by the WHO - undernutrition, macronutrient-related malnutrition, and overweight, obesity and diet-related NCDs (WHO, 2024). Due to the lack of access to highly nutritious food, such countries continue to experience the debilitating effects of poor nutrition, and as a result rates of overweight, obesity and NCDs are surging (Popkin et al., 2020; Wells et al., 2020). Indeed, as stated by the WHO, it is not uncommon to see evidence of malnutrition and obesity in the same household (WHO, 2025).

Promotion of a healthier eating pattern may be the key component to the prevention of NCDs. In the last decades, a variety of diets have been proposed to encourage healthier food choices. In recent years the Mediterranean diet has become one of the most widely accepted diets supporting health and well-being. It is based primarily on plant-based, locally grown produce, healthy fats, moderate consumption of white meat, and red wine with meals (Guasch-Ferré & Willett, 2021). There is strong evidence that with its focus on whole foods and limiting conventionally produced sweets, the Mediterranean diet is an effective tool in combating noncommunicable diseases as well as lowering overall inflammation levels (D'Innocenzo et al., 2019; Martinez-Lacoba et al., 2018; Muscogiuri et al., 2022). As stated by the WHO, health is "a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity" (WHO, 1946). As such, it is essential to consider the effects of diet on mental health-related outcomes, as well as physiological outcomes. Beyond the beneficial effects of diet on bodily health and disease prevention, a recent review underlines how nutritional interventions can be integrated into the treatment of mental health disorders, as well as support healthy emotionality (Patil & Mehdi, 2025). In fact, another review by Ventriglio et al. (2020) highlights that the Mediterranean diet specifically can be utilized to aid in the improvement of depressive symptoms.

Considering the previously stated, the importance of food choices, and what drives them, becomes evident. By understanding food-related decisions, we can create effective public health interventions for the fostering of population-wide healthier diets.

1.1 Food Choices - Deciding What To Eat

1.1.1 Biological and Neurophysiological Influences on Eating Behavior

Food choices are complex and influenced by many intricate interactions, with both brain and biology-based, as well as social factors playing a role. Food-related decision-making is a multi-component behavior that demands an understanding of the many factors involved. The most notable brain-related influences on eating behavior come from homeostatic, hedonic and cognitive control (Jacquin-Piques, 2025).

While in our evolutionary past, eating used to be driven by homeostatic mechanisms to restore energy reserves, nowadays it is impacted by a variety of additional factors, including but not limited to individual preferences, stress, cultural traditions, previous experiences and governmental policies (Hill et al., 2022; Mozaffarian et al., 2018). Thanks to Berthoud (2011) we know that food-related behaviors are driven from the complexities of brain mechanisms and functions, once again emphasizing the different interconnected levels that lead to eating. Additionally, one of the key takeaways from the author is that overindulgence in food might not always be under conscious control, in part because of the interaction at the neurological level between what is necessary for survival and what is enjoyable.

What is more, food is not only a biological necessity, but it is also a rewarding, pleasurable stimulus. Importantly, the differentiation between the neurological underpinnings of reward and homeostasis underline the fact that biological necessity is not a requirement for a rewarding experience (Finlayson et al., 2007). This is to say that food is not only valuable to us because it restores depleted energy reserves, but because it can make us feel good. This pleasure derived from food has been exploited by the food industry for years, with food engineers working to create the most enjoyable products possible (Moss, 2013). With that the characteristic climate in Western, higher-income countries of abundance and easy access to tasty, hyper-palatable food, inhibition and control over food consumption become difficult (Davidson et al., 2019). Knowing how food choices come to be is a crucial step in combatting the rising obesity and malnutrition levels worldwide.

As noted above, homeostasis is the key driver of eating to replenish energy stores. Information from various parts of the body needs to be integrated for the facilitation of homeostasis. This integration occurs in the brain. Homeostatic control of eating behavior is embedded in the ventromedial and lateral hypothalamus, as well as the arcuate nucleus (Chae & Lee, 2023). Through various mechanisms that are spread throughout the gastrointestinal system, the hypothalamus gets feedback from the body on the current energy and nutritional needs. The gut-brain axis is one of the most important pathways through which signals on hunger and satiety are transmitted to the brain to determine future behavior. This transmission occurs via a variety of factors, hormones, and mechanisms, including gastric distention after food consumption and causing a release of serotonin by gut endocrine cells, release of leptin by adipose tissue and insulin by the pancreas (Stover et al., 2023).

On the other hand, cortico-limbic areas, associated with reward valuation, also seem to impact what, when and how much we eat. This involvement of the brain's reward system in food consumption is the root of the hedonic drive and control of eating behavior. The brain's reward network includes the ventral tegmental area (VTA), striatum, nucleus accumbens (NAcc), amygdala, and the prefrontal cortex (PFC) (Chae & Lee, 2023). Human behavior has developed over the course of evolution to match an environment with few food resources, making food stimuli all the more enticing and rewarding. However, this adaptive development can become a risk factor in the contemporary world, where resources are plentiful (Stover et al., 2023) and so consumption is driven higher. It has been argued that due to the plentifulness of food in Western countries hedonic valuation can be a powerful driver of food consumption, potentially trampling homeostatic signals (Berthoud, 2011; Bielser et al., 2016). Despite these findings, the relationship between homeostatic control and hedonic influences on eating behaviors remains deeply complex. Thanks to a recent review by Berhoud et al. (2017) it is possible to delve into different mechanisms influencing food intake and explore the involvement of the hypothalamus (homeostatic control) and cortico-limbic areas (hedonic control and drive) and their interaction with each other outside of awareness. In this way, we get a clearer picture of the brain mechanisms behind food intake behavior and choices.

Furthermore, cognitive control is crucial in the shaping of food choices by playing a modulating role over homeostatic and hedonic drive (Jacquin-Piques, 2025). One of the main brain areas associated with executive and cognitive control over ingestive behavior is the prefrontal cortex. The PFC integrates sensory information with signals from the hypothalamus and reward-related brain centers, thus determining decision-making and goal-directed behavior (Stover et al., 2023). Cognitive control is influenced by considerations such as typical mealtimes, family eating habits carried over from childhood, social norms, and culturally determined ideal body shape and size, etc. As such, cognitive control allows the individual to ignore homeostatic hunger signals for a time, e.g., in cases of dieting, and make a conscious decision about what and when to eat. Furthermore, cognitive control allows for the juxtaposition of short-term (i.e. the pleasurable experience of food consumption) with long-term goals (i.e., maintenance of one's health status and weight). Additionally, proper executive functioning is necessary to assess and direct eating and appetitive behavior, oftentimes curbing the impulsivity to reach for high-calorie, palatable foods via inhibitory control mechanisms (Dohle et al., 2018). Despite homeostatic signals, food intake remains a voluntary behavior dependent on the individual's decision whether and what to eat. What is more, cognitive and inhibitory control over food intake are highly dependent on previous consequences of food consumption, future expectations, perception of food items, and attentional biases toward specific foods (Davidson et al., 2019). In addition, Davidson et al. (2019) highlight the complicated, bidirectional relationship between obesity and cognitive control impairments. While there is a substantial amount of evidence suggesting that impairments in cognitive control might be at the foundation of obesity, obesity in combination with the typical Western diet, has also been implicated in a reduction of inhibitory control (Davidson et al., 2019). This is known as the vicious cycle of obesity (Haslam & James, 2005), where lower inhibition drives obesity, which in turn contributes to lower inhibition of eating behavior. There are a variety of underlying modulatory mechanisms over inhibitory control outlined in the review, such as neurohormonal signals (e.g. insulin, leptin, glucagon-like peptide-1), environmental food-related cues, and interference with hippocampal function, thus affecting hippocampal-dependent learning and memory. In this way, understanding the factors that drive obesity (e.g., excess availability of and access to highly-caloric foods), as well as the brain mechanisms and functions underlying eating behavior, become essential in successfully promoting healthy eating habits.

Stover et al. (2023) outlines that, while there are the aforementioned internal considerations, such as hunger, that drive eating, the brain also creates a subjective valuation of food products based on their properties. Some of these properties include flavor and taste profile, as well as texture. In fact, some research has shown that foods high in both fats and carbohydrates are particularly rewarding (DiFeliceantonio et al., 2018). Creating this subjective valuation of food integrates visual cues (processed by the fusiform gyrus) with bodily sensations, emotional experiences, and executive signals. The associated brain areas are the insula, striatum, amygdala, the hypothalamus, the brainstem, and the ventromedial PFC (Stover et al., 2023).

1.1.2 Social, Economic, and Environmental Influences on Eating Behavior

Factors such as economic welfare, food item characteristics, and long-standing dietary habits can impact eating behavior. Beheshti et al. (2017), using an agent-based model simulation, found that low-income individuals tend to have poorer diets, which persist even when their income is increased. They argue that this lack of dietary improvement following a higher income may stem from enduring dietary habits that are formed early on in their life and remain stable into adulthood. Some studies have also investigated the relationship between socio-economic status (SES), diet quality, and food choices (Singleton et al., 2020). It has been shown that people with a lower SES tend to have less access to healthy food options in their environment, thus making appropriate and health-promoting choices challenging. Furthermore, people with a lower SES suffer from more chronic conditions that can be traced back to poor diet (Harrison & Taren, 2018; Leocádio et al., 2021).

What is more, the food environment also has a considerable influence on food choices and consumption. The food environment refers to certain sensory properties of food, such as odor, texture, and, naturally, taste (Stover et al., 2023). For example, a systematic review and meta-analysis by Appleton et al. (2021) found that harder, bulkier food items lead to faster satiation, and thus lower consumption. Similar results were found in a randomized control trial by Teo et al. (2022), where they compared soft vs hard, and minimally vs ultra-processed meals. Participants attended four lunch sessions where they were allowed to eat as much as they wanted to.The article reports that in both the minimally and ultra-processed conditions, the harder meal was consumed more slowly, while soft-textured ultra-processed foods led to the highest amount of calories consumed.

Interestingly, recent research also shows that even the macronutrient composition of food items can be a driver of further consumption (Baugh et al., 2022). This occurs through modulation of the bacterial composition and richness of the gastrointestinal tract to which diet is a main contributor (Klingbeil & De La Serre, 2018). This modulation has especially been raised as a concern in the context of the modern Western food climate, where UPFs are readily available for immediate consumption. Part of what makes UPFs so dangerous and detrimental to human health is that they are produced from cheap commodities (e.g. maize, wheat, soy) that have been broken down using industrial methods and enhanced through artificial additives (Monteiro et al., 2019), with the goal behind this processing being to increase profit margins. What is more, aggressive marketing techniques and brand loyalty ensure consumers will go back for more. UPFs are created to be highly palatable, leading to increased food intake and often replacing more nutritious foods (The Lancet, 2025). Due to the industrial ingredients and processes necessary for UPFs, as well as their generally low content of dietary fibers, protein, minerals and vitamins (Monteiro et al., 2019), they have been shown to cause significant health issues and serious concern for health professionals (Dai et al., 2024). Besides the highly enticing formulations of these food products, which are specifically engineered to maximize reward experience for the consumer and are also aggressively marketed to people from all age groups. This combination of enjoyable taste, rigorous marketing, and their generally lower price compared to some fresh fruits and vegetables, means that consumers have all the reasons to come back to these products.

As it has been established above, food choices are dependent on a wide variety of factors - from practicalities, such as availability, accessibility, and affordability to characteristics of the food items themselves to complex interactions between brain areas and circuits. While making food choices is an everyday behavior that every person takes part in, it is not quite as easy as simply picking up an item at the grocery store. However, there are additional crucial components shaping food decisions that have not been discussed so far here. These are food liking, food wanting, emotions, and calorie content and will be the focus of the following sections.

1.1.3 Food Liking and Food Wanting

Food carries a reward value that is disconnected from satisfying certain biological needs. This rewarding experience can conceptually be explained through two separate psychological constructs - liking and wanting. When we talk about liking, we refer to the pleasurable, hedonic experience derived from eating (Baugh et al., 2022; Finlayson et al., 2007; Jacquin-Piques, 2025). On the other hand we refer to wanting as the motivational drive to get food (Baugh et al., 2022; Finlayson et al., 2007; Jacquin-Piques, 2025). Specifically, liking and wanting are distinct concepts, and so some clarifications are necessary to understand their differences and how they drive food consumption. Firstly, food liking directly determines food intake, considering that people gravitate towards purchasing foods they like (Bielser et al., 2016), and it remains rather stable across situations (Berthoud et al., 2017). On the other hand, wanting (the motivational drive to eat) is hunger-level dependent (Finlayson, 2007; Jacquin-Piques, 2025). Additionally, wanting implies not only a force, but also a direction - meaning the desire for specific foods (Finlayson, 2007). In this regard, it is important to remember that liking or wanting alone is not enough to lead to food intake. As such, it starts becoming clearer how these two concepts determine situation-specific food-related decisions.

At the neurological level, liking is associated with embedded, more specific hedonic hotspots that are responsible for the pleasurable experience of eating, and wanting is controlled by a more widely distributed network (Morales & Berridge, 2020). Both liking and wanting can operate at the implicit, as well as the explicit level, with complex interactions between the two processes being a powerful driving force in eating (Finlayson et al., 2007). This is to say that processes related to the "affective" liking and "motivational" wanting for food can modulate behavior outside of conscious awareness (Finlayson et al., 2008). In fact, in their colloquial use, both liking and wanting refer to the conscious experience of pleasure and desire, respectively. However, in research both implicit liking and wanting, respectively, that is operating outside of conscious awareness, have been found to impact eating behavior (Finlayson et al., 2007). The clinical implications of distinguishing between liking (hedonic experience) and wanting (motivational drive) have become crucial in explaining and understanding certain maladaptive eating behaviors, such as eating disorders and obesity. For example, some evidence suggests that binge eating could be associated specifically with excessive wanting of food but not necessarily with the heightened liking of said foods (Morales & Berridge, 2020).

