NEURODYNAMIC RESPONSES TO REPEATED VISUAL STIMULI: AN EEG STUDY OF FOOD HABITUATION

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Abstract

This research investigates how the brain responds to repeated and novel exposure to visual food cues by examining neural habituation and dishabituation using electroencephalography (EEG). It is motivated by growing concerns over food-related attentional biases, which are often linked to compulsive eating behaviours and rising obesity rates. By focusing on the process of neural habituation and dishabituation, this research aims to uncover patterns that may explain persistent food attention and motivation or difficulty disengaging from high-calorie food cues.

Habituation refers to the brain's reduced response to repetitive stimuli, while dishabituation represents a renewed neural reaction following the presentation of a novel stimulus. This study uses a combination of EEG-based measures, including event-related potentials (ERPs), oscillatory activity across different frequency bands, and functional connectivity, to observe how these neural processes unfold over time. ERP components such as P2, N2, and LPP are employed to capture distinct cognitive stages like early attention, motivation, reward processing, stimulus evaluation, and emotional engagement. Oscillatory activity in different frequency bands provides insight into the dynamics of cognitive control, while functional connectivity, assessed using the weighted phase lag index (WPLI), reflects how different brain regions coordinate their responses during stimulus processing.

To effectively pursue the research objectives, the study involved 24 participants, equally divided into high and low BMI (Body Mass Index) groups, with 12 individuals (six male, six female) in each. Each participant completed nine sessions per condition (high-calorie, low-calorie, and non-food), and each session included 40 trials. Of these, 30 trials represented the habituation phase and were grouped into five sets of six trials each (trial groups 1 to 5) to examine changes in neural response over time. The remaining 10 trials, grouped as trial groups 7 and 8, were used to evaluate the dishabituation phase. This structure enabled the investigation of both sustained exposure effects and neural response recovery while ensuring sufficient data within each condition to support robust statistical analysis.

The findings reveal that high-calorie foods tend to sustain neural engagement more than low-calorie or non-food stimuli. ERP responses to high-calorie images remained elevated across repeated exposures, indicating slower habituation. In contrast, non-food and low-calorie images exhibited more typical patterns of habituation, with brain responses diminishing over time, particularly in the parietal and frontal regions. During the dishabituation phase, all image categories, regardless of calorie content, elicited a renewed neural response when a novel stimulus was introduced, highlighting the brain's sensitivity to change even after prolonged exposure.

These observations suggest that individuals may differ in how quickly they habituate or recover neural responses to different types of visual food cues. For instance, those with lower BMI showed stronger habituation to non-food stimuli, whereas participants with higher BMI sustained greater engagement, particularly with high-calorie images. These differences may be informative for developing personalized interventions to help regulate food intake.

The central contribution of this thesis lies in identifying a robust set of EEG-based neural markers of food habituation and dishabituation. These include key

ERP components (P2, N2, LPP), theta-band oscillations observed in frontal regions, and connectivity dynamics between frontal and parietal regions measured through WPLI. Together, these markers provide a comprehensive picture of how attention and motivational systems respond to food cues over time.

Beyond the theoretical contributions, the research also points to practical applications. The EEG markers identified could be used to monitor real-time attentional engagement and may be integrated into neurofeedback tools. These tools could help individuals train their brains to reduce sensitivity to unhealthy food cues. Additionally, the insights gained could inform public health strategies, such as limiting high-calorie food advertisements or promoting mindful eating practices that encourage cognitive disengagement from tempting stimuli.

In summary, this research presents an integrative EEG-based approach to understanding how the brain processes visual food stimuli. By combining time-domain, frequency-domain, and connectivity measures, the study reveals that high-calorie foods resist habituation and maintain neural salience, offering valuable insights into the cognitive and motivational mechanisms behind eating behaviours. These findings hold the potential for informing both clinical interventions and public health strategies aimed at combating diet-related challenges.

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Chapter 1

Introduction

Eating involves repeated presentation of visual, olfactory and gustatory cues of food consumption (Epstein et al. 2009a). One outcome of repeated stimulus presentation is habituation to that external stimulus. Habituation is described as a general model of how repeated stimuli presentations influence the response and is universal across response systems (Groves and Thompson 1970; Epstein et al. 2009a). In food-related habituation, it is described as a reduction in the physiological and behavioural response to eating when an eating episode occurs. It may provide a model to understand factors that are important for stopping eating or satiation during food consumption. For example, continuous presentation of a cheeseburger reduces the liking towards the cheeseburger over time, which is measured by reduction in salivary secretion (Epstein et al. 2009a).

Obesity is described as a disorder that involves eating more food than required. Research says that slower habituation might be related to overeating, so obesity may be a disorder related to slower habituation and, thus, greater energy intake. In the existing literature, obese children show a slower habituation rate than slim children (Epstein et al. 2008). Additionally, obese adults show slower rates of salivary habituation than slimmer adults (Epstein, Paluch and Coleman 1996a). There is also a possibility that slimmer children who habituate at a slower rate are more inclined to become overweight or obese in future. Therefore, habituation could be a risk factor for the development of obesity. One of the most critical findings in food habituation research is that habituation helps to explain eating that is not controlled by energy deficiency. Thus, habituation provides insight into individual behaviour and interventions that will modify eating that is not controlled by an energy deficiency.

The process of food habituation is a fundamental psychological and physiological phenomenon in which repeated exposure to the same meal results in a decrease in the urge to consume that food. By reducing the attractiveness of food after it has been consumed for the first time, this procedure helps regulate food intake and prevents excessive eating after it has been consumed. Because it provides insights into how our eating behaviours are influenced by repeated exposure to food stimuli, understanding food habituation is vital in the context of current dietary habits and the rising prevalence of obesity. This is because it describes how our eating behaviours are influenced by food stimuli.

So, understanding and researching food habituation is important for the following reasons:

- Understanding Eating Behaviours: A greater comprehension of the mechanisms underlying eating behaviours is provided by research on food habituation. We can gain a better understanding of the elements that contribute to overeating and unhealthy eating habits by researching how and why our desire for particular meals declines after repeated exposure.

- Obesity and Overeating: Given the rise in obesity rates around the world, it is critical to look into the ways in which food habituation might be used to encourage better eating practices. Interventions that lessen the likelihood of overeating can be developed by understanding the role that habituation plays in controlling food intake, especially in situations when there are lots of high-calorie food signals.

- Impact of Modern Environments: The continuous visual and olfactory stimuli present in today's food environment can interfere with the natural processes of habituation. Studies can shed light on the ways in which elements such as advertising, media consumption, and dietary diversity affect habituation and, in turn, energy intake.

- Development of Interventions: Through learning more about food habituation, researchers may create focused interventions that support people in controlling their eating habits. Better weight management and general health can be achieved, for example, by employing tactics that decrease a person's inclination to unhealthy meals while preserving their interest in healthier options.

- Cognitive and Neural Mechanisms: Examining the neural and cognitive processes that underlie food habituation can provide light on the many brain areas and cognitive functions that are involved in controlling food consumption. This information can help with the development of more successful nutritional interventions and eating disorder therapies.

In summary, research into food habituation is essential for addressing the complex issues surrounding eating behaviours and obesity. By exploring the mechanisms of habituation and its disruption, we can develop more effective strategies to promote healthy eating and prevent overeating, ultimately contributing to improved public health outcomes.