Pleasure and hedonic value have become an integral part of food choice and consumption (Blechert et al., 2014a). Different characteristics of the food stimulus, individual preferences, and even features of the environment can influence food liking and wanting (Leng et al., 2017). As described by Jacquin-Piques (2025), food pleasantness is an important factor influencing specifically the hedonic control of eating behavior. They propose four physiological components to understanding food pleasantness, one of which is, indeed, the reward system. For instance, anticipatory information signalling in response to viewing palatable food has been related to dopamine release in the nucleus accumbens, which is associated with motivational drive.

Some studies indicate that foods that have undergone some level of transformation (e.g. cooking, fermenting, etc.) are more attractive to people, with explanations being rooted in evolutionary needs (Coricelli et al., 2019). Energy content in transformed foods is more easily accessible to our bodies in comparison to that of raw foods. This easy access to calories makes foods that have undergone some form of transformation more rewarding. Additionally, some research suggests that one of the reasons why UPFs are so enticing is that due to their ultra-processed nature, their calories are more easily available for absorption, making them highly rewarding foods (Kelly et al., 2022).

1.1.4 Emotions

Going beyond individual preferences, eating behavior and food choices are influenced by a multitude of other factors. As discussed above, there are certain influences on eating behavior that operate without our conscious awareness, and emotions constitute one of those influences. The role of emotions is, perhaps, one of the most researched influences on eating behavior, with papers exploring different components of emotion (valence versus arousal), as well as focusing more specifically on the relation between negative emotions and unhealthy food consumption (Devonport et al., 2019; Ljubičić et al.. 2023; Songsamoe et al., 2019; Xie et al., 2023). In the literature, it has long been established that food can be seen as a self-medication tool against extreme, usually negative, emotions (Berthoud et al., 2017; Ljubičić et al.. 2023) and a way to comfort oneself in the face of daily stressors (Finch et al., 2019). In their systematic review, Khoshghadam and Rajabi (2024) found that over the years, four distinct relations have emerged between emotions and food choices. These are: (1) using unhealthy food as a coping mechanism against negative emotions, (2) food as a reward for positive emotions, (3) focus on the different dimensions of emotions and how they affect food choices, and finally (4) how different food-related sensory characteristics influence one's perception of reward. Following this line of research, it is clear that the relationship between emotions and food consumption is not linear, and it is far from simple. It has been found that some people's eating behavior is heavily influenced by their emotions (i.e., high emotional eaters), while for others emotions do not play as large a role (i.e., low emotional eaters). When comparing high emotional eaters with low emotional eaters, Blechert et al. (2014a) found that the former group experienced stronger food cravings following the induction of strong negative emotions, while that was not the case for the low emotional eaters. In a choice-based conjoint analysis study, a German sample was asked to decide between purchasing various yogurt options with differing attributes (Brückner et al., 2023). After clustering the participants into 3 different groups based on emotions (positive, rather positive, indifferent), they discovered that the positive cluster gravitated towards the healthier plain yogurt option compared to the people in the indifferent category. Despite this study focusing on only one food item, these results offer an insight into the importance of emotions to promote healthier food choices, starting from the grocery shopping experience itself.

Understanding how consumers make food-related decisions daily is a complicated matter. Since there is such a wide variety of factors influencing food choices, it is necessary to consider how those might interact with each other. An example of such a study was conducted to compare the predictive value for food choices of food liking versus food liking combined with food-evoked emotions (Dalenberg et al., 2014; Gutjar et al., 2015). Following their experiment, Dalenberg et al. (2014) established that investigating liking alone is not enough to reliably predict subsequent food preferences. Instead, adding food-evoked emotions, and differentiating between negative and positive valence, increased the predictive power of their model.

1.1.5 Calorie Content and Its Influence on Food Choices

Calorie content is perhaps one of the most important features of food, as the main goal of ingestive behavior is to replenish exhausted energy stores in the body. High-calorie foods in particular are more effective in accomplishing this goal and thus come with a higher reward. In fact, high-calorie foods tend to elicit a higher reward response in the brain (Zheng et al., 2022). On the other hand, low-calorie foods support the maintenance of a normal weight and can protect against adverse health outcomes.

In their systematic review and meta-analysis of neuroimaging studies Zheng et al. (2022) describe an appetitive brain network that is implicated in the processing of visual food cues with different caloric content - from initial visual information processing to top-down cognitive control over eating behavior. Some of the identified regions implicated in this differential processing include the PFC (value-based decision-making), the orbitofrontal cortex and amygdala (encoding of subjective value), the insula (integration of sensory information), and the superior parietal lobe, inferior temporal gyrus and fusiform gyrus (allocation of attentional processes).

In a study by Kirsten et al. (2022) the neural processing and behavioral preferences for low- versus high-calorie foods were measured in three imaginary situational contexts - normal, daily eating (baseline), a reward condition, and a diet condition. In the baseline condition, participants were asked to imagine a regular day after work, in the reward condition, that they were returning after giving a blood donation, feeling weak, and in the diet condition, that they were aiming to lose weight. While, as expected, the participants showed a preference for the high-calorie foods in the reward condition, that was not the case in either the baseline or the diet situations, where the people predominantly chose the low-calorie options. Additionally, by examining frontal alpha asymmetry, the study discovered that, in general, the approach motivations were higher for the low-calorie foods. The authors hypothesize that this effect might have come to be due to a default tendency towards a more restrained eating style. When looking into two event-related potentials (ERPs), late positive potential (LPP) and P300, they discovered that LPP was, unsurprisingly, higher for the more rewarding stimuli (i.e., high-calorie), while the P300 more closely resembled the results of the behavioral task. In addition, they concluded that the context plays an important role in determining top-down regulation of behavior and attentional allocation.

There has been a lack of studies directly comparing the possible differences in processing of high- versus low-calorie foods (Kirsten et al., 2022). This gap in the literature calls for further examination of how the two groups are perceived, also at the brain level.

1.2 Electroencephalography

Electroencephalography (EEG) is one of the most widely used neuroscientific tools to record the brain's electrical activity. It measures the postsynaptic potentials of the neurons of the cerebral cortex and provides information on cognitive processing in real time (Songsamoe et al., 2019). As such, EEG allows neuroscientists to investigate implicit processing of stimuli. EEG measures the brain's electrical signals via electrodes placed on the scalp, facilitated by a conductive gel to lower the electrode resistance and improve the quality of the signal. To ensure the replicability of results and reliable acquisition of data, the 10-20 system of electrode placement was proposed by Jasper (1958). This montage system ensures equal distances between electrodes. Today, this is the foundational system accepted by the scientific community worldwide. The first set of guidelines about it was published by Klem et al. (1999). The introduction of this unified system for electrode placement allowed for more accurate and reliable studies that can easily be replicated (Woodman, 2010). While the original 10-20 system included 21 electrodes, it has been extended to include more electrodes (i.e., the 10-10 or 10-5 systems). Nowadays, a wide variety of electroencephalography equipment is available to researchers, differentiated by the number and type of electrodes (passive or active) on the EEG cap. In addition to the electrode placement, there are also varying types of electrodes - gel-based, water-based, or dry ones. The main difference lies in the conductive substance, or lack thereof, used to lower the impedance and enable clear signal recordings (Müller-Putz, 2020). More details on modern-day EEG systems and electrode subtypes can be found in the chapter by Müller-Putz (2020).

Two of the most widely accepted ways to analyze EEG data concern frequency bandwidths or event-related potentials (ERPs). In order to utilize frequency bandwidths, the raw EEG signal has to be grouped into different categories, with research identifying that some bandwidths correspond to specific mental states. For instance, beta waves (13-30 Hz) are typical for a normal, awake state, alpha waves (8 -12 Hz) are usual during sleeping/dreaming, and theta waves (4-8 Hz) are typical for deep meditative states. A way to utilize these bandwidths is to look into activity disparities between the two hemispheres. Differences have been found in the amplitudes of alpha waves when comparing brain regions from the left and right hemispheres that have been associated with a variety of cognitive processes. Notably, Van Bochove et al. (2016) found alpha wave asymmetries in posterior-occipital brain regions during a resting state condition, which were related to reported hedonic evaluation of different foods. This method was also used by Kirsten et al. (2022) to determine the differences in processing of high- and low-calorie foods.

Another way to examine the EEG signal is by using a composite, averaged waveform - that is the averaged EEG signal resulting from exposure to a specific stimulus across multiple trials.

The resulting waveform, after processing, is called an ERP, since it characterizes the brain activity in response to a specific stimulus.

1.2.1 Event-Related Potentials

As discussed in the previous section, event-related potentials are a non-invasive method to look at cognitive processing via scalp recordings of neuronal activity. In this section, how ERPs are realized, what they mean, and how they can be used in food-related research will be discussed. Indeed, an ERP component can be defined as "a scalp-recorded voltage change that reflects a specific neural or psychological process" (Luck & Kappenman, 2013, p. 4). There are two main properties of neuronal organization necessary to facilitate large enough electrical brain signals that can be detected through the dura, the skull, and the skin - (1) a large population of cells needs to fire simultaneously and (2) these neurons need to be oriented in a relatively similar direction for their signals to sum up (Woodman, 2010). Event-related potentials largely stem from the electrical activity of the pyramidal neurons of the cortex due to their perpendicular orientation relative to the cortical surface. Due to the fast transmission of electrical signals by the neurons, the temporal resolution of ERP components is down to the millisecond making them a highly precise tool to study cognitive functioning across small time frames (Helfrich & Knight, 2019).

ERPs are time-locked to a particular stimulus, enabling us to make inferences about underlying perceptual and evaluative processes. The experimental procedure behind ERPs includes presenting the participant with a stimulus multiple times, then averaging the EEG data across trials, thus making the response specific to that stimulus, easily distinguishable (Müller-Putz, 2020).

Since the introduction of the ERP technique, various ERP components have been recognized as useful in studying different cognitive processes, from initial perception of and attention to the stimulus, to working memory, to the selection and execution of appropriate motor sequences. What is more, there are also ERPs seen after the execution of a behavior that have been associated with error monitoring (Woodman, 2010). Typically, the feature that is most discussed in studies utilizing various ERP components is the peak of the waveform. However, some researchers urge caution because the division of the waveform into discrete peaks can be rather arbitrary (Luck & Kappenman, 2013; Woodman, 2010). As an alternative to the exclusive focus on the peak of the waveform, it is necessary to consider the timing of the component (Woodman, 2010), especially because an increasing number of studies suggest that there are distinct differences between earlier and later potentials with relation to the presented stimulus.

For further, more detailed explanation on the ERP technique, refer to the book by Luck (2014).

1.2.2 Event-Related Potentials in Food Research

EEG has a long history in food research. As a method to look at the functioning and processing of the brain, it is a way to gain a better understanding of how food choices are made based on cognitive and emotional variables. EEG's measurement of brain processes makes it an invaluable tool in the realm of food and consumer research. Songsamoe et al. (2019) provide an intriguing overview of the use of EEG in consumer food research to measure emotions and motivational drives that are the result of food appearance, sensory properties of food (such as, taste and texture) and how food consumption affects brain function.

What is more, ERPs are a highly flexible tool to study a variety of cognitive processes (e.g., inhibition, attention, emotions, etc.) in different settings (e.g., fasted vs satiated) (Carbine et al., 2018). ERPs specifically give us a way to study how particular characteristics of food influence cognitive and perceptual processes (Carbine et al., 2018; Coricelli et al., 2019).

David et al. (2023) give an essential overview of the importance of incorporating neuroscientific methods, such as EEG, into food-related research to gain a better understanding of the processes underlying wanting, liking, and choice. As an example, one of the most researched ERP components in relation to food stimuli, is the late positive potential (LPP; Blechert et al., 2014a; David et al., 2023). It has been implicated in a variety of cognitive processes, including higher-order attention that aids in (food-related) decision-making (Carbine et al., 2018), responses to emotionally salient images (Blechert et al., 2014a), differences in emotional response to food (Y. Liu et al., 2024), and differentiation in food processing between obese and normal-weight participants (Nijs et al., 2008).

1.3 Front-of-Pack Nutrition Labels

It has been reported that food packaging is crucial for brand differentiation in today's market where new products make their debut on the grocery store shelves constantly (Rundh, 2016). As such, packaging can become an irreplaceable part of the marketing strategy of food companies. In fact, marketing is an essential part of determining one's food choices with larger companies having more dominant positions on the market (Martinho, 2020). As such, a plan of action that also promotes the conscious choices of foods is necessary to empower the consumers to make informed decisions about the nutritional profile of their food. Here, labels, both on the front and the back of packaging, are crucial to provide easy-to-access information. Indeed, Ni

Mhurchu et al. (2018) report that nutrition labels are effective at swaying consumers towards healthier food choices.

Front-of-pack labels (FoPLs) have been developed as one of the various strategies across the globe to combat unhealthy eating and facilitate more health-conscious purchases (Andreani et al., 2025; Cecchini & Warin, 2016). These different labelling methods have been proposed with two clear goals: (1) to make healthy dietary choices easier for the everyday consumer, with their format being easily accessible to comprehend (Peters & Verhagen, 2024) and (2) encourage industry-wide reformulation of products, to improve their nutritional profile (Kanter et al., 2018; Ter Borg et al., 2021). Considering the typical Western diet of ready-to-consume, oftentimes ultra-processed foods, such FoPLs are meant to clearly identify healthier foods for the consumer. Typically, front-of-pack nutrition labels provide information about some of the most "critical" ingredients with respect to human health in the product, such as the saturated fat, sugar, and sodium content (Donini et al., 2022). These labels can also inform the consumer about the healthiness of a product, as is the case with interpretive FoPLs that will be discussed later in this section. A parallel often drawn, in relation to the aim of FoPLs, is to the labelling regulations for the tobacco industry (Ewert, 2024; Kanter et al., 2018).

In 2004 the WHO took up an initiative to promote the consumption of healthier foods. One of the components of the initiative included the introduction of FoPLs as a way to battle the rapidly spreading obesity epidemic (WHO, 2004). As a result, various labelling systems have been introduced across the globe. These include the Multiple Traffic Light (MTL), Reference Intakes (RIs), Health Star Rating (HSR), and Nutri-Score, to name a few (Talati et al., 2019; Temple, 2020). There are various ways to categorize FoPLs, either based on the information taken into account in their algorithms or the type of information the label itself provides. Resulting from this, FoPLs can be divided into two groups based on their informativeness - reductive and interpretive. Reductive labels contain information about the nutritional composition of the product without drawing specific conclusions on its health properties (Talati et al., 2019). Typical examples of reductive labels include the nutrient-specific labels that focus on the quantities of said nutrients present in pre-packaged foods. On the other hand, interpretive labels aim to provide a straightforward interpretation of where the food item fits into a healthy diet (Talati et al., 2019). For example, Multiple Traffic Light and Nutri-Score fall into the interpretive group, as they use a color-coding system that allows the consumer to immediately judge the relative "healthiness" of the item. Examples of the different types of front-of-pack nutrition labels are presented in Figure 1.

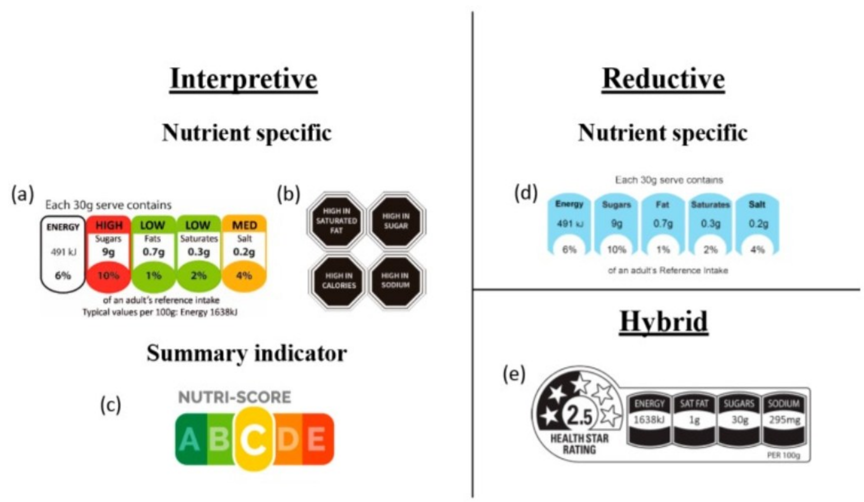

Figure 1. Examples of Interpretive and Reductive Front-of-Pack Labels

Note. Examples of different front-of-pack label (FoPL) formats and their classifications: (**a**) multiple traffic lights; (**b**) warning labels; (**c**) Nutri-Score; (**d**) reference intakes; and (**e**) health star rating. From "Consumers' Perceptions of Five Front-of-Package Nutrition Labels: An Experimental Study Across 12 Countries," 2019, by Z. Talati, M. Egnell, S. Hercberg, C. Julia, S Pettigrew. *Nutrients, 11*(8), p. 2 (http://dx.doi.org/10.3390/nu11081934). CC BY-NC-ND 4.0.

1.3.1 The Case of Nutri-Score - An Example of Interpretive, Color-Coded Food Label

Possibly one of the most recognizable interpretative FoPLs on the market, Nutri-Score was originally proposed by a French research team in 2014 (Julia et al., 2014) and subsequently adopted in 2017 (Julia et al., 2018). It is composed of letter grades, A to E, and corresponding colors (from dark green to red) that reflect the relative nutritional value of pre-packaged food items, allowing consumers to make well-informed decisions on what to purchase (Julia et al., 2018). In this case, a dark green A signifies a relatively healthy item, while a red E means that the product's nutritional profile is rather poor. Nutri-Score was adapted from a model proposed by the UK Food Standards Agency/Office of Communication that aimed to control the advertising of food items to children (Julia et al., 2014; van der Bend et al., 2022). Nutri-Score provides an overall evaluation of how healthy a product is instead of focusing on specific nutrients (van der Bend et al., 2022). More specifically, the algorithm, classifying foods into one of the five categories of Nutri-Score, works based on 100 g or 100 ml of the food or beverage instead of being guided by portion sizes. As an interpretive FoPL, Nutri-Score allows for making judgements on the food's healthiness at a glance, making it easy for consumers to decide what to buy at the point of purchase.

1.3.2 Food Labels' Impact on Food Choices

Front-of-pack labels, with their clarity and simplicity, are aimed at encouraging healthier food choices. Indeed, many studies have investigated the effectiveness of the various labelling systems. For example, in their meta-analysis and systematic review Cecchini and Warin (2016) investigated how effective nutrition labelling is in increasing the selection of healthier products. They found that implementing food labels may be crucial in tackling the obesity crisis, as well as unhealthy diets. In fact, some research shows that there is demand from consumers for the implementation of front-of-pack nutrition information across different countries (Talati et al., 2019). In a study by Brückner et al. (2023) consumers from both the positive and indifferent emotional clusters showed a preference for the yogurt options marked with a Nutri-Score “A” label. Despite that not being the central research question of the paper, this finding is a testament that easily accessible nutritional information might make healthy food choices easier while remaining relatively unaffected by emotions. What is more, some research underlines that the mandatory introduction of front-of-pack labels would yield better results than having them voluntarily, as is the case in most countries that have already introduced various FoPLs (Song et al., 2021).

Additionally, another systematic review and network meta-analysis by Song et al. (2021) focusing on the effectiveness of two types of interpretive FoPLs - color-coded and warning labels - found that, indeed, both types of labels are effective in contributing to better purchasing behavior (Song et al., 2021). The authors emphasize that the different labelling systems may serve different purposes and elicit different psychological mechanisms through which consumers make better choices. For example, color-coded labels, such as the MTL System or Nutri-Score, encourage consumers to purchase more healthful products, while the warning labels (e.g. Nutrient Warning or Health Warning) are more successful at dissuading consumers from choosing unhealthy alternatives. This superior performance of color-coded labels when it comes to promoting healthier choices can be explained through the notion that colors carry meaning (Elliot & Maier, 2014). Indeed, as shown by Schuldt (2013), a green label specifying the calorie content of the product is associated with a perception of that item being healthier.

While the results of a review by Shrestha et al. (2023) suggest that FoPLs remain an effective tool to increase consumer comprehension and purchasing intentions of healthier products across various socio-economic contexts, their effect on actual purchasing behavior and consumption remain unclear, especially among low SES populations. A possible explanation for this can be that there are other obstacles to people from lower SES backgrounds, such as unaffordability of healthier food items (An et al., 2021).

Conversely, some papers fail to find a significant improvement in consumer food choices as a result of exposure to FoPLs. In their systematic review Muzzioli et al. (2025) examined how potent Nutri-Score is for steering consumers towards better food choices. They found that the majority of studies had nonsignificant results in altering consumer purchasing behaviour towards a more nutrient-dense shopping basket in experimental and real-world settings alike. Particularly, there was a lack of the expected avoidance towards the lower nutritional categories (namely "C", "D", and "E"). Considering these results, it seems that even though comprehension of the information the label provides is high, actual behavior change remains non-significant. What is more, there is some evidence that the color red (which is typical for many interpretive FoPLs, signifying the lower nutritional quality of a food) may be associated with more positive perceptions of sweet ultra-processed foods (Lemos et al., 2020). This means that a red label may, in fact, encourage customers to purchase these sweet, ultra-processed foods, instead of dissuading them from those, as is the goal of color-coded FoPLs.

In addition, some authors have also raised the issue about the effectiveness of FoPLs in combatting NCDs (An et al., 2021; Donini et al., 2022; Dubois et al., 2021). The reasoning behind this stems from the inherent focus of nutrition labels on single food products or a very limited number of specific nutrients. They argue that, instead, a shift in focus towards examining the quality of one's entire dietary pattern is necessary to address the adverse effects of a poor diet (Donini et al., 2022). In a systematic review by An et al. (2021), the authors concluded that the results on FoPL effectiveness remain inconclusive. This is because, notably, 10 out of the 15 included studies had been conducted in naturalistic food purchasing environments (e.g., supermarkets, vending machines). These results show that, while in laboratory settings certain FoPLs perform well, their effectiveness in a real-world setting may be limited. Additionally, Dubois et al. (2021) also conducted a study in a naturalistic setting. After comparing the performance of four labels across 1266 different products from four categories across 60 grocery stores, the authors concluded that despite significant results in laboratory settings, when tested in a real-world grocery store even the best FoPL (in this case, Nutri-Score) fails to provide the same large results. Another meta-analysis from Ikonen et al. (2020) came to similar conclusions - even though FoPLs indeed do change perceived healthiness of products, that does not necessarily lead to significant changes in purchasing behavior towards healthier options. This seems to be the case due to the broad spectrum of factors, for example tastiness, influencing purchasing and eating behavior. Moreover, FoPLs are at risk of creating a halo effect - i.e. increasing the perceived healthiness of vice products (Ikonen et al., 2020). Ikonen et al. (2020) note that FoPLs are less effective in swaying one’s behavior when it comes to familiar products, since then one is less likely to pay close attention to the nutrition information. This shows that some promising results from laboratory studies may not replicate quite as well in a real-world shopping environment.

What is more, in recent years issues about the quality of evidence supporting front-of-pack labelling schemes have been brought up. Concerns have been raised by some authors (Peters & Verhagen, 2024) about the true effectiveness of front-of-pack labels, specifically Nutri-Score. In their systematic review the majority of studies that support the positive effects of Nutri-Score are, in fact, published by authors who are in one way or another connected to the original group that developed the system. When looking into papers with less favorable assessments of Nutri-Score, the authors discovered that those were mostly produced by independent researchers. Peters and Verhagen (2024) then go on to call for more independent research to ensure the validity and reliability of results on FoPLs.

In summary, the evidence on how effective front-of-pack labels are and how much they can modulate eating choices, remains inconclusive. While it generally seems that the interpretive, color-coded labels perform best in improving consumer understanding, as well as increasing purchasing intention for healthier products, it remains unclear whether they impact actual eating behavior as well. The literature on FoPLs remains divided, with some studies finding significant effects supporting the implementation of such labels, while others refute it. Thus, the importance of further investigation becomes evident.

1.3.3 The European Union and the Deployment of Nutri-Score: What Went Wrong?

In 2020, the European Commission (EC) launched its Farm-to-Fork strategy, which postulated concrete goals for the European Union for the reduction of food waste, more sustainable food production, and a push for a healthier diet. As part of the goals promoting healthier and more sustainable diets, the EC set out to implement a harmonized FoPL scheme within the EU by the end of 2022 (European Commission, 2020). The strongest contender for that role has been Nutri-Score (Devaux et al., 2024). However, such legislation has not yet been mandatorily implemented across the EU (Julia et al., 2025), with countries having the option of voluntary adoption. So far, eight European countries have adopted Nutri-Score in such a way: France, Belgium, Luxembourg, Spain, Germany, Switzerland, the Netherlands, and Portugal. Even so, some issues have been highlighted. As a result of this voluntary implementation by several European countries, the Nutri-Score algorithm had to be modified to coordinate its use across contexts (Merz et al., 2024).

What is more, there has been a large backlash against Nutri-Score, coming particularly from Southern European countries. One of the main players in this controversy is Italy. On an international level, Italy is well known for its rich cuisine, with diverse dishes typical of each of the 20 regions. In fact, as of December 2025, the entire Italian cuisine was recognized as part of the Representative List of Intangible Cultural Heritage of the United Nations Educational, Scientific and Cultural Organization (UNESCO, 2025). The Italian lifestyle, and more specifically the traditions surrounding food, is part of what makes the country so highly renowned in international contexts. Considering the importance of their national dishes and products, it has been argued that the argument around the implementation of the Nutri-Score front-of-pack labelling system in Italy was shaped by political views and pride instead of a focus on public health (Fialon et al., 2022).

Conversely, in a commentary, Ewert (2024) scrutinizes the lack of action from EU structures to make FoPLs (specifically, Nutri-Score) compulsory. According to the article, this is due to weak regulations in combination with strong lobbying from southern European countries, such as Italy, that eventually results in “food patriotism”. Ewert (2024) states that a stronger and more stable policy of the EU on FoPLs will be in the interest of public health.

Chapter 2. Current Study and Methods

2.1 Aims and Research Question

Despite the large body of literature on food-related decisions and what influences them, much remains unclear. While individual preferences and cultural norms are at play when it comes to food (Jayasinghe et al., 2025), successful marketing techniques from big food production companies are making palatable, albeit less healthy, food options more attractive to the consumer (Clark et al., 2026). Effective public health policies that stimulate the consumption of healthier products are necessary. In addition, the concerns raised about the quality of research on FoPLs deem their further investigation necessary (Peters & Verhagen, 2024). Considering the lack of clarity on how effective food labels are in encouraging healthier consumer choices and bringing meaningful changes in eating behavior, more research is required on the matter. In an attempt to elucidate the effects of FoPLs with respect to the argument outlined above, this study aims to identify if, and how, food labels modulate food choices. For this purpose, a label was created and named "NutriLevel" (Figure 2). To investigate the effects of the label on food-related choices a two-phase research protocol was conducted. Firstly, a pilot study was carried out to understand the feasibility of the proposed experimental design. Secondly, an experimental design was employed to understand the potential modulations in food choices as the result of a food label. In the experimental phase, we collected EEG data to measure how food is evaluated at the level of the brain following exposure to a specific food label.

Figure 2. Example of NutriLevel, an Interpretive Label Used for This Study

2.2 Pilot Study

To inform the design of the main experimental procedure, a pilot study was conducted. The pilot consisted solely of the behavioral task of the experiment, as this phase was done to determine if there was a modulation effect by the labels and to ensure that the task was indeed an appropriate measure of liking and wanting.