1.1 Motivation

Existing literature on food habituation utilises measures such as salivation levels, facial muscle movements, reinforcing responses, and neuroimaging techniques like Functional Magnetic Resonance Imaging (fMRI) (Epstein et al. 1992; Epstein and Paluch 1997; Temple et al. 2006; Wagner et al. 2006). While these methods provide valuable insights, they are often impractical for real-world intervention studies due to their invasive nature and resource requirements. Similarly, subjective measures, such as self-reported questionnaires and scales, are prone to response bias and are considered less reliable.

Designing effective interventions for food habituation requires practical and objective measurement techniques, as methods like measuring salivary responses, for example, are not feasible in everyday settings. This research focuses on understanding the changes in brain responses to food habituation using EEG data analysis techniques. EEG provides a deeper insight into neural activity during habituation and offers several advantages, such as practicality, cost-effectiveness, and the ability to capture real-time brain activity. These features make EEG an ideal and reliable approach for studying food habituation in real-world applications.

1.2 Key Terms and Concepts

To aid comprehension, this section provides concise definitions of the core concepts central to this thesis.

- **Food Habituation**: This refers to the brain's adaptive reduction in neural response to repeated food-related stimuli. When a person is repeatedly exposed to the same food—such as consuming multiple cheeseburgers, the associated brain regions involved in attention, reward, and salience begin to show diminished activation. This neural dampening occurs because the stimulus becomes familiar, leading the brain to treat it as less significant. As a result, the perceived appeal of the food declines, supporting the natural process of satiety. In this research, food habituation is examined by tracking how EEG signals change in response to repeated presentations of the same food images, providing insight into the brain's dynamic engagement with food cues over time.

- **Dishabituation**: The sudden return of a response to a previously habituated stimulus when a novel or different stimulus is introduced. It indicates that the original decrease in response was not due to fatigue but active neural regulation.

- **Electroencephalography (EEG)**: A non-invasive method for recording electrical activity from the scalp, which reflects neural processes. EEG offers millisecond-level temporal precision, making it ideal for tracking rapid changes in brain responses to stimuli.

- **Event-Related Potentials (ERP)**: These are specific patterns in EEG signals that occur in response to discrete stimuli (like food images). Key ERP components discussed in this thesis include:

  P2: Reflects early attention and sensory processing (150–250 ms post-stimulus).

  N2: Often associated with conflict monitoring or stimulus evaluation (200–350 ms).

LPP (Late Positive Potential): Indicates sustained attention and emotional engagement (400–800 ms).

- **Neural Markers**: Objective, measurable indicators of brain activity that reflect underlying cognitive or emotional states. In this research, ERP components such as P2, oscillatory patterns (like theta power), and connectivity metrics serve as neural markers of habituation.
- **Frequency Bands**: EEG signals are categorised into distinct frequency ranges that correspond to different cognitive functions:

  Theta (4–7 Hz): Associated with focused attention and cognitive control.

  Alpha (8–13 Hz): Linked to relaxation and sensory inhibition.

  Beta (13–30 Hz): Related to active engagement and problem-solving.
- **Functional Connectivity**: Refers to the coordination or synchronisation of activity between different brain regions. In this thesis, it is measured using the Weighted Phase Lag Index (WPLI), which captures how consistently brain areas exchange information during food cue processing.

1.3 Research Objective

This research investigates the following research questions:

1. Can a reliable EEG feature be identified as a marker/measure of visual food habituation?

   Research has shown that the habituation to food has been occurring, and the outcome measures were documented by salivation levels, facial muscle movements, reinforcing responses, and neuroimaging techniques like fMRI and subjective questionnaires (Epstein et al. 1992; Epstein and Paluch 1997; Temple et al. 2006; Wagner et al. 2006; Epstein et al. 2009a). However, these outcome measures are unreliable and not practically applicable in the real world if an intervention is designed to explore food habituation behaviour. So, objective data, such as EEG, need to be collected to identify the occurrence of food habituation. Unfortunately, to date, there has been little research looking into food habituation in relation to visual stimuli neurophysiologically. So, one of the primary objectives of this research is to identify reasonable measures or markers for food habituation using different EEG features.

Previous research on repeated food stimuli has focused on cognitive responses and motivational behaviour using varied food class images with differing calorie values (Lietti et al. 2012; Wolz et al. 2017). Studies show that Late Positive Potential (LPP) is less affected by repetition in high-energy food images compared to low-energy or neutral food images, likely due to food variety, which strongly influences appetite behavior (Epstein, Temple and Bouton 2009; Epstein et al. 2009b). Differentiation in food variety is linked to reward properties, cognitive encoding, and attentional allocation (Lietti et al. 2012; Wolz et al. 2017). However, whether repeated exposure to the same food image modulates cognitive processes differently for varying energy values remains unexplored.

While food-specific EEG research is limited, studies on generic auditory/visual habituation show changes in ERP components like P300 and LPP with stimulus repetition (Megela and Teyler 1979; Asmaro et al. 2012). Other EEG features, such as arousal, valence, and ERP markers like N100 and P300, have been used to analyse habituation (McNamara, Wulbrand and Thach 1999; Ravden and Polich 1998; Zorjan, Schwab and Schienle 2020).

This research builds on these foundational studies by focusing specifically on visual food habituation. It aims to extract and analyse EEG features to identify reliable measures or markers of food habituation. By bridging the gap between generic habituation research and food-specific contexts, this study provides a novel approach to understanding attentional and motivational neural dynamics in response to repeated food stimuli.

2. Does the extracted EEG habituation marker reflect different calorie food and non-food variations?

   Research shows that a slow habituation rate leads to overeating in children and adults (Epstein et al. 2008). For example, a pizza (high in calories and fat) will show slower habituation than a low-calorie apple. The slower habituation to high-calorie food has a more significant impact on health, cardiac problems and other health risk factors. This might lead to obesity, reduced physical activity and reduced life expectancy. Currently, in the UK, 67% of men and 60% of women are overweight or obese (Public Health England 2020). So, in this research, we would like to explore if the EEG data could identify the differences in habituation rate between high-calorie fatty food and low-calorie healthy food. To date, no research has looked at such habituation differences between calorie food variations. In this research, we will be looking at the change in habituation rate between high-calorie and low-calorie foods.

   This study tends to address a critical gap in the existing literature on whether EEG markers can reflect differences in habituation rates between high and low-calorie foods. Existing neurophysiological studies on food stimuli have mainly focused on attentional biases, motivation and neural responses between different energy-valued foods without systematically examining habituation differences between calorie food variations. For example, studies have shown distinct neural responses to high-calorie and low-calorie foods, such as higher amplitudes in ERP components like N2 and LPP for high-calorie foods, suggesting differential attentional and motivational significance (Carbine et al. 2017; Asmaro et al. 2012). However, these studies do not address how habituation rates differ between such foods.

To date, no research has explicitly explored the role of EEG habituation markers in distinguishing calorie food variations. This study aims to fill this gap by analysing the habituation rate changes between high-calorie and low-calorie food stimuli using EEG data. By doing so, this research not only contributes to understanding the neural mechanisms underlying food habituation but also provides potential insights into behavioural interventions targeting obesity and overeating.

3. Is it possible to identify brain connections representing food stimuli habituation using connectivity analysis in EEG to understand food habituation?

   Identifying brain connections involved in food stimuli habituation is critical to understanding the neural mechanisms underlying eating behaviours, which are directly linked to conditions like obesity and eating disorders. Food habituation, the gradual decrease in response to repeated food exposure, is known to influence satiety and energy intake, as seen in behavioural and physiological studies (Epstein, Temple and Bouton 2009). While traditional measures such as salivary response or subjective ratings provide insight into habituation, they are limited in uncovering the neural dynamics driving this process. Connectivity analysis in EEG, particularly using weighted phase lag index (WPLI), provides an advanced method to explore these neural interactions.

EEG-based connectivity measures analyse how different brain regions interact during cognitive or sensory tasks. Unlike localised amplitude analysis, connectivity measures assess functional integration and communication between brain regions, which is essential for understanding complex processes like habituation (Friston 2011). Specifically, event-related connectivity analysis enables us to track temporal changes in neural communication, making it a powerful tool for studying dynamic processes like food habituation, which unfold over repeated trials.

Among connectivity metrics, WPLI is uniquely suited for analysing food habituation due to its ability to capture true functional connections while minimising volume conduction and noise effects (Vinck et al. 2011). Volume conduction can artificially inflate connectivity estimates by creating spurious correlations, especially in EEG data with closely spaced electrodes. WPLI circumvents this by focusing only on consistent phase lag relationships, providing a more accurate representation of genuine inter-regional communication. Furthermore, WPLI is sensitive to task-related changes in connectivity, which is critical for studying habituation. For instance, during repeated exposure to food stimuli, changes in WPLI between regions like the prefrontal cortex (attention and decision-making) and sensory areas (visual or gustatory processing) can indicate how neural communication adapts as habituation occurs.

Previous studies have demonstrated that food-related stimuli elicit strong neural responses, particularly in reward and attention networks. For instance, research has shown that food cues activate regions like the orbitofrontal cortex, insula, and parietal areas (DelParigi et al. 2007; Goldstone et al. 2009). Connectivity between these regions is believed to mediate attentional and motivational processes related to food. However, studies focusing on functional connectivity, particularly using WPLI, are limited in the context of food habituation. Existing research employing EEG connectivity measures for food stimuli primarily focuses on power correlations or coherence (Carbine et al. 2018; Nijs et al. 2010a). While valuable, these methods are more susceptible to volume conduction and often lack the specificity needed to isolate true functional connections. WPLI offers a superior alternative by addressing these limitations and providing more robust insights into neural interactions.

This research aims to fill the gap by using WPLI to investigate whether specific brain connections represent food habituation. By focusing on time-frequency domain connectivity changes across repeated trials, we can identify how neural networks adapt to food-related stimuli. Understanding these connections is crucial for uncovering mechanisms behind sustained attention or reduced responsiveness to repeated food cues, which are core aspects of food habituation. Due to time constraints, this study will be conducted as a pilot study, setting the groundwork for possible future analysis.

1.4 Research Contribution

This research makes several novel contributions to the field of cognitive neuroscience and eating behaviour by investigating neural responses to repeated food and non-food visual stimuli using EEG. The key contributions of this work are as follows:

1. **Identification of Neural Markers of Food Habituation**: The study systematically identifies EEG-based neural markers associated with habituation to repeated visual food stimuli. ERP components such as P2, N2, and LPP in the parietal and frontal regions were found to be modulated by stimulus repetition. These components reflect early attentional allocation, motivation towards high-calorie stimuli, reward processing, stimulus evaluation, and sustained engagement, offering a multi-stage understanding of food cue processing.

2. **Integration of Habituation and Dishabituation Protocols**: The experimental design includes both habituation and dishabituation paradigms, which allows for a more complete assessment of how the brain adapts and recovers from repeated stimulation, offering a richer profile than most existing studies.

3. **Novel Use of Time-Frequency and Functional Connectivity Measures**: Beyond traditional ERP analysis, the study applies time-frequency analysis (e.g. theta-band oscillations) and functional connectivity (WPLI) to capture dynamic brain responses. These methods provide deeper insights into how different brain regions during the habituation process, which has rarely been addressed in food-related EEG studies.

4. **Differential Responses to Food Types and Stimulus Categories:** The research demonstrates that high-calorie food images elicit slower neural habituation compared to low-calorie and non-food images. This effect highlights the sustained attentional and reward-related engagement driven by high-calorie stimuli, contributing to a deeper understanding of food-related cognitive attentional and motivational processes.

5. **Contribution to BMI-Based Neural Profiling:** This study shows that

BMI influences habituation patterns during early-stage processing of visual stimuli, particularly in the parietal region. These findings offer insights into individual neural variability in eating behaviours and may inform the development of personalised dietary interventions.

6. **Implications for Future Intervention Design**: The findings provide a neural foundation for developing attention-based or EEG-guided interventions. Tools such as neurofeedback systems or digital behaviour-modification platforms may benefit from real-time tracking of habituation to food cues.

These contributions collectively extend the field's understanding of the neural mechanisms underlying eating behaviour, attentional control, and food cue reactivity. The study also offers methodological innovations through its combined use of ERP, time–frequency, and connectivity-based EEG features.

1.5 Covid Statement

The original aim of this thesis was to investigate neurodynamic responses to repeated visual stimuli, focusing on food habituation and dishabituation processes. This research required collecting a substantial dataset of EEG recordings from participants exposed to repeated food and non-food visual stimuli. The goal was to explore how brain responses, particularly related to attention and motivation, change over time when presented with high-calorie, low-calorie, and non-food images. By identifying patterns in these neural responses, the study aimed to better understand the mechanisms underlying prolonged engagement with food cues and their role in overeating and obesity.

Unfortunately, the onset of the COVID-19 pandemic significantly disrupted the original research plan. Within the first three months of the PhD, strict lockdowns were imposed, making data collection impossible for nearly a year. Given the uniqueness and novelty of this research, no existing datasets could be used as an alternative. This left us unable to proceed with the experimental phase for an extended period, causing considerable delays to the project timeline.

Once restrictions eased during the second year, we managed to collect data from 12 participants, a small but valuable dataset under the circumstances. However, a second lockdown soon followed, forcing another halt to data collection. Despite the limited sample size, we made the most of the situation by analysing the available data and successfully publishing our preliminary findings in a conference paper, which is included in Chapter 4 of this thesis.

Following the easing of restrictions after approximately four additional months, we resumed data collection and successfully recruited another 14 participants, bringing the final dataset to 26 participants. This marked a significant turning point, as the initial data challenges were overcome, enabling us to conduct a robust analysis of the complete dataset. We followed all COVID rules and regulations imposed by the University while collecting the data.

Over the subsequent year and a half, we were able to finalise the analysis for Chapters 5, 6, 7, 8, and 9, covering key aspects of habituation and dishabituation responses to visual food stimuli. Despite the pandemic's setbacks, we achieved notable progress, including the publication of two additional conference papers, which are presented in Chapters 6 and 9 of this thesis. Furthermore, we are in the process of preparing two journal articles based on the findings of Chapters 5 and 7. These articles will be submitted to peer-reviewed journals following the submission of this thesis.

The pandemic posed unique and unexpected challenges, requiring adaptability and persistence throughout the research process. While the initial two years were heavily impacted by COVID-19, the successful collection of a complete dataset and subsequent analysis represents a significant achievement under difficult circumstances. This research provides critical insights into the brain mechanisms of habituation and dishabituation to food stimuli, offering a deeper understanding of how attention and motivation contribute to eating behaviours. Such findings are highly relevant in the context of addressing overeating and obesity, and we hope they will inform future interventions aimed at promoting healthier eating habits.