2.2.1 Participants

30 Italian participants (16 males and 14 females) were recruited using convenience sampling among students of the University of Pavia, Istituto Universitario di Studi Superiori Pavia, and leveraging personal contacts. Participant age ranged from 19 to 35 years (M = 24.23, SD = 3.78). Psychology students from the University of Pavia who participated in the pilot study were awarded ⅛ academic credit (CFU), as participation in experiments is a requirement in the undergraduate psychology program.

2.2.2 Procedure and Stimuli

After arrival, participants were asked to sign the informed consent and privacy forms. Afterwards, they viewed a short presentation with information and instructions about the proceedings of the study. After completion of the presentation, participants were asked to fill out a priming questionnaire on LimeSurvey (https://www.limesurvey.org/). The goal of the priming questionnaire was to introduce the participants to the concept of NutriLevel label and provide a brief overview of the origin of the label. Additionally, there was a brief explanation of what each level of the label signified. Such a description was provided for the three NutriLevel labels of interest in this study - dark-green “A” (highest nutritional profile), yellow “C” (medium nutritional profile), and a dark-red “E” (lowest nutritional profile). To ensure correct comprehension of the label’s meaning, participants were asked three questions at the end of the priming questionnaire where they had to correctly identify which five words equaled which label. For example, for the words “high quality”, “healthy products”, “well-being”, and “healthy lifestyle” corresponded to a dark-green “A” label. This was done for all three labels. Accuracy scores across participants were collected to understand comprehension levels.

Upon completion of the priming questionnaire, participants were given the behavioral task. The behavioral task was created using the computer software E-Prime 3.0 (version 3.0.3.219; Psychology Software Tools, Pittsburg, PA, 2016). It consisted of four blocks of 96 trials each, amounting to a total of roughly 30 minutes. Each trial was composed of a presentation of a NutriLevel label, followed by a food item. Afterwards, participants were asked to answer, using a Likert scale (from 1: not at all to 7: very much), two questions: (1) “If you tasted a piece right now, how much do you think you would like it?”; (2) “How much do you want this food?”. These questions were used to measure, respectively, wanting and liking of the specific food item presented. What is more, the questions appeared in a different order in each of the blocks to minimize participant learning effects.

The food pictures used were acquired from two different databases - FoodPics (Blechert er al., 2014b) and FRIDa (Foroni et al., 2013) and they were assessed and balanced by valence, arousal, frequency of consumption, tastiness, wanting, and perceived healthiness. The foods also varied on two dimensions - calorie content (high versus low) and processing (unprocessed versus processed).

A representation of a single trial is available in Figure 3.

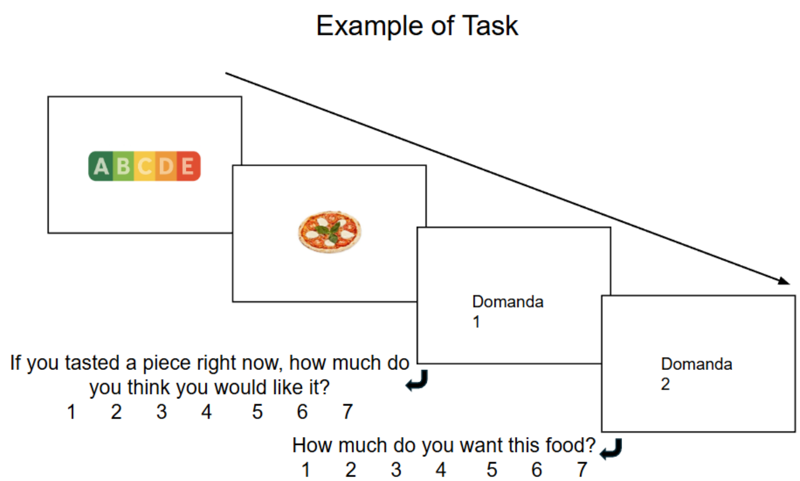

Figure 3. Example of a Single Trial

2.3 Main Study

2.3.1 Participants

A total of 43 participants were recruited for this study. The same recruitment techniques were used here as for the pilot study. Participants were screened for the following inclusion criteria: (1) being between the ages of 18 and 45; (2) no history of any eating disorders; (3) no extensive and/or recent scars to the skulls; (4) no history of epilepsy; (5) no use of psychotropic drugs or psychostimulants; (6) no neurological or psychiatric disorders; (7) no learning disorders (e.g. dyslexia); (8) no color blindness; and (9) no participation in a transcranial magnetic stimulation (TMS) experiment in the week leading up to this experiment. One participant had to be excluded upon arrival in the laboratory due to using psychoactive substances, meaning the final sample consisted of 42 participants (22 males and 20 females). Participants' age ranged from 20 to 32 years (M = 24.29; SD = 3.43). As in the pilot study, psychology students from the University of Pavia were awarded ½ academic credit (CFU) for their participation. The education levels of the participants in the main study are available in Figure 4.

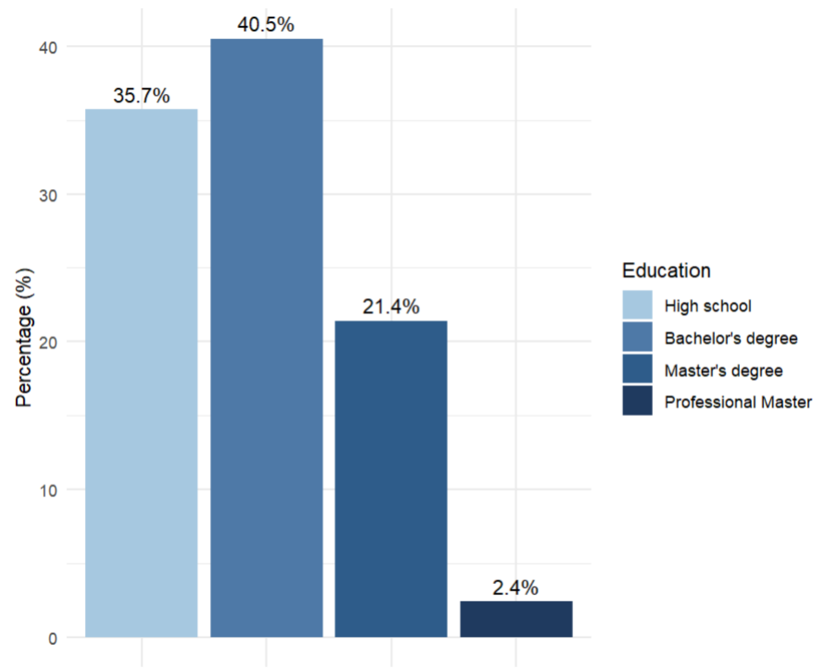

Figure 4. Education Levels of Participants in the Main Study

2.3.2 Questionnaires

Prior to attending the scheduled laboratory session, participants were asked to fill out a series of questionnaires. This was done to get a better idea of the participants' typical eating behavior and habits. The questionnaires were: the 14-item Mediterranean Diet Adherence Screener (MEDAS-14) (Schröder et al., 2011), Eating Disorder Examination Questionnaire (EDE-Q) (Fairburn & Beglin, 1994), Teruel Orthorexia Scale (TOS) (Barrada & Roncero, 2018), and Difficulties in Emotion Regulation Scale - Short Form (DERS-SF) (Gratz & Roemer, 2004; Kaufman et al., 2016).

2.3.2.1 MEDAS-14

The MEDAS-14 questionnaire is used to assess an individual's dietary pattern, more specifically one's compliance with the Mediterranean diet (Schröder et al., 2011). Originally created in 2004, the MEDAS questionnaire initially consisted of nine questions (Martínez-González et al., 2004). The questionnaire was expanded with five additional items for the purposes of the Prevención con Dieta Mediterránea (PREDIMED) randomized trial, which assessed the beneficial effects of following the Mediterranean diet on the prevention of cardiovascular disorders (Estruch et al., 2006). The current version of the questionnaire, MEDAS-14, consists of a total of 14 items; 12 relating to food consumption frequency (e.g., "How many times do you consume nuts per week?") and two questions on food intake habits (e.g., "Do you use olive oil as a principal source of fat for cooking?") (Schröder et al., 2011). A higher score on the MEDAS-14 signifies a higher level of adherence to the Mediterranean diet. While at first the MEDAS-14 questionnaire was validated in an explicitly Spanish sample in the PREDIMED study (Schröder et al., 2011), it has since been validated in other samples, including an Italian- (García-Conesa et al., 2020), as well as in an English-speaking sample (Papadaki et al., 2018).

2.3.2.2 EDE-Q

The EDE-Q is a widely accepted self-report measure to study eating pathology (Calugi et al., 2017). It was created in 1994 as a self-report version of the Eating Disorder Examination (EDE) (Cooper & Fairburn, 1987), which is typically administered by an interviewer (Fairburn & Beglin, 1994). The EDE-Q concerns behaviors across the past four weeks (28 days) prior to administration. The questionnaire consists of 28 items that are divided across four subscales: Restraint, Eating

Concern, Shape Concern, and Weight Concern. Example items include: "Have you had a definite desire to have an empty stomach with the aim of influencing your weight or shape?" (Restraint), "Have you had a definite fear of losing control overeating?" (Eating Concern), "Have you felt fat?" (Shape Concern), and "Has your weight influenced how you think about (judge) yourself as a person" (Weight Concern). For this study, the latest version of the questionnaire was used, EDE-Q 6.0 (Fairburn & Beglin, 2008). Research supports the validity and reliability of the EDE-Q (Berg et al., 2012). The EDE-Q has also been validated in an Italian sample (Calugi et al., 2017).

2.3.2.3 TOS

The TOS differentiates between two dimensions of orthorexia - orthorexia nervosa (unhealthy preoccupation with consuming healthy foods) and healthy orthorexia (an interest in eating healthy) (Barrada & Roncero, 2018). The main difference between the two dimensions is that orthorexia nervosa has negative impacts on social and emotional well-being, similar to other eating pathologies. TOS consists of 17 items in total (Barrada & Roncero, 2018), with nine questions referring to healthy orthorexia and eight questions referring to orthorexia nervosa. Some examples include "I mainly eat foods that I consider to be healthy." (healthy orthorexia, HeOr) and "I feel guilty when I eat food I do not consider healthy." (orthorexia nervosa, OrNe). Responses are collected on a 4-point scale (0 = strongly disagree; 3= strongly agree). TOS has also been validated in an Italian-speaking sample (Falgares et al., 2023).

2.3.2.4 DERS-SF

The Difficulties in Emotion Regulation Scale (DERS) was first created in 2004 as a multidimensional measurement of emotion regulation (Gratz & Roemer et al., 2004). While originally consisting of 36 items, Kaufman et al. (2016) discovered that similar results can be obtained with half of the items, thus creating the Difficulties in Emotion Regulation Scale - Short Form (DERS-SF). It consists of six subscales: Non-acceptance (nonacceptance of negative emotions), Goals (inability to engage in goal-directed behaviors when experiencing negative emotions), Impulses (troubles controlling impulsive behavior when experiencing negative emotions), Strategies (restricted access to effective emotion regulation strategies), Awareness (lack of emotional awareness), and Clarity (lack of emotional clarity) (Gouveia et al., 2022; Gratz & Roemer, 2004). Each subscale consists of three questions. Some example items include: "I care about what I am feeling." (Awareness), "When I'm upset, I feel guilty for feeling that way" (Non-acceptance), and "When I'm upset, I have difficulty getting work done." (Goals). Responses are given on a scale from 1 to 5. The DERS-SF has been validated in an Italian sample (Rossi et al., 2023).

2.3.3 Procedure and Stimuli

After ensuring the validity of the behavioral task in the pilot phase, we moved forward with the main experiment. Results from the pilot experiment confirmed that labels modulate participants' food liking ($F = 5.880$, $p = .015$) and wanting ($F = 4.439$, $p = .042$). Liking of foods following an "A" label was higher compared to liking of foods following a "C" ($t = 2.394$, $p = .047$) or an "E" label ($t = 2.570$, $p = .047$), while there were no significant differences in liking of foods labelled with "C" compared to "E" ($t = 1.830$, $p = .078$). Wanting of foods following a "C" label was higher in comparison to "E" label ($t = 2.557$, $p = .048$), while wanting of foods labelled with "A" was not significantly different than foods labelled with "C" ($t = 1.861$, $p = .077$) or "E" ($t = 2.167$, $p = .077$).

Participants were scheduled to come to the laboratory in one of three time slots; 9:00 - 11:30, 11:45 - 14:00, or 14:15 - 17:00. The procedure was similar to that of the pilot, with some minor differences. Firstly, after completing the LimeSurvey priming questionnaire, participants were invited into the silent chamber of the laboratory, where the main experiment was to take place. We proceeded with the montage of the EEG cap. The task consisted of six blocks with 96 trials each. The trials were the same as the pilot experiment, presenting the sequence: label, food image, wanting and liking rating. The questions about wanting and liking ratings were presented in a counterbalanced order across blocks and participants. In total, we used 32 food pictures for the task that were divided into 16 natural foods (e.g., *avocado, hazelnuts, blueberries*) and 16 processed foods (e.g., *bagels, boiled egg, mashed potatoes*). Within the 16 natural foods, eight were high and eight were low in calories, and the same was true for the 16 processed foods. Some examples of the four categories of food picture stimuli are presented in Figure 5. Each block lasted about 7 minutes, thus, the whole experiment took between 43 and 60 minutes to complete, depending on how many breaks the participant took between blocks.

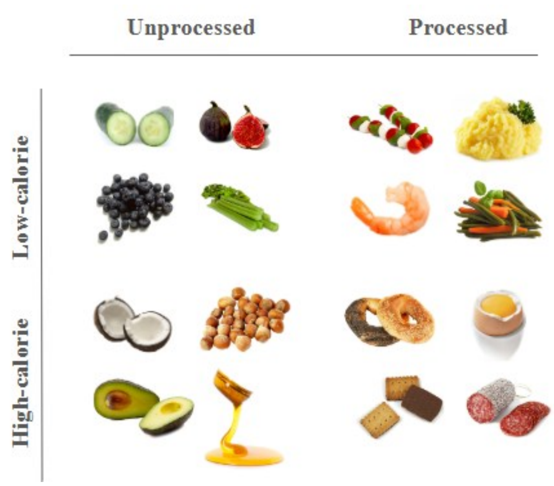

Figure 5. Examples of the Food Stimuli Across the Four Groups

2.3.4 EEG Acquisition

EEG recordings were obtained using a 64-channel cap with passive electrodes and conductive gel to ensure the acquisition of a clear signal. To obtain the signal we used g.Tec cap and amplifier, as well as software (https://www.gtec.at/). A sampling rate of 512 Hz was used. Channel locations are available in Figure 6.

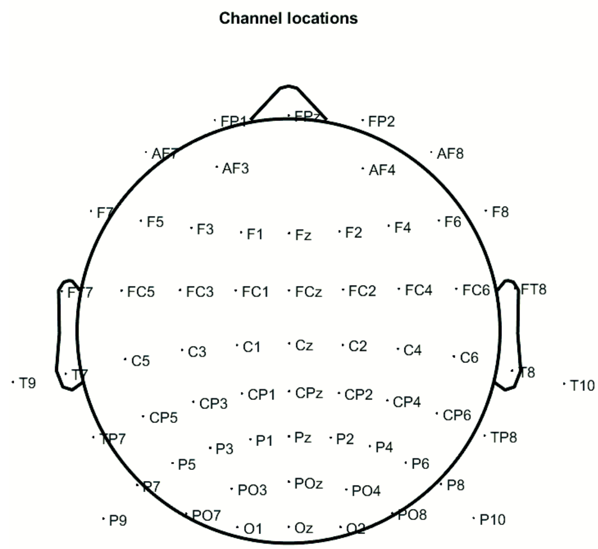

Figure 6. Locations of the 64 Channels on the EEG Cap

2.3.5 Statistical Analyses

For the analysis of the behavioral data on the modulatory effects of NutriLevel on food liking and wanting, we used R programming language version 4.4.3 (R Core Team, 2025) and RStudio Integrated Development Environment (Posit Team, 2025; version 2025.05.1+513). Two linear mixed-effects models (LMMs) were performed using Restricted Maximum Likelihood (REML) estimation method to determine the effects of the label, as well as the level of processing and calorie-content of the food, on liking and wanting. To run the LMMs, the R *lme4* package was used (Bates et al., 2015). In all analyses, results with a p-value < .05 were considered significant.

In addition to the above outlined analyses, the correlations of liking and wanting with questionnaire measures were explored, focusing specifically TOS scores. This was done using two separate cumulative link mixed models (CLMMs) for liking and wanting scores, respectively. Cumulative link mixed models were used since the TOS does not have a specific cutoff point, after which orthorexia nervosa can be applied. In the current analyses, the cutoff of 18.5 was selected as it is the median TOS score within this sample. After this division based on sample median, n = 25 participants were in the HeOr group and n = 17 were in the OrNe group. CLMMs allow for the analysis of dependent variables that were measured on an ordinal scale, while still allowing for the introduction of random effects (Taylor et al., 2023). To fit the CLMMs, the *ordinal* package was used (Christensen, 2025).

Due to time constraints, only exploratory preliminary ERP analyses using 10 out of the 42 total participants were performed for the purposes of this report. Preprocessing and analyses of the EEG data were performed using MATLAB (version: 9.5.0 (R2018b); The MathWorks, Inc., 2018). Specifically, the EEGLAB toolbox was utilized (version 2021.1; Delorme & Makeig, 2004) for the analyses of the signal. Preprocessing and filtering of the data were performed prior to conducting the statistical analyses. A high-pass filter at 1 Hz and a low-pass filter at 40 Hz were applied, and the data were resampled at 600 Hz. After visual inspection of the electrodes' signals, up to 6 (~10%) noisy electrodes were removed per participant and their signal was interpolated from the surrounding electrodes. Independent component analysis was done for artifact removal. By applying an approach similar to the one employed in a paper by Blechert et al. (2014a), ERP waveforms from the frontal and parieto-occipital regions were visually inspected for potential differences in between the different label and calorie content conditions.

Chapter 3. Results

3.1 Behavioral Data

3.1.1 Liking

A linear mixed-effects model was conducted predicting liking scores using the presented label, level of processing, and calorie content as fixed factors. Results showed a significant effect of label ($\chi^2(2) = 30.69$, $p < .001$), calorie content ($\chi^2(1) = 379.39$, $p < .001$), and level of processing ($\chi^2(1) = 4.33$, $p = .01$) on food liking, as well as a significant interaction between calorie content and processing ($\chi^2(2) = 104.20$, $p < .001$).

Post-hoc pairwise comparisons using Bonferroni adjustment revealed significant differences in liking for foods labelled with "A" compared to "C" ($\chi^2(1) = 9.17$, $p = .007$) or "E" ($\chi^2(1) = 28.19$, $p < .001$) labels, while there was no significant difference in liking between foods labelled with "C" or "E" ($p = .067$). Estimated marginal means are presented in Table 1.

Label	*EMM*	*SE*	Lower CI	Upper CI
"A"	4.25	0.122	4.01	4.49
"C"	4.14	0.122	3.91	4.38
"E"	4.07	0.122	3.83	4.31

Table 1. Liking Scores Based on the Three Labels

Note. EMM = Estimated Marginal Mean; SE = Standard Error; CI = Confidence Interval. Means are averaged across levels of processing and calorie content.

Additionally, the post-hoc analysis showed that high-calorie foods were more liked than low-calorie foods across both unprocessed ($\chi^2(2) = 74.504$, $p < .001$) and processed items ($\chi^2(2) = 409.089$, $p < .001$). Estimated marginal means are available in Table 2 and the results are visible in Figure 7.

Calorie Content	Processing	*EMM*	*SE*	Lower CI	Upper CI
HC	Unprocessed	4.36	0.122	4.12	4.60
LC	Unprocessed	4.06	0.122	3.82	4.30
HC	Processed	4.53	0.122	4.29	4.77
LC	Processed	3.66	0.125	3.42	3.91

Table 2. Liking Scores for High- and Low-Calorie Foods (LMM)

Note. EEM = Estimated Marginal Means; SE = Standard Error; CI = Confidence Interval; HC = high-calorie; LC = low-calorie; Means are averaged across the different labels.

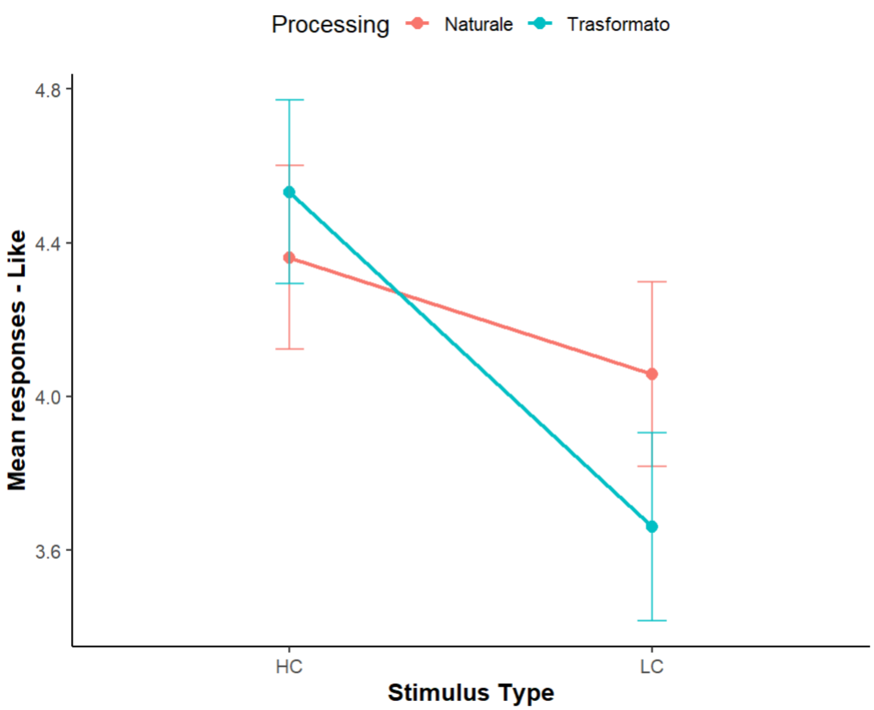

Figure 7. Liking for High- and Low-Calorie Foods of Processed and Unprocessed Foods (LMM)

3.1.2 TOS Scores and Liking

The results from the CLMM that included individual TOS scores suggest a significant three-way interaction term between calorie content, food processing level, and TOS group ($\chi^2(1) = 5.22$, $p = .022$). Additionally, there is a significant main effect of label condition ($\chi^2(2) = 33.52$, $p < .001$).

Post-hoc analyses applying a Bonferroni correction showed that foods labelled with "A" were significantly more liked than both foods labelled with "C" ($z = 3.01$, $p = .0078$) or "E" ($z = 5.16$, $p < .001$), regardless of calorie content, processing and TOS group. No significant differences in liking between foods labelled with "C" and with "E" were found ($p = .0867$). Estimated marginal means following the CLMM on liking are available in Table 3.

Figure 8 illustrates the differences in liking for high- and low-calorie unprocessed and processed foods within the two TOS groups, HeOr and OrNe. Notably, there are significant differences in liking of high- and low-calorie foods, particularly in the HeOr group. This is true for both unprocessed and processed foods.

Label	Processing	Calorie Content	TOS	*EMM*	*SE*	Lower CI	Upper CI
"A"	Unprocessed	HC	OrNe	0.1348	0.175	-0.2085	0.47824
"C"	Unprocessed	HC	OrNe	0.0825	0.176	-0.2615	0.42649
"E"	Unprocessed	HC	OrNe	0.0663	0.176	-0.2778	0.41037
"A"	Processed	HC	OrNe	0.1609	0.177	-0.1855	0.50744
"C"	Processed	HC	OrNe	0.0756	0.177	-0.2704	0.42153
"E"	Processed	HC	OrNe	0.0691	0.177	-0.2772	0.41540
"A"	Unprocessed	LC	OrNe	0.4749	0.177	0.1276	0.82219
"C"	Unprocessed	LC	OrNe	0.3057	0.177	-0.0405	0.65196

“E”	Unprocessed	LC	OrNe	0.3077	0.177	-0.0388	0.65430
“A”	Processed	LC	OrNe	-0.2477	0.189	-0.6186	0.12317
“C”	Processed	LC	OrNe	-0.24	0.189	-0.6095	0.12958
“E”	Processed	LC	OrNe	-0.3665	0.189	-0.7369	0.00380
“A”	Unprocessed	HC	HeOr	0.5039	0.147	0.2166	0.79117
“C”	Unprocessed	HC	HeOr	0.4106	0.146	0.1237	0.69762
“E”	Unprocessed	HC	HeOr	0.3224	0.147	0.0353	0.60959
“A”	Processed	HC	HeOr	0.9256	0.148	0.6355	1.21582
“C”	Processed	HC	HeOr	0.7435	0.148	0.4538	1.03314
“E”	Processed	HC	HeOr	0.6959	0.148	0.4064	0.98534
“A”	Unprocessed	LC	HeOr	-0.0771	0.148	-0.3675	0.21318
“C”	Unprocessed	LC	HeOr	-0.2262	0.148	-0.5162	0.06366
“E”	Unprocessed	LC	HeOr	-0.2941	0.148	-0.5840	-0.00415
“A”	Processed	LC	HeOr	-0.1354	0.158	-0.4443	0.17354
“C”	Processed	LC	HeOr	-0.1858	0.157	-0.4927	0.12116
“E”	Processed	LC	HeOr	-0.3930	0.157	-0.7011	-0.08495

Table 3. Liking Scores for High- and Low-Calorie Foods, With TOS Scores Included (CLMM)

Note. EEM = Estimated Marginal Means; SE = Standard Error; CI = Confidence Interval; HC = high-calorie; LC = low-calorie; OrNe = orthorexia nervosa; HeOr = healthy orthorexia

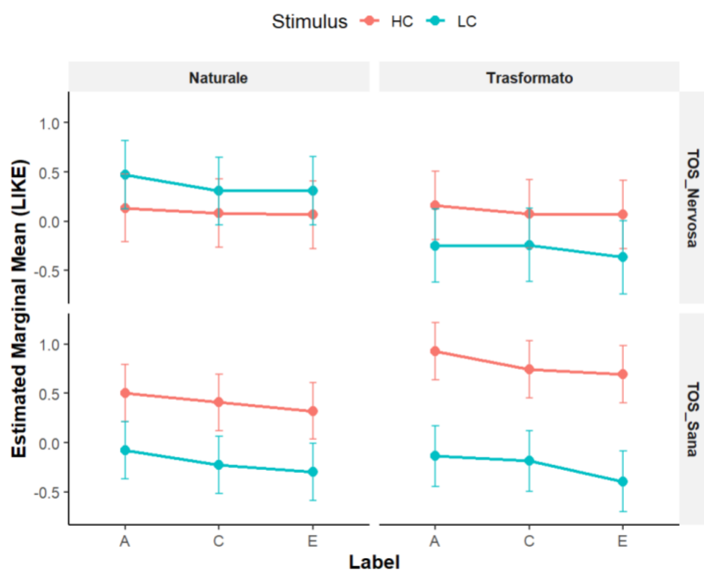

Figure 8. Liking of High- and Low-Calorie Foods Separated by Level of Processing and TOS Group

3.1.3 Wanting

A linear mixed-effects model was conducted using label, calorie content, and level of processing as the fixed factors. The results reveal a significant main effect of label ($\chi^2(2) = 158.51$, $p < .001$) and calorie content ($\chi^2(2) = 200.02$, $p < .001$), and an interaction between calorie content and processing level ($\chi^2(2) = 128.06$, $p < .001$). A visual representation of the results is available in Figure 9.