In summary, while COVID-19 presented substantial obstacles, this research ultimately overcame these challenges to deliver meaningful contributions to the field of eating behaviour and neurodynamic responses.

1.6 Thesis Outline

The research thesis is organised as follows. Chapter 2 provides the background and a comprehensive review of the relevant literature, establishing the foundation for the study. Chapter 3 outlines the experimental design, procedural details, and the steps involved in the data processing pipeline. Chapter 4 discusses the study on attentional bias towards high- and low-calorie food images during repeated visual food stimuli analysed through ERP. Chapter 5 explores ERP analysis of habituation effects for high- and low-calorie food and non-food visual stimuli, focusing on time-domain analysis.

Chapter 6 investigates ERP analysis of dishabituation effects for high- and low-calorie food and non-food visual stimuli using time-domain analysis. Chapter 7 delves into the time-frequency analysis of habituation effects for high- and low-calorie food and non-food visual stimuli. Chapter 8 examines functional connectivity analysis related to food and non-food visual stimuli. Chapter 9 explores ERP differences based on BMI in response to habituation to repeated food and non-food visual stimuli. Finally, Chapter 10 concludes the thesis by summarising the findings and discussing their implications.

1.7 Publications

Published Journal Articles / Conference Papers

1. **A. Duraisingam, R. Palaniappan, D. Soria, Attentional bias towards high and low calorie food on repeated visual food stimuli: An ERP study. Engineering in Medicine and Biology Society (EMBC), 43rd Annual International Conference of the IEEE, Mexico, 2021.**

   This paper investigates whether there is any differentiation in motivation behaviours and cognitive responses when the same food image is repeatedly presented (free viewing) and analysed in different brain regions. The details of this paper are given in chapter 4.

2. **A. Duraisingam, D. Soria, R. Palaniappan, Unraveling Neurophysiological Attentional Habituation Dynamics of Food and Non-Food Paradigms: ERP Correlates with BMI in Response to Repetitive Visual Stimuli. 5th International Conference on Data Intelligence and Cognitive Informatics, India, November 2024.**

   This paper investigates how individuals with different Body Mass Index (BMI) levels respond to repeated exposure to specific food and non-food visual stimuli and aims to uncover the underlying neural mechanisms that contribute to differences in attentional and motivational processes. The details of this paper are given in chapter 9.

3. **A. Duraisingam, D. Soria, R. Palaniappan, The Habituation-Dishabituation ERP Responses to Repeated Visual Food Cues. 8th IEEE-EMBS Conference on Biomedical Engineering and Sciences, Malaysia, December 2024.**

   This paper investigates to determine how neural responses vary with the introduction of new stimuli and to assess the reliability of the habituation and dishabituation processes for different types of food and non-food images. The details of this paper are given in chapter 7.

Submitted Journal Articles / Conference Papers

1. **Examining the Neurophysiology of Attentional Habituation to Repeated Presentations of Food and Non-Food Visual Stimuli**
   Currently under review in the journal *Algorithms* (MDPI). This article investigates cognitive and motivational responses to repeated presentations of high- and low-calorie food images using EEG time-domain analysis. It focuses on significant ERP effects and interactions across multiple time windows and brain regions, providing insights into attentional habituation patterns and their neurophysiological correlates.

2. **Calorie-Dependent Differential Habituation to Repeated Food Cues Assessed via EEG Functional Connectivity**

Submitted paper at the *IEEE International Conference on E-health Networking, Application & Services (IEEE HealthCom 2025)*, to be held from October 21–23, 2025, in Abu Dhabi, United Arab Emirates. This paper analyses ERP responses to repeated visual stimuli, examining causal information flow by grouping brain activities across different regions of interest (ROIs) and analysing the causality relationships between them using advanced EEG analysis.

Achievements

- **Research Recognition in SSRN Preprint**

  My research is gaining significant attention, having been featured as a preprint in the prestigious SSRN archive. This recognition underscores the relevance and impact of my work, positioning it as a valuable contribution to the fields of neuroscience and eating behaviour research (Duraisingam, Soria and Palaniappan 2022).

- **Media Coverage**

  My research on how individuals with varying Body Mass Index (BMI) levels respond to repeated exposure to specific food and non-food visual stimuli 9 has garnered significant public interest. The findings reveal that high-calorie foods capture more attention compared to low-calorie and non-food stimuli. A news story authored by the Research and Innovation Office, University of Kent, was published on the University of Kent website, bringing my work to a wider audience. The article not only emphasises the scientific implications of my study but also demonstrates its relevance to societal challenges like overeating and obesity (Emily Collins 2024).

Following the publication of the paper in the IEEE conference proceedings, the Research and Innovation Office at the University of Kent has planned to issue a press release to the national media.

- **Winner of the University of Kent 3MT Competition and National quater finalist**

  I was privileged to win the University of Kent's Three Minute Thesis (3MT) competition and national quarter-finalist, which is a testament to my ability to present complex research in an engaging and accessible way. This achievement reflects the clarity and impact of my work in the academic community (Vitae 2022).

Chapter 2

Background and Literature Review

2.1 Chapter Outline

This chapter provides a comprehensive review of the theoretical and empirical foundations of food habituation and its neural correlates using EEG. It introduces classical and cognitive models of habituation, explores food-related attentional biases, and examines the distinct neural responses to high-calorie, low-calorie, and non-food stimuli. The chapter discusses key EEG measures, including ERP components, time-frequency features, and functional connectivity, and outlines their relevance in studying neural adaptation. It also covers EEG signal processing techniques, the use of cluster-based permutation tests for robust statistical analysis, and behavioural assessment through the Craving Experience Questionnaire. Finally, it highlights critical gaps in the literature and motivates the current research focus on systematic, multimodal analysis of habituation and dishabituation across different BMI groups.

2.2 Theoretical Foundations of Habituation

The history and foundational context of habituation were first articulated by Thompson and Spencer in their seminal 1966 paper (Thompson and Spencer 1966), which laid the groundwork for understanding this fundamental process. Their pioneering work identified and characterised the key aspects of habituation, which Groves and Thompson further elaborated in 1970 (Groves and Thompson 1970). These two papers have since become citation classics, widely regarded as authoritative references on the characteristics of habituation.

In 2009, a symposium revisited and revised the definitions of habituation for greater clarity, making only minimal changes to the defining characteristics (Rankin et al. 2009). Notably, the core descriptions and characteristics established in 1966 have largely stood the test of time, with most revisions aimed at enhancing clarity rather than making substantial alterations. Despite being described as ”the simplest form of learning” and having been extensively studied behaviourally, the neural mechanisms underlying habituation remain surprisingly poorly understood. Researchers suggest that habituation plays a critical role in allowing animals to filter out irrelevant stimuli and concentrate on those that are significant, making it a foundational process for other forms of learning. Therefore, understanding the basic principles of habituation is crucial for grasping the mechanisms that underlie more complex forms of learning and cognition.

Habituation is a neurocognitive process where repeated exposure to a stimulus leads to a gradual reduction in the neural response, which is central to the present study on food-related attentional and motivational changes. According to Thompson and Spencer (Thompson and Spencer 1966) and later refined by Rankin et al. (Rankin et al. 2009), this response decrement typically follows an exponential pattern and may stabilise at an asymptotic level. In EEG-based paradigms, such as those used in this thesis, this reduction can be observed through diminished event-related potential (ERP) amplitudes across repeated trials, especially in low-calorie and non-food stimuli. One key characteristic relevant to the analysis is the phenomenon of stimulus specificity, where the neural decline is selective to the repeated stimulus and does not generalise to novel stimuli, allowing for controlled dishabituation testing. Additionally, spontaneous recovery, the reappearance of a response after stimulus withdrawal, is essential in validating that observed habituation is not due to fatigue but a genuine cognitive adaptation.

This research also considers the principle of dishabituation, where introducing a novel stimulus temporarily restores the response to the habituated stimulus, a feature confirmed in the ERP recovery patterns identified in non-food stimuli. Furthermore, long-term habituation, where response decrements persist across extended periods, has implications for understanding sustained attentional bias toward high-calorie food. The study leverages these principles to measure neurodynamic habituation across different food categories using EEG-derived markers, particularly focusing on ERP component changes and connectivity dynamics. Overall, the classical characteristics of habituation provide a theoretical foundation that supports the experimental design and validates the observed neural markers of food-specific habituation processes in this work.

Traditional Habituation Models and Their Relevance to This Research

Theoretical models of habituation offer essential foundations for understanding how the brain processes repeated stimuli, which directly informs the objectives of this research, namely to identify EEG-based markers of food habituation and to explore differences in habituation responses across food categories. Among the most widely cited frameworks are Sokolov's stimulus–Model Comparator theory, Groves and Thompson's Dual-Process Theory, and Wagner's Sometimes Opponent Process (SOP) model. Each model contributes a different perspective on the mechanisms behind response decrement, and collectively, they help shape a conceptual framework for investigating habituation through neurophysiological data.

One of the earliest and most influential ideas comes from Evgeny Sokolov, who proposed that the brain forms an internal model of a stimulus through repetition. Once this model is built, further exposure to the same stimulus doesn't trigger the same level of neural activation because the brain essentially recognises it as familiar and unimportant (Sokolov 1960, 1963). This idea is particularly relevant to our goal of using EEG to detect when the brain begins to 'tune out' food stimuli that are no longer novel. Sokolov's theory supports the premise that neural activity should decrease as a sign that the brain is updating its internal expectations.

A slightly different but complementary perspective is offered by the Dual-Process Theory, developed by Groves and Thompson (Groves and Thompson 1970). This model argues that habituation doesn't happen in isolation; it's actually balanced by a second process called sensitisation. While habituation reduces the response over time, sensitisation can temporarily boost it, especially when the stimulus is intense or emotionally charged. This idea helps us think about why not all food images are processed the same way. For instance, high-calorie foods may hold stronger motivational relevance, making them more resistant to habituation. As such, this model encourages us to consider both diminishing and amplifying neural responses when interpreting EEG data.

The SOP model, introduced by Wagner and further developed by Uribe-Bahamonde and colleagues (Wagner 1981; Uribe-Bahamonde et al. 2019), adds a memory-based perspective. According to this theory, each stimulus activates a set of memory elements that shift between different states of attention and engagement. With repeated exposure, more elements move into a low-activation state, meaning the stimulus no longer receives the brain's full attention. What is interesting here is the model's focus on timing and priming, ideas that translate well into EEG research, where we measure brain responses millisecond by millisecond. The SOP framework also explains how new or unexpected stimuli can re-engage attention, which ties directly into our interest in dishabituation.

Altogether, these classical models offer more than just historical background, they help us make sense of the complex neural patterns we expect to see when people are exposed to repeated food stimuli. They also guide our hypotheses about how different types of food images might be processed differently, and how these processes might be reflected in EEG features like ERPs or changes in connectivity. By building on these well-established theories, this research aims to bridge the gap between behavioural models of habituation and their neural correlates in the human brain.

2.3 Behavioural and Physiological Measures of Food Habituation

This section reviews behavioural and physiological research on food habituation and dishabituation, focusing on non-neurophysiological measures such as salivary responses, facial muscle activity, and motivated behaviour. These studies form a crucial empirical foundation for the current research, which aims to investigate neural signatures of habituation using EEG. Understanding how habituation has been traditionally observed in overt physiological and behavioural responses allows for a clearer interpretation of corresponding neural changes. Moreover, these findings highlight the significance of habituation and dishabituation in the regulation of food intake, providing theoretical and empirical context for examining repeated visual food stimuli in the present study.

Habituation refers to a reduction in physiological or behavioural response following repeated exposure to the same food stimulus (Epstein, Temple and Bouton 2009). One of the most well-established physiological indicators of this process is salivation. Studies have shown that when individuals are repeatedly presented with the same food stimulus, salivary output decreases progressively, reflecting diminished arousal and interest in the food item (Epstein et al. 1992, 2009a; Wisniewski et al. 1997). This effect has been observed consistently across age groups and serves as a robust, objective measure of short-term habituation during a meal.

In addition to salivation, facial muscle activity has been utilised to measure affective and motivational responses to food. For example, Epstein et al. (Epstein and Paluch 1997) recorded zygomatic and corrugator muscle activity and observed a reduction in facial responses with repeated food presentations. This pattern further supports the hypothesis that food stimuli lose their motivational salience over time through habituation.

Behavioural assessments of motivated effort also provide evidence for habituation. Several studies have employed operant tasks in which participants must perform actions, such as key presses or problem-solving tasks, to earn access to food. Results consistently show that the amount of effort participants are willing to exert decreases with repeated presentations of the same food item, reflecting a behavioural decline in food reinforcement (Temple et al. 2007a,b; Epstein, Temple and Bouton 2009).

Complementing these findings, dishabituation studies demonstrate that the suppressed response to a habituated food stimulus can be restored by introducing a novel stimulus. This effect has been documented through both salivary and behavioural measures. For instance, Epstein et al. (Epstein et al. 2009c) found that when participants were exposed to a new food stimulus after habituation had occurred, salivation and motivated responses to the original food increased. Such findings confirm that the decline in response is not due to fatigue or sensory adaptation but is specific to the habituation process. These results underline the stimulus-specific nature of food habituation and the potential for external novelty to interrupt the habituation sequence.

A significant factor influencing dishabituation is food variety, which has been shown to delay habituation and increase overall food intake. When individuals are presented with a range of foods differing in taste, texture, or appearance, the habituation process is disrupted, often resulting in sustained or renewed interest in eating. This ”variety effect” is well-documented across age groups. For instance, Temple et al. (Temple et al. 2007b; Epstein et al. 2008) reported that increased food variety delayed the onset of satiation and promoted greater energy intake, particularly in individuals with higher BMI. These findings suggest that variety acts as a dishabituating factor, maintaining arousal and attentional engagement across the eating episode.

Importantly, individual differences in habituation and dishabituation rates have been associated with body weight. Obese individuals tend to exhibit slower habituation and stronger dishabituation effects, which may contribute to higher energy intake (Epstein, Paluch and Coleman 1996b; Epstein et al. 2008; Temple et al. 2008b). This has led to the proposal that impaired habituation, and exaggerated dishabituation may serve as behavioural risk factors for overeating and obesity.

In summary, behavioural and physiological studies offer compelling evidence that habituation and dishabituation are key mechanisms in eating regulation. These findings underscore the importance of examining similar patterns through neurophysiological methods, as pursued in the current research. By bridging traditional measures with EEG-based neural responses, this study aims to enhance the understanding of how the brain modulates attention and motivation in response to repeated food cues.