Post-hoc pairwise comparisons using Bonferroni correction showed that foods labelled with "A" were significantly more wanted than foods labelled with either "C" ($\chi^2(1) = 56.347$, $p < .001$) or "E" ($\chi^2(1) = 139.39$, $p < .001$). In addition, foods labelled with "C" were significantly more wanted than foods labelled with "E" ($\chi^2(1) = 18.489$, $p < .001$). Estimated marginal means for wanting scores across the three labels can be found in Table 4.

Label	*EMM*	*SE*	Lower CI	Upper CI
“A”	3.75	0.125	3.51	3.99
“C”	3.50	0.125	3.25	3.74
“E”	3.35	0.125	3.11	3.60

Table 4. Wanting Scores Based on the Three Labels

Note. EEM = Estimated Marginal Means; SE = Standard Error; CI = Confidence Interval. Means are averaged across levels of processing and calorie content.

High-calorie foods were significantly more wanted compared to low-calorie ones ($\chi^2(2) = 259.58$, $p < .001$), and this held true for both unprocessed ($\chi^2(2) = 14.64$, $p < .001$) and processed foods ($\chi^2(2) = 312.44$, $p < .001$). Estimated marginal means are available in Table 5.

Calorie Content	Processing	*EMM*	*SE*	Lower CI	Upper CI
HC	Unprocessed	3.64	0.125	3.39	3.88
LC	Unprocessed	3.51	0.125	3.26	3.75
HC	Processed	3.81	0.125	3.63	4.11
LC	Processed	3.12	0.127	2.87	3.37

Table 5. Wanting Scores for High- and Low-Calorie Foods (LMM)

Note. EEM = Estimated Marginal Means; SE = Standard Error; CI = Confidence Interval; HC = high-calorie; LC = low-calorie; Means are averaged across the different labels.

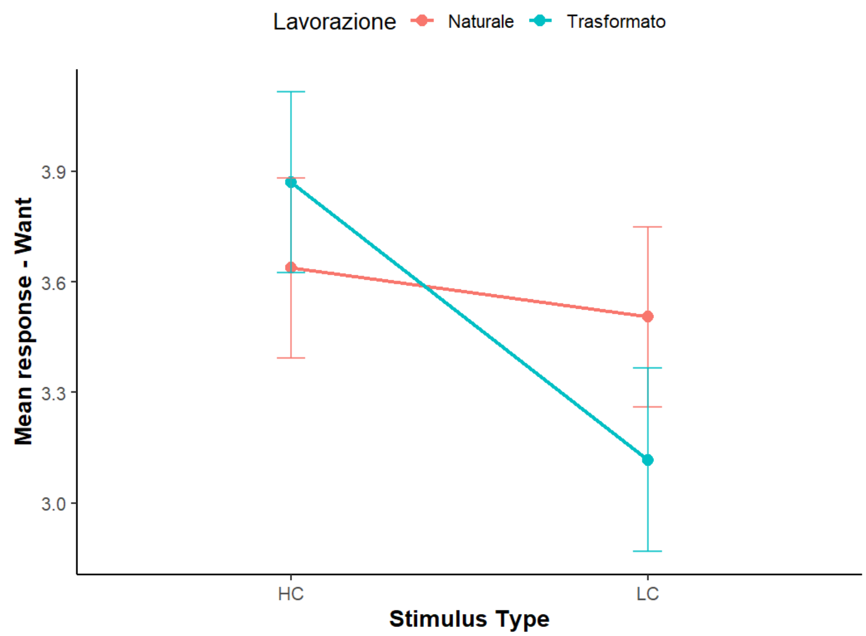

Figure 9. Wanting for High- and Low-Calorie Foods of Processed and Unprocessed Foods (LMM)

3.1.4 TOS Scores and Wanting

The results from the cumulative link mixed model investigating the relationship between TOS groups, label, calorie content, and processing level on food wanting yielded four significant two-way interactions between: (1) calorie content and processing level ($\chi^2(1) = 92.67$, $p < .001$), (2) label condition and TOS group ($\chi^2(2) = 35.61$, $p < .001$), (3) calorie content and TOS group ($\chi^2(2) = 225.95$, $p < .001$), and (4) processing level of the foods and TOS group ($\chi^2(2) = 87.29$, $p < .001$). Visual representation of wanting for high- and low-calorie foods in each TOS group, separated by processing level, is available in Figure 10.

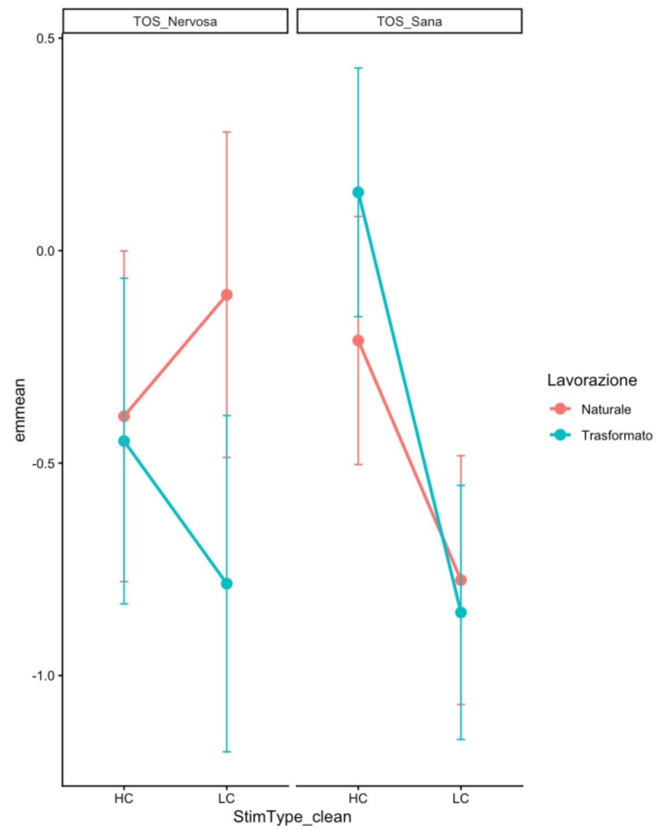

Figure 10. Wanting of High- and Low-Calorie Foods, Separated by Level of Processing and TOS Group

Post-hoc analyses using Bonferroni adjustment were performed. When looking into the effects of label conditions separated by the TOS group, label "A" significantly increased wanting of foods compared to labels "C" ($z = 7.484$, $p < .001$) or "E" ($z = 12.39$, $p < .001$) in the group of participants with healthy orthorexia. Additionally, in the same group wanting was higher for food labelled with "C" compared to "E" ($z = 5.056$, $p < .001$). The same trend was not observed in the TOS orthorexia nervosa group, where the foods labelled with "A" were significantly more wanted than foods labelled with "E" ($z = 3.168$, $p = .004$). There were no significant differences between foods labelled with "A" and "C" ($p = .329$) and "C" and "E" ($p = .338$). Estimated marginal means are available in Table 6.

In the group categorized with healthy orthorexia high-calorie foods were significantly more wanted than low-calorie foods (z = 22.994, p < .001). No significant differences in wanting for high- and low-calorie foods were observed in the OrNe group (p = .544). Estimated marginal means are available in Table 7.

	HeOr				OrNe			
Label	*EMM*	*SE*	Lower CI	Upper CI	*EMM*	*SE*	Lower CI	Upper CI
"A"	-0.152	0.149	-0.444	0.1404	-0.352	0.197	-0.739	0.0343
"C"	-0.459	0.149	-0.751	-0.1670	-0.432	0.196	-0.816	-0.0475
"E"	-0.665	0.149	-0.958	-0.3728	-0.511	0.197	-0.897	-0.1246

Table 6. Wanting EMMs for the Three Labels in Each TOS Group (CLMM)

Note. EEM = Estimated Marginal Means; SE = Standard Error; CI = Confidence Interval; HeOr = healthy orthorexia; OrNe = orthorexia nervosa; Means are averaged across calorie content and processing level.

	HeOr				OrNe			
Calorie Content	*EMM*	*SE*	Upper CI	Lower CI	*EMM*	*SE*	Upper CI	Lower CI
HC	-0.0373	0.148	-0.327	0.2523	-0.4191	0.195	-0.802	-0.0361
LC	-0.8136	0.149	-1.105	-0.5222	-0.444	0.196	-0.828	-0.0598

Table 7. Wanting EMMs of High- and Low-Calorie Foods in Each TOS Group (CLMM)

Note. EEM = Estimated Marginal Means; SE = Standard Error; CI = Confidence Interval; HeOr = healthy orthorexia; OrNe = orthorexia nervosa; HC = high-calorie; LC = low-calorie; Means are averaged across label condition and processing level.

Upon investigating wanting for high- and low-calorie processed and unprocessed foods, it became evident that high-calorie processed foods were more wanted than low-calorie processed (z

= 15.759, $p < .001$), high-calorie unprocessed ($z = 4.455$, $p < .001$), and low-calorie unprocessed foods ($z = 8.499$, $p < .001$). Additionally, high-calorie unprocessed foods were more wanted than low-calorie unprocessed foods ($z = 4.253$, $p < .001$), which in turn were more wanted than low-calorie processed foods ($z = 9.005$, $p < .001$). Estimated marginal means are available in Table 8.

Calorie Content	Processing	*EMM*	*SE*	Lower CI	Upper CI
HC	Unprocessed	-0.301	0.124	-0.544	-0.0576
LC	Unprocessed	-0.440	0.123	-0.681	-0.1986
HC	Processed	-0.156	0.123	-0.397	0.0855
LC	Processed	-0.818	0.127	-1.066	-0.5698

Table 8. Wanting EMMs of High- and Low-Calorie Foods across Processing Levels

Note. EEM = Estimated Marginal Means; SE = Standard Error; CI = Confidence Interval; HC = high-calorie; LC = low-calorie; Means are averaged across label condition and TOS group.

3.2 Preliminary Qualitative EEG Analyses

3.2.1 Brain Processing in the Different Label Conditions

Figure 11 shows the ERP waveforms based on the different label conditions from the frontal brain region. Two different waveforms are presented per label condition - one showing the brain activity following label exposure for high-calorie foods, and one - for low-calorie foods.

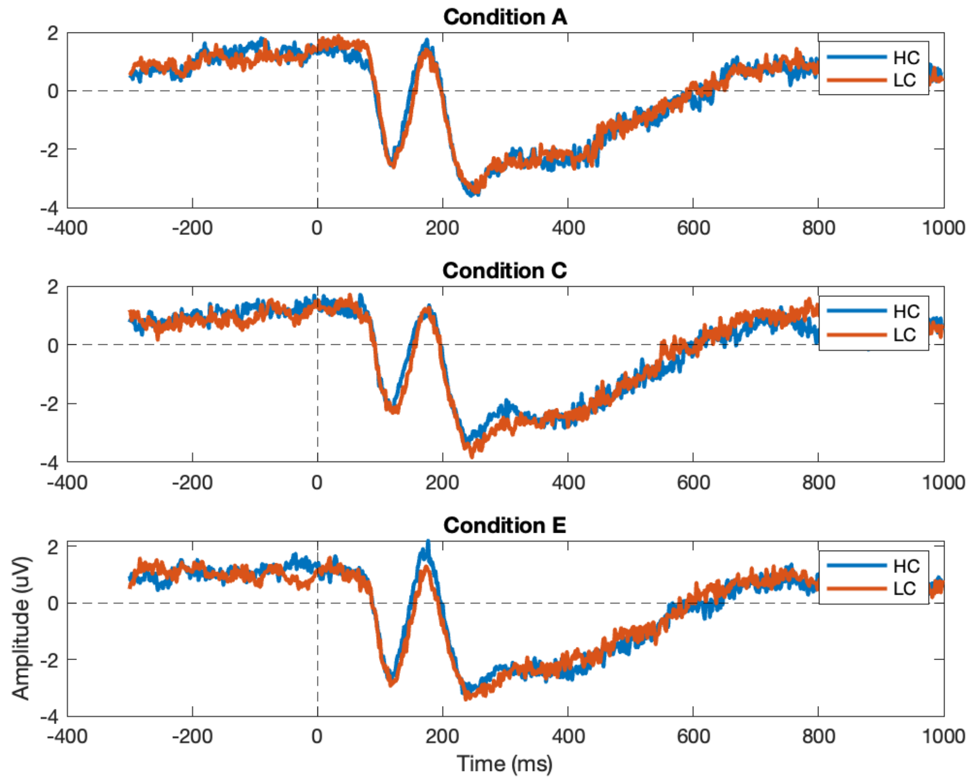

Figure 11. Frontal ERP Waveforms in the Different Label Conditions

Based on qualitative visual exploration of the waveforms, some differences across conditions become apparent. Firstly, the negative (at roughly 100 ms post-stimulus) and positive (at roughly 180 ms post-stimulus) deflections in the "C" label condition appear to be less extreme compared to the respective ones in the "A" and "E" conditions. Additionally, within the "E" label condition, some differences between brain processing of high- and low-calorie foods are visible, with the amplitude of the positive peak at around 180 ms being larger for high-calorie foods. For all three label conditions, there is a sustained frontal late negativity starting at around 220 ms, suggesting cognitive effort and potentially decision-making processes.

Figure 12 depicts the ERP waveforms derived from parieto-occipital regions under the three label conditions. Similarly to Figure 11, two waveforms are available per condition for brain responses to high- and low-calorie foods, respectively.

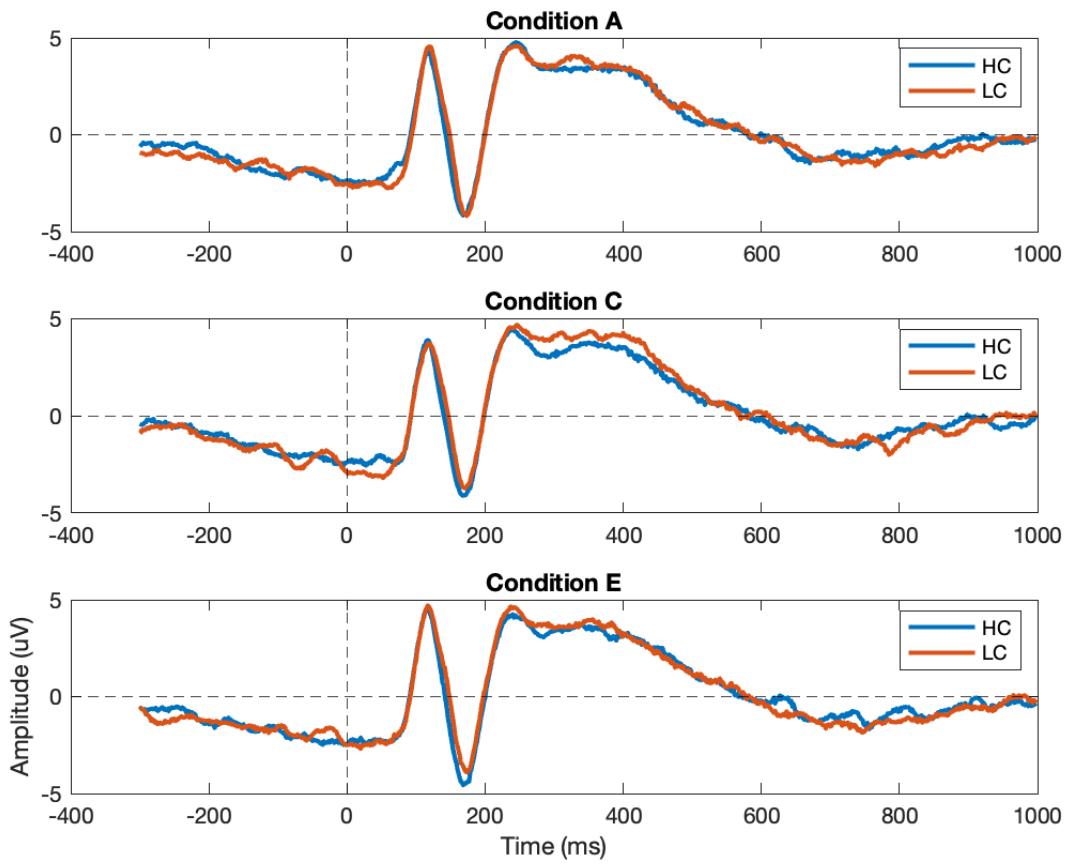

Figure 12. Parieto-Occipital ERP Waveforms in the Different Label Conditions

Following a visual inspection of Figure 12, similar differences emerge. Amplitudes of the first positive (at around 150 ms) and negative (at around 180 ms) peaks are smaller in the "C" label condition compared to "A" and "E" conditions. In condition "C" the second positive peak - at roughly 220 ms - appears larger than the first one. Such a difference might point to potential differences in early and late processing of the stimuli.

3.2.2 Brain Processing of High- and Low-Calorie Foods

Figure 13 illustrates grand-average ERPs from frontal regions for high- and low-calorie foods. Three separate lines are available, one for each label condition.

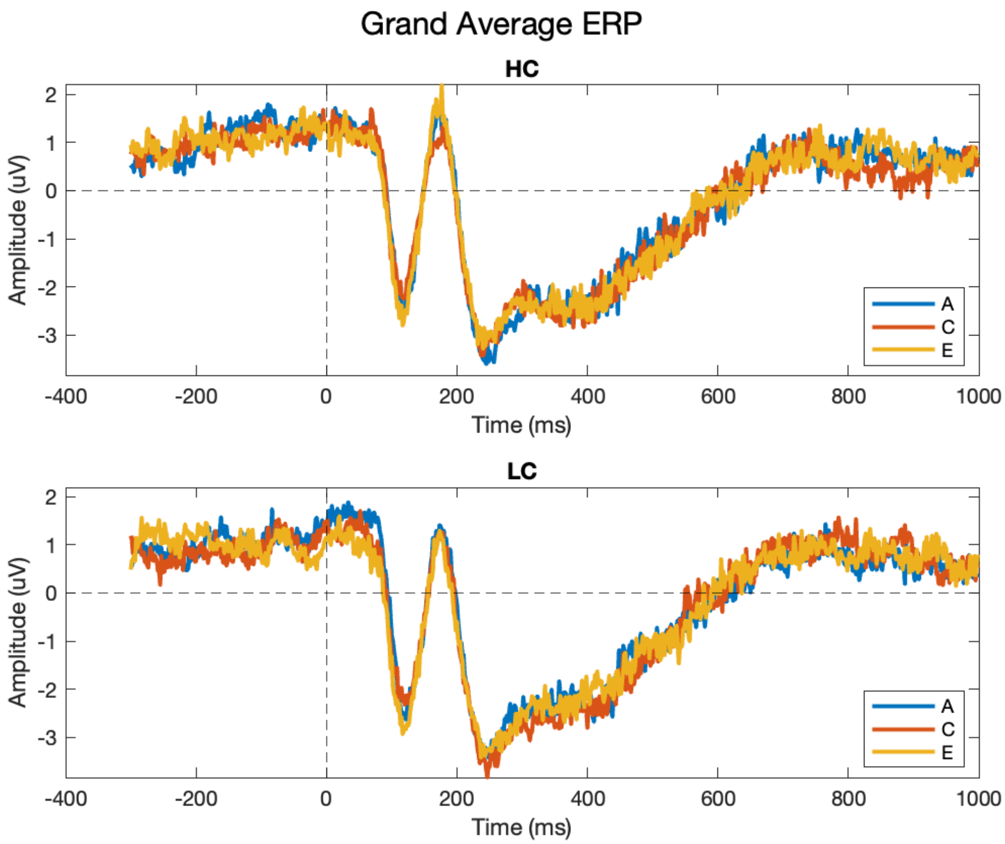

Figure 13. Frontal ERP Waveforms for High- and Low-Calorie Foods

Upon visual inspection of the graphs, differences between processing of high- and low-calorie foods emerge. Notably, both the early negativity and early positivity appear to have larger amplitudes for high- compared to low-calorie foods. However, these observed differences seem small.

Figure 14 demonstrates the ERP waveforms from parieto-occipital regions for high- and low-calorie foods, with separate lines representing the three label conditions.

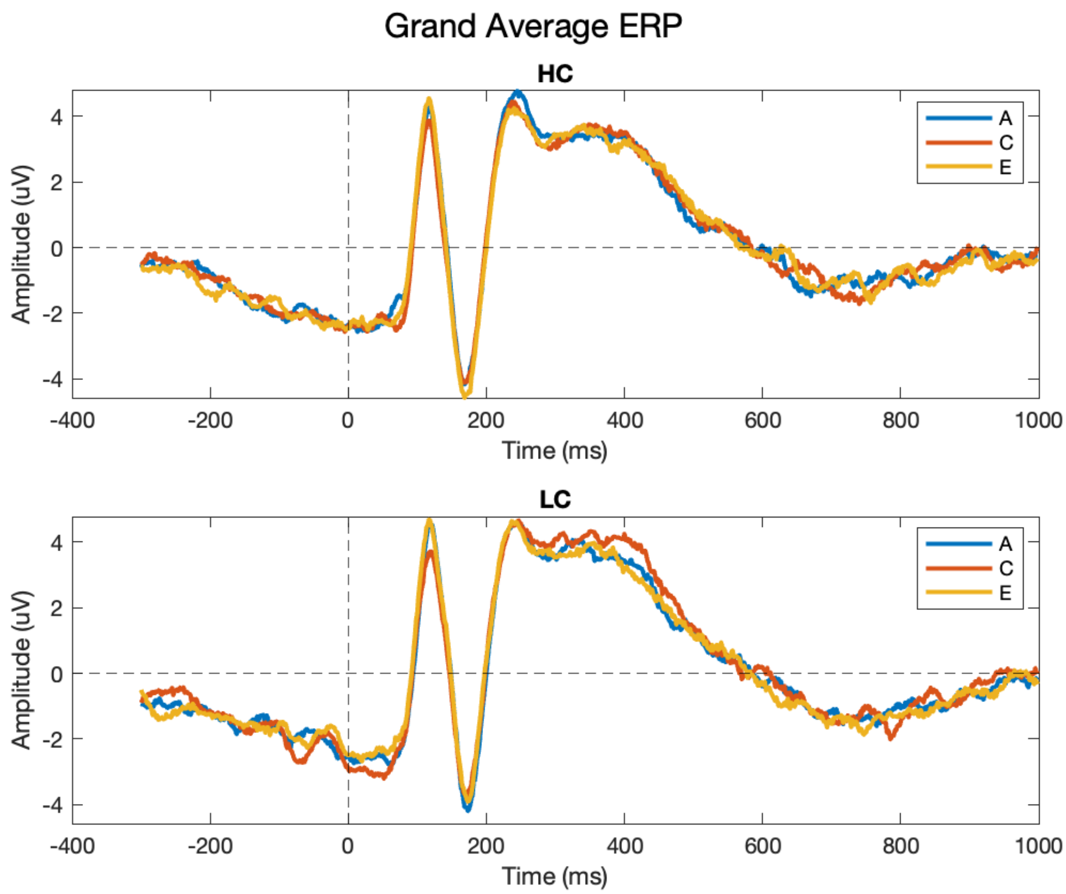

Figure 14. Parieto-Occipital ERP Waveforms for High- and Low-Calorie Foods

Visual inspection of the ERP waveforms reveal rather similar brain activity across the conditions. Interestingly, within the low-calorie foods, the largest positive amplitude is seen after foods presented with a label "E". In addition, overall amplitudes in the ERP components appear larger in the low-calorie foods.

Chapter 4. Discussion

The debate surrounding a wide introduction of FoPLs remains central, particularly in the context of the European Union. While the goal of adopting such a policy was clearly stated by the European Commission in the Farm-to-Fork strategy in 2022 (EC, 2022), such an adoption of a unified FoPL has not been yet accomplished, partly due to valid concerns about the necessity and adequacy of the proposed labels. In addition, consumer understanding of and behavior change following exposure to FoPLs is still poorly understood, with evidence both supporting and disproving the beneficial effects of labels being available.

The goal of this thesis was to identify the differences in liking and wanting of high- and low-calorie processed and unprocessed foods after being exposed to a color-coded FoPL (i.e., NutriLevel). By utilizing a task in which participants were first presented with a label (dark green "A", yellow "C", or dark red "E"), then a food item, and subsequently were asked to rate how much they liked and wanted that food in the moment, we aimed to understand if and how liking and wanting of different foods can be modulated through an easy-to-implement tool. Additionally, EEG data were collected with the aim to identify potential variations in brain processing of the food items, following exposure to the interpretative, color-coded NutriLevel. As such, this report adds to the scientific evidence on the usefulness of FoPLs, thus hoping to bring clarity to the ongoing debate.

The results of this study reveal that a color-coded, interpretative FoPL, does indeed modulate liking and wanting responses for foods from different categories. Foods that were labelled with the dark green "A" were significantly more liked and wanted than foods that were preceded by the other two labels (yellow "C" or dark red "E"). There has been some disagreement in the literature regarding how FoPL color affects healthiness perception of the product. One one hand, Lemos et al. (2020) suggests that a red color induces unintended approach motivation towards unhealthy UPFs compared to amber or green colors presented prior to the food product. On the other hand, previous research on the psychological importance of color has indicated that a green color is automatically associated with approach motivations, thus encouraging a specific behavior (Schuldt, 2013). In the case of color-coded FoPLs, this would mean that foods with a dark green label (typically marking the product as healthy) would be more sought after than foods with lower nutritional ratings (yellow/amber or dark red). The results of this study fall in line with the latter, since a dark green label "A" was associated with higher liking and wanting in both low- and high-calorie processed and unprocessed foods. Since hedonic valuation and wanting are two of the most important determinants of individual eating behavior, it can be argued that increased scores in liking and wanting following a dark green "A" might, indeed, encourage healthier food consumption. Still, whether these effects translate to actual shopping behavior remains to be verified.

When separating the sample into two groups based on TOS score, some interesting differences emerged. Regardless of calorie content, processing, and TOS group, foods labelled with "A" were better liked compared to foods labelled with the other two labels. This is interesting since, independent of one's concern with healthy eating, participants' liking and wanting were influenced by the healthiness score of the item. Such a result shows that healthiness is an important factor in food choices in healthy populations and those with pathological tendencies alike. Significant differences in liking of high- and low-calorie foods only in the HeOr group were revealed. Similar differences were not observed in the OrNe group, which is characterised by an unhealthy preoccupation with healthy eating (Scarff, 2017). Previous research suggests that people struggling with orthorexia nervosa show less food reward reactivity (Aiello et al., 2026).

Interestingly, people with HeOr and OrNe showcase vastly different motives behind their food choices, with weight control and emotional regulation being particularly important for people with orthorexia nervosa (Depa et al., 2019).

Different wanting patterns were also observed between the two TOS groups. While in the HeOr group wanting for low-calorie foods was lower than for high-calorie ones, irrespective of processing level, low-calorie processed foods were more wanted than both low-calorie unprocessed and high-calorie processed foods. Even though these differences were not significant, they suggest that there are different motivational drivers in people with HeOr compared to OrNe. Additionally, these results might suggest a complex relationship between OrNe and food warning, with processing and calorie content being an important feature. These results highlight the multifaceted nature of orthorexia (Horovitz & Argyrides, 2023), once again creating differentiation between a healthy interest in healthy foods and an unhealthy obsession with healthy eating.