Habituation in Clinical and Overeating Populations

The process of habituation has shown distinct patterns in clinical populations, particularly among individuals with obesity, binge eating disorder (BED), or other maladaptive eating behaviours. Research indicates that these groups often demonstrate attenuated or slower habituation to food cues, leading to sustained attention and heightened motivational response even after repeated exposure (Epstein et al. 2008; Temple et al. 2007a). For example, obese individuals may exhibit prolonged salivary responses and elevated neural engagement (e.g., sustained P3 and LPP amplitudes) compared to lean individuals, suggesting impaired stimulus-specific learning mechanisms. This diminished habituation has been linked to greater energy intake, impaired satiety signalling, and reduced capacity for inhibitory control over eating (Temple et al. 2008b). From a neural perspective, such atypical habituation patterns may reflect altered functional connectivity and reduced top-down regulation from prefrontal regions, thereby perpetuating overeating tendencies. The current study addresses these disparities by systematically comparing EEG-based habituation markers across individuals with different BMI levels. By identifying neurophysiological differences in how food cues are processed and adapted over time, this research seeks to contribute to our understanding of obesity-related vulnerabilities and support the development of more targeted behavioural or neurofeedback interventions.

2.4 Neurophysiological Foundations of Food Cue Processing

To understand how the human brain processes repeated food stimuli, neurophysiological tools such as EEG are widely employed. EEG provides high temporal resolution to capture subtle variations in brain activity, making it ideal for studying habituation, a gradual decline in neural response due to repeated exposure to the same stimulus. This section outlines the fundamental principles of EEG, the neural markers relevant to food cue habituation, and how these measures are mapped across the cortex. The goal is to establish a technical foundation for interpreting EEG-derived signals such as event-related potentials (ERPs) and oscillatory frequency bands within this research.

EEG: A Neurophysiological Monitoring System

Electroencephalography (EEG) is a non-invasive technique for recording electrical activity generated by neuronal populations, particularly cortical pyramidal cells (Palaniappan 2010). Neurons communicate via synaptic transmission, where an electrical impulse travels from a pre-synaptic axon to a post-synaptic dendrite, generating post-synaptic potentials. These cumulative signals are detected by scalp electrodes and amplified for analysis.

EEG can be acquired using invasive or non-invasive methods (Malmivuo and

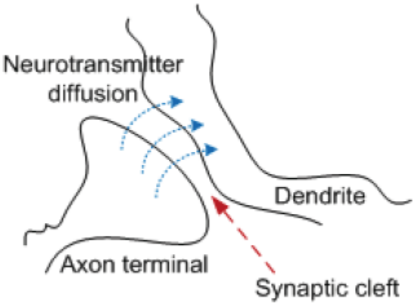


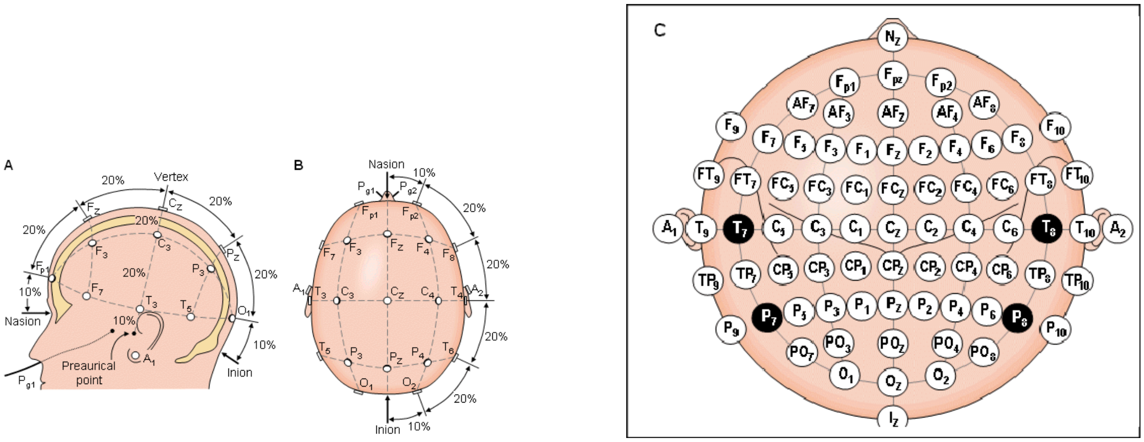
Figure 2.1: Illustration of synaptic transmission (Palaniappan 2010)

Plonsey 1995). Invasive methods provide high spatial accuracy but are clinically risky. The non-invasive approach employed in this study places electrodes on the scalp and is widely accepted in cognitive and clinical neuroscience due to its safety and reliability.

Electrode Placement and Cortical Mapping

For consistent signal acquisition, standardised systems such as the 10–20 international electrode placement protocol are used (Jasper 1958). Electrodes are positioned at 10% and 20% intervals relative to key anatomical landmarks, allowing for reproducible and anatomically relevant recording locations. Later extensions, such as the 10–10 and 10–5 systems, offer higher spatial resolution.

In this research, a 32-channel Neuroelectrics Starstim system (Neuroelectrics 2020) is employed to record from frontal, parietal, temporal, occipital, and central regions areas implicated in attention, visual processing, and motivational responses to food.



(a) 10–20 electrode layout (b) Cortical region mapping

Figure 2.2: Standard EEG electrode placements

ERP and Their Functional Significance

ERPs are time-locked voltage fluctuations extracted from the EEG signal in response to specific sensory, cognitive, or motor events. By averaging EEG data over multiple trials aligned to stimulus onset, ERPs allow researchers to isolate neural processes involved in stimulus perception, evaluation, and response. ERPs are particularly valuable in food cue research due to their millisecond-level temporal resolution, enabling the detection of rapid neural changes associated with attention, motivation, and emotional engagement with food stimuli.

In the context of food cue processing, various ERP components provide insights into different stages of cognitive and emotional responses:

- **P1, N1, P2:** These early components occur within the first 150–200 ms following stimulus onset. P1 and N1 are typically generated in the occipital and parietal regions and are associated with initial sensory encoding and attentional selection of visual stimuli (Becker et al. 2016). The P2 component reflects early

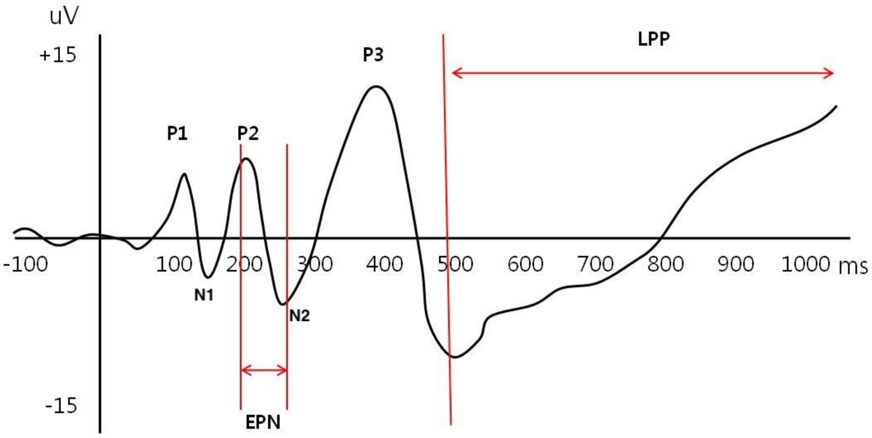


Figure 2.3: Illustration of ERP components: P1, N1, P2, N2, P3, and LPP (Lee 2011)

evaluation of stimulus features and salience.