Even though this thesis presented preliminary ERP results from the conducted experiment, the outcomes suggest some intriguing conclusions. Firstly, the smaller amplitude of the frontal ERP peaks following foods labelled with a “C” label compared to the other two label conditions could be a measure of a potential cognitive conflict. While a dark green “A” (healthy) and a dark red “E” (unhealthy) have clear-cut meaning, making judgements about food relatively simple, the yellow “C” can be seen as an intermediate label. As such, it does not provide a specific answer about the healthiness of the food item - as the middle ground between a clear “healthy” score and a clear “unhealthy” score, a yellow “C” label might require more effortful consideration of the food product. Thus, evaluation happens less automatically. Similar differences in brain processing of the three labels are visible in the parieto-occipital ERP peaks - the amplitude of the ERPs under the label “C” condition are smaller than those for labels “A” and “E”.

Both high- and low-calorie foods labelled with "E" evoke larger early positive and negative amplitudes in frontal and parieto-occipital regions alike. While there are some differences between brain activity for each of the food groups, these differences appear small and require additional statistical analysis to determine if they are indeed significant.

This study is not without its limitations. Firstly, the experimental procedure was conducted in a laboratory setting, meaning that participants did not get the chance to physically interact with the food items. This has been pointed out as a weakness previously (Donini et al, 2022), as generalizations of results from the laboratory to a real-world shopping environment (i.e., a grocery store) may be limited (Dubois et al., 2021). Consequently, participants might feel differently about the interpretability of the FoPL after having had multiple exposure sessions in regular environments. Additionally, as the introduction of FoPLs has been a controversial topic and has not yet happened in the Italian context (Fialon et al., 2022), the participants' first exposure to an FoPL was immediately before completing the experimental task. Research on habitual behaviors/perception has shown that habits can be powerful predictors of one's eating behavior, with individuals requiring little additional information when making decisions out of habit (Riet et al., 2011). As eating is an integral part of people's daily lives, it has become highly automated - for example, individuals prefer to repeatedly buy the same food items at the same grocery stores (Ersche et al., 2017). This is frequently the case with food, which is why it is necessary to apply habit-focused interventions when attempting to nudge behaviors towards healthier alternatives (Riet et al., 2011). In this case it is necessary to consider whether FoPLs are powerful enough tools to bring about substantial change in habitual food purchasing and consumption behaviors. Through regular exposure in real-life shopping situations, consumers might become accustomed to interpreting FoPLs and using them to compare products, thus accomplishing one of the goals of such labels - namely, simplifying the shopping experience for healthy foods. Given that the participants do not have regular exposure to FoPLs as part of their food shopping routine, seeing an FoPL for the first time might have impacted their subsequent perception of the presented food items.

Furthermore, as part of our study, participant hunger levels were not recorded prior to completing the experimental task, nor was it required of them to eat a meal at a specific time before coming into the laboratory. Hence, their hunger levels might have varied depending on what time they had scheduled their participation in the experiment, as one of the time slots was during lunch time (11:45 - 14:00). As is seen in the literature, wanting is directly dependent on hunger levels (Finlayson, 2007; Jacquin-Piques, 2025; Stevenson et al., 2017), with liking showing smaller changes between a hungry and satiated state (Stevenson et al., 2017). Since we did not control for participants' hunger levels, this could have been a confounding factor, especially for the reported wanting of foods.

Furthermore, the sample consisted primarily of highly educated individuals that were attending university at the moment, or had already graduated from university. Berčík et al. (2024) shows that younger and more educated individuals tend to choose products based on a better FoPL score (e.g., Nutri-Score) more closely than other populations. As such, this might not have been a representative sample of the general population. While affordability is a large concern when it comes to healthy diets, it has been argued that educational background might be even more important for determining one's dietary pattern (Olstad & McIntyre, 2025). Koç & Van Kippersluis (2017) showed that higher-educated individuals are more concerned about the adverse effects of overconsuming unhealthy foods, while the same cannot be said for lower-educated individuals. The paper argues that while nutritional information bridges the gaps between the two groups, it does not completely eliminate them. In light of this, it becomes evident how a sample consisting of less educated participants might yield different results, and thus, it is vital to consider the effects of FoPLs on different populations.

While EEG is a powerful tool in the modern neuroscientist's toolbox, it is necessary to consider its strengths and limitations when interpreting EEG data. For one, while the EEG signal is characterized by excellent temporal resolution (Helfrich & Knight, 2019), the nature of EEG recordings makes specific spatial localization of the source of neuronal activity hard to determine (Müller-Putz, 2020). While there are certain methodologies that allow for approximate source localization of the signal, EEG has nowhere near as high spatial resolution as, for example, magnetic resonance imaging (MRI). Additionally, because the electrodes recording the signal are placed directly on the scalp of the subject, EEG is limited to obtaining information primarily from the cerebral cortex. Considering this, how feasible it is to record brain electrical signals from subcortical regions remains in question (Seeber et al., 2019) with some papers suggesting that a high-density EEG protocol with a minimum of 100 electrodes would be necessary for a reliable recording of deeper brain functions using scalp EEG (Liu et al., 2017). This becomes a crucial consideration when researching eating behavior since there are multiple deeper brain areas involved, particularly concerning the reward network (e.g., nucleus accumbens, ventral tegmental area, etc.). With that in mind, EEG remains an invaluable tool as it allows us to gain insight about brain processing that is otherwise inaccessible to researchers. Due to its high temporal resolution, EEG recordings reflect changes in the brain's electrical activity within milliseconds, thus providing a continuous stream of information on the rapid changes in brain processing (Songsamoe et al., 2019).

On the other hand, this thesis comes with certain strengths. Firstly, the sample was rather balanced, with nearly equal numbers of men and women. Research on (pathologic) eating behavior and habits frequently consists mainly of female populations, thus lacking generalizability to males and their experiences around food (Murray et al., 2018). This is concerning because what is valid for one gender might not necessarily apply to the other. Furthermore, research on the eating behavior of males is crucial since they tend to be underrepresented in eating disorder estimations (Murray et al., 2018). One particular area, in which gender differences have been described with regards to eating behavior and disorders, is the emotional cycle (Vuillier et al., 2022). Such differences are necessary to understand in order to create interventions that are effective in females and males alike. So, ensuring a mixed and balanced sample when examining various aspects of eating behavior is crucial to the generalizability of results.

Additionally, the experimental task included different categories of foods ((1) unprocessed low-calorie, (2) processed low-calorie, (3) unprocessed high-calorie, (4) processed high-calorie). Even though FoPLs are aimed to be put on the packaging of processed foods, it is essential to see how perception of such products compares to that of natural foods. This is the case particularly because of the concerns raised that a good FoPL, depending on the underlying assessment mechanism, might facilitate consumers to perceive nutritionally poor food products as healthy (Schuldt, 2013). In light of this, the inclusion of both processed and unprocessed foods is an important and informative feature of this study.

This paper is part of a growing amount of research supporting the wide use of FoPLs. However, it is necessary to discuss certain aspects that have been found to be troubling in order to maintain a full understanding of the state of the art. To begin with, concerns have been raised about the algorithms on which FoPLs are built. More specifically, van der Bend et al. (2022) point out that the Nutri-Score algorithm evaluates foods and beverages based on 100g or 100ml of the product. While this might be an appropriate portion for some items, that is not the case for the majority of highly processed packaged foods (van der Bend et al., 2022). In addition to this, FoPLs shift the focus away from the synergistic effects of different foods by providing specific information on single nutrients or a small pool of nutrients (as is the case with summary FoPLs) (Donini et al., 2022). Indeed, while a product might not be harmful in small quantities, prolonged or frequent exposure might cause it to become so. What is more, some manufacturers might be tempted to fortify products with beneficial nutrients (e.g., fiber) with the aim to have better FoPLs on their products, while not necessarily negating unfavorable components of the food item (van der Bend et al., 2022).

Muzzioli et al. (2025) point out that despite research moving forward and focusing more and more on the applicability and effects of FoPLs, due to the fact that their algorithms are continuously updated, the usability of such labels remains under question. Muzzioli et al. (2025) proposes that, in order to have correct and convincing evidence in support of or against FoPLs, their underlying algorithms need to be stabilized instead of repeatedly altered. Such a step would, in turn, allow for reproducibility and stability of scientific results, thus guaranteeing more accurate conclusions about the effects of different FoPLs.

In addition to the already discussed issues, it has been pointed out that while easy-to-interpret features of labels are highly appreciated by consumers, oversimplifying FoPLs might omit desired information and so labels might instill less trust into the buyers (Talati et al., 2019). Likewise, since a green label has been shown to induce approach motivation for food products, some researchers have voiced concerns about a scenario in which people might see nutritionally-poor UPFs as healthy simply because they have been labelled with a relatively high score (Schuldt, 2013). Concerns such as these once again call for a careful consideration of the algorithms through which foods get scored on a particular label.

Lastly, but equally important, it has been discussed that instead of promoting an overall healthy diet, FoPLs might shift the focus of consumers to specific individual nutrients (Donini et al., 2022). While that might be important for addressing particular nutrient deficiencies, a focus on one's entire dietary pattern might be a better approach to supporting general health (Donini et al., 2022; Freeland-Graves & Nitzke, 2013). As it has been pointed out by Freeland-Graves and Nitzke (2013), remaining overly focused on individual nutrients or foods might create more consumer confusion. For this reason they propose that, instead, a focus on moderation, variety, and proportionality with regards to one's diet as part of a health-conscious lifestyle is a more beneficial approach.

The importance of research on factors affecting eating behavior and healthy habits is critical in psychological and neuroscientific research. After having discussed the limitations of the current paper, also with reference to already existing research, it becomes evident that more effort needs to be made to understand what drives food choice. As such, some recommendations are apparent. Firstly, as an extension to the preliminary qualitative EEG analyses, full statistical testing of the EEG data is necessary to delineate the specific differences across conditions. While there are some subtle differences in the ERP waves upon visual inspection, their significance is currently unknown. Additionally, the relationship between neurophysiological and behavioral data needs to be examined. While the behavioral results are promising regarding the effectiveness of FoPLs in modulating food liking and wanting, their correlation with the neurophysiological results would allow for a deeper understanding of the changes brought by FoPLs.

Secondly, it is important to examine how reproducible this line of research is, in a real-world shopping setting. Currently, a large portion of the available studies have been conducted in a laboratory context, thus limiting the generalizability of results to actual behavior change (An et al., 2021; Ikonen et al., 2020; Peters & Verhagen, 2024). For example, in the present paper, participants were not able to choose from different versions (or brands) of the same product, as is the case in a regular grocery store. It is prudent to investigate how brand loyalty and habit affect food choice with respect to the presence of FoPLs. Some research suggests that FoPLs might be less effective in encouraging better purchases when they are applied to already familiar products or brands (Ikonen et al., 2020). To what extent can a better FoPL nudge a consumer to buy a product from a brand, different from what they are accustomed to purchasing?

Furthermore, extending the research through the utilization of a wide variety of tools is vital for the advancement of our understanding of food choices and healthy behaviors. As it has been mentioned previously, while EEG is a powerful tool in the neuroscientist's toolbox, it comes with certain constraints as to the type of data collected. Consequently, by employing other tools, such a functional MRI (fMRI), a more complete understanding of what brain parts are involved in choosing specific foods following exposure to FoPLs. Additionally, using fMRI would allow for the investigation of deeper brain structures that help modulate eating behavior, which is not possible when using EEG.

What is more, since this report presented preliminary brain processing findings from the available EEG data, an analysis of the full sample of 42 participants is necessary. Conducting the full analysis would provide convincing support for the results presented above. As an additional step, the results from the behavioral task need to be correlated with the EEG data. Such an integration of different data modalities provides a more complete picture of cognitive processes, as well as better predictions of unobserved processes (Turner et al., 2016).

Expanding on the research done on different FoPLs, it is crucial to get further insight into the effects produced by different labels. While the current paper found favourable results for the implementation of a color-coded interpretative label (i.e., NutriLevel), it is necessary to thoroughly evaluate the effects of other types of labels (e.g., nutrient-specific interpretive labels, such as MTL, or reductive labels, such as Reference Intakes) as well, as results may be type-specific.

Lastly, different populations of people should be examined in the future. Our sample consisted predominantly of young people (ages 20 - 32). However, it is not apparent whether the same effects seen here would transfer to older individuals, or people from different socio-economic backgrounds. Indeed, research suggests that there are a multitude of factors influencing food purchases, including emotions (Berthoud et al., 2017; Finch et al., 2019), the sensory properties of food (Appleton et al., 2021; Stover et al., 2023), and individual dietary habits (Beheshti et al., 2017), with affordability being at the top of that list, especially for individuals from a lower socioeconomic standing (An et al., 2021; Beheshti et al., 2017; Shrestha et al., 2023).

Chapter 5. Conclusion

The results of this study support the notion that interpretative, color-coded FoPLs can modify liking and wanting of foods. While in general high-calorie foods remain more liked and wanted than low-calorie options, a green label “A” has been associated with more liking and wanting across the food categories. This is an important discovery since liking (hedonic valuation) and wanting (the motivational drive to obtain food) are two of the main factors affecting individual food choices. In the modern world of abundance of food, being nudged towards healthier products is a step towards improving nutritional knowledge and consumption of healthier foods. Additionally, the interactions between TOS group, processing level, and calorie content and their effects on food liking and wanting once again highlight the differences between an interest in healthy food and a maladaptive obsession with healthy eating.

Even though the ERP results and interpretation are preliminary, some conclusions can be drawn. While foods labelled with “A” and “E” evoke similar brain activity in frontal and parieto-occipital regions alike, amplitudes of the ERP waveforms following a “C” label are smaller. An ambiguous label category, such as the yellow “C”, might require more effortful consideration on the part of the consumer. This is in conflict with the goal of FoPLs to make healthy food choices simpler.

With that in mind, it is necessary to remember that FoPLs are intended to be placed on the fronts of packaged, typically highly processed foods. While the intention is to encourage the consumption of healthier foods, the focus should not shift towards incorporating more UPFs in one’s diet simply because of a dark green “A” on the front of the package. Instead, a better approach is to maintain focus on eating a wide variety of whole foods, with the occasional packaged items. The choice of said packaged items might indeed be simplified with the introduction of a unified FoPL.

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