- **N2:** Emerging around 200–350 ms post-stimulus, the N2 component is related to stimulus discrimination and cognitive control, often interpreted as reflecting conflict monitoring or the detection of novelty, which is particularly relevant when novel or high-salience food stimuli are presented repeatedly.
- **P3 (P300):** The P3 or P300 component typically peaks between 300–600 ms and is linked to the allocation of attentional resources and stimulus evaluation. In food cue studies, enhanced P300 amplitudes have been observed in individuals with high external eating tendencies or during states of food deprivation, suggesting increased motivational relevance of food cues (Nijs et al. 2010a).
- **Late Positive Potential (LPP):** Extending beyond 600 ms, the LPP reflects sustained attention and emotional processing. Food stimuli, particularly high-calorie or palatable images, often elicit larger LPPs, indicating their affective salience. The LPP is sensitive to individual differences in dietary restraint,

hunger, and emotional eating (Leland and Pineda 2006).

Tracking changes in ERP amplitudes across repeated food cue presentations enables researchers to quantify habituation. A decline in component amplitudes, particularly P3 and LPP, is typically interpreted as reduced attentional and affective engagement with the stimulus, suggesting that the brain has become habituated to the repeated food cue. Conversely, the re-emergence of larger ERP amplitudes following the introduction of a novel stimulus may indicate dishabituation, a critical mechanism for understanding food variety effects on eating behaviour.

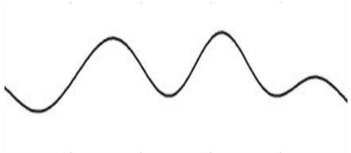
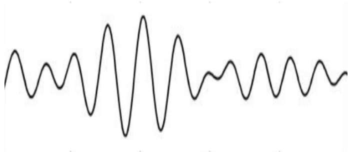
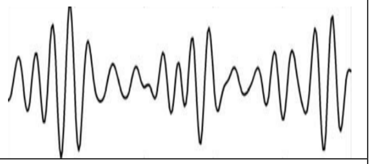
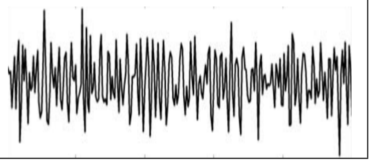
EEG Frequency Bands and Their Functional Significance

Beyond time-locked ERP responses, EEG also provides information about ongoing brain rhythms or oscillatory activity, which reflect different states of consciousness, cognitive processing, and affective engagement. These oscillations are classified into distinct frequency bands, each associated with specific neurophysiological and psychological functions (Müller-Putz, Riedl and Wriessnegger 2015).

Each frequency band is believed to reflect distinct functional processes. For instance, increased alpha activity is typically associated with cortical idling or disengagement, while decreased alpha may signal heightened sensory processing. Beta rhythms reflect active attention and mental effort, making them particularly relevant in food cue paradigms where cognitive engagement varies across stimulus types. Gamma activity is linked to perceptual binding and attentional selection, though its precise role in food cue processing is still being explored.

Frequency band analysis complements ERP findings by revealing broader patterns of cortical engagement. For example, a reduction in beta or gamma power during repeated presentations of a food image could be interpreted as a neural correlate

Table 2.1: EEG Frequency Bands (Müller-Putz, Riedl and Wriessnegger 2015)

Frequency Bands	**Band width**	**Associated mental states**	**Pattern**
Delta	1-4 Hz	Deep sleep, coma	
Theta	4-8 Hz	Meditation, sleep, drowsiness	
Alpha	8-13 Hz	Relaxation, readiness, when eyes closed	
Beta	13-25 Hz	Anxiety, high attention	
Gamma	25-200 Hz	Decision making, arousal, peak performance	

of habituation, consistent with decreasing ERP amplitudes. Thus, combining time-domain (ERP) and frequency-domain (spectral power) analyses provides a more comprehensive understanding of how the brain adapts to repeated exposure to food-related stimuli.

The present study investigates neural habituation to food cues using both ERP and frequency band analysis. Repeated presentations of high-calorie, low-calorie, and non-food images are used to examine whether neural responses diminish over time. EEG provides a powerful lens to capture these dynamic changes, revealing how attentional and motivational systems adapt to food-related stimuli. The combined analysis of ERP components and spectral features offers a comprehensive approach to identifying habituation and dishabituation effects in response to food cues.

Functional Connectivity and Its Functional Significance

Functional connectivity refers to the temporal correlation and synchronisation of neural activity between spatially distinct brain regions, providing insights into how distributed cortical networks interact during cognitive and affective processing (Friston 2011). In the context of EEG, functional connectivity is often assessed using measures such as Phase-Locking Value (PLV), coherence, and Weighted Phase Lag Index (WPLI), which quantify the degree of coupling between signals across electrode sites (Vinck et al. 2011). Unlike event-related potentials or spectral power that focus on localised responses, functional connectivity captures dynamic communication between brain areas, thus revealing network-level mechanisms underlying attentional control, salience detection, and affective regulation. This makes it particularly valuable in studies involving complex stimuli like food cues, where simultaneous engagement of sensory, cognitive, and emotional systems is expected. By examining connectivity patterns, researchers can infer how brain regions collaborate to process repeated stimuli and adapt to changing motivational relevance over time. Therefore, functional connectivity serves as a critical neural marker for understanding not just local activation but the coordinated dynamics of the brain's response to sustained or novel environmental inputs.

Neurophysiological Studies on Food Cue Habituation

Neurophysiological methods such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) have become increasingly pivotal in understanding how the brain responds to repeated exposure to food-related stimuli. These tools allow researchers to examine both the temporal unfolding and spatial localisation of neural responses that underlie habituation and dishabituation, key processes in the regulation of eating behaviour.

EEG, particularly through Event-Related Potentials (ERPs), has enabled detailed exploration of how attentional and emotional processes respond to food cues over time. ERP components are time-locked to stimulus presentation and reflect distinct cognitive stages. Early components like P1 and N1, typically appearing within the first 150–200 ms, capture initial sensory and attentional engagement, often modulated by the salience and novelty of food images (Becker et al. 2016). Slightly later, the P2 and N2 components reflect early cognitive evaluation and conflict monitoring, respectively, often showing heightened responses to motivationally relevant stimuli such as palatable foods (Schwab et al. 2017).

Of particular interest in habituation research is the P3 (or P300) component, which peaks between 300–600 ms and is sensitive to the motivational significance of stimuli (Nijs et al. 2010a). A consistent finding across ERP studies is that P3 amplitude tends to decline with repeated presentation of the same food cue, a neural marker of habituation. When a novel stimulus is introduced after this repetition, P3 amplitude often rebounds, indicating dishabituation (Nijs, Franken and Muris 2009). This attentional re-engagement suggests that the brain re-evaluates the new stimulus as salient, reinforcing the concept that habituation is stimulus-specific.

In the later stages of processing, the Late Positive Potential (LPP) provides insight into sustained emotional and attentional engagement. Studies have reported that LPP amplitude is generally larger for food-related images than for neutral content, especially among individuals with higher food responsiveness or disordered eating tendencies (Leland and Pineda 2006; Stockburger et al. 2009). Repeated exposure leads to a decline in LPP, consistent with reduced emotional intensity and attentional investment, further supporting the habituation framework (Stockburger et al. 2008).

Complementing ERP findings, EEG frequency analysis offers a broader perspective on the brain's ongoing oscillatory activity in response to food-related stimuli. While ERPs provide precise timing of stimulus-related processing, frequency-based measures reveal the underlying neural dynamics that sustain attention, motivation, and emotion over longer timeframes.

In EEG research, time-frequency analysis has proven particularly useful for tracking how brain rhythms fluctuate in response to different types of food cues. One of the key insights from this line of research relates to the role of motivational tendencies, specifically approach and avoidance behaviours, in food-related decision-making. These motivational processes are often reflected in asymmetric activity in the frontal cortex, typically measured via alpha power differences between the hemispheres. For example, recent findings indicate that low-calorie foods tend to evoke stronger left-frontal alpha suppression, a marker associated with approach-related motivation, compared to high-calorie foods (Kirsten, Seib-Pfeifer and Gibbons 2022). This suggests that individuals may engage more actively or positively with low-calorie options under certain conditions, counter to the traditional assumption that high-calorie foods are universally more appealing.

Beyond alpha activity, increased beta and gamma power have been observed in contexts involving emotional salience and cognitive engagement, particularly in individuals who display heightened sensitivity to food cues. These high-frequency bands are typically associated with active attention, arousal, and integrative sensory processing. Notably, gamma oscillations have been linked to the reward value of food stimuli and may serve as neural markers for the emotional and motivational significance attributed to these cues (Franken et al. 2003). Together, these time-frequency measures enrich our understanding of habituation by highlighting how the brain's ongoing attentional and affective states evolve during repeated food cue exposure, reinforcing the value of incorporating both ERP and frequency-based approaches in food-related EEG research. These oscillatory patterns suggest that neural habituation involves both changes in attentional allocation and motivational evaluation.

While EEG and ERP techniques provide excellent temporal resolution, fMRI contributes detailed spatial insights into which brain regions are engaged during food cue processing. Studies have shown that repeated exposure to palatable food images or tastes leads to reduced activation in key reward-related regions such as the orbitofrontal cortex (OFC), striatum, and insula (Small et al. 2001; Rolls 2000). These reductions align with the concept of sensory-specific satiety and are consistent with the neural basis of habituation. Conversely, dishabituation effects have been observed as renewed activation in these areas upon the introduction of novel food stimuli (Ochsner, Silvers and Buhle 2012).

Importantly, individual differences play a role in the extent and pattern of neural habituation. For instance, obese individuals and those with binge eating tendencies often display attenuated reductions in brain activity across repeated food cue exposures. Stoeckel et al. (Stoeckel et al. 2008) found that obese participants continued to show elevated activity in the medial OFC and nucleus accumbens, suggesting impaired habituation mechanisms that may contribute to persistent food cravings and overeating.

Overall, findings from neurophysiological studies, both EEG- and fMRI-based, underscore the dynamic and context-dependent nature of food cue habituation. These studies demonstrate that repeated exposure to food stimuli can diminish attentional and emotional responses at both temporal and spatial neural levels. They also highlight how dishabituation and individual variability influence the persistence of food-related neural activation. This body of evidence lays the groundwork for the current research, which aims to explore the temporal patterns of neural adaptation to repeated food cues using EEG, focusing specifically on ERP components and habituation dynamics across different food categories.

2.5 Signal Processing and Feature Extraction

Signal processing is a crucial step in EEG research, enabling researchers to transform, filter, and extract meaningful information from raw brain signals. EEG signals are typically low in amplitude and easily affected by noise from muscular movement, electrical interference, and eye blinks. Therefore, digital signal processing (DSP) techniques are used to improve signal-to-noise ratio and optimise the data for meaningful analysis (EEGLAB 2023). In general, DSP has applications across a range of disciplines, including audio, speech, image, and biomedical signal processing. In neuroscience, particularly EEG research, it plays a vital role in the reliable extraction of event-related potentials and spectral features linked to specific cognitive states.

As EEG technology becomes more portable and accessible, the volume and complexity of the data collected also increase. This necessitates robust, automated preprocessing pipelines to manage artefacts and preserve cognitive signals of interest. In this study, we employed the EEGLAB toolbox, an interactive MATLAB-based environment developed by the Swartz Center for Computational Neuroscience (EEGLAB 2023). EEGLAB is widely adopted in the neuroscience community and supports a wide range of preprocessing tasks, including filtering, epoching, artefact rejection, and independent component analysis (ICA). These steps help remove artefacts such as eye blinks and muscle activity, enabling cleaner signal extraction for further ERP and time-frequency analyses.

The use of EEGLAB and similar toolboxes is well-established in recent literature. Researchers have applied it to both single-trial and averaged EEG datasets across various domains, including cognitive workload (Kosmyna, Lindgren and Lécuyer 2018), BCI research (Sousa et al. 2017), and emotional response studies. The modular structure of EEGLAB allows it to adapt to specific research goals, making it ideal for studies like the present one, which requires precise detection of ERP components across repeated trials of food-related stimuli.

In this research, EEG signals were filtered using a bandpass filter to remove very low-frequency drift and high-frequency noise, typically outside the range of 0.1–30 Hz, which is considered optimal for ERP detection. Epoching was performed around stimulus onset, with baseline correction applied using the pre-stimulus interval. Artefact components were identified using ICA, and only clean, task-relevant trials were retained for final analysis. These steps were essential for isolating ERP components such as P2, N2, and LPP, which are known to reflect attentional and emotional processing in response to food stimuli.

Additionally, time-frequency analysis was conducted to capture spectral power variations in frequency bands such as theta (4–8 Hz) and alpha (8–13 Hz), which are linked to cognitive control and visual attention. These spectral features complement ERP measures and provide a broader understanding of how food-related stimuli are processed over time.

Overall, the signal processing and feature extraction pipeline employed in this study ensures that the neural responses captured are both clean and interpretable. This foundation is critical for investigating habituation effects and drawing meaningful conclusions about the role of food cues in attention and motivation.

2.6 Cluster-based Permutation Tests

EEG data are complex because they are recorded from multiple locations on the scalp over time. This means that the signals are collected from many channels at different moments, depending on how often the data are sampled. In this study, we divided the data into segments (called epochs) based on either time-based or frequency-based analysis. For example, in time-based analysis, we looked at brain activity from -0.2 seconds (before the stimulus) to 1.2 seconds (after the stimulus). The EEG was recorded from 32 channels, and since the sampling rate was 500 Hz, this gave us a total of 22,400 data points per epoch. Each participant (total of 26 participants) had 360 epochs in total. This amount of data is typical for EEG studies, but analysing it properly is not always straightforward. Choosing the right time windows, frequency bands, and brain regions to focus on is crucial to accurately studying the effects of different conditions.

To make sure our hypotheses are clear and backed by previous research, choosing the right time windows, frequency bands, and brain regions (ROIs) is important. This process isn't always simple. If there is already solid research on the topic, we can use that to guide our choices. But if we are studying something new and there isn't much previous research, it becomes much harder to decide which time and frequency range to focus on. One statistically robust way to determine suitable time/frequency windows and channel sites is cluster-based permutation tests (CBPT). Because of a large number of statistical comparisons, it is not possible to control false alarm rate (FAR) (probability of false detection) by using standard statistical procedures (e.g. t-test) which operate on single samples (Maris and Oostenveld 2007; Maris 2004). This is referred to as a multiple comparison problem (MCP). CBPT is a type of non-parametric test which elegantly handles the MCP and helps control FAR for high-dimensional data, especially EEG data. The significant advantage of this approach is that this test does not require prior knowledge about the distribution and reduces a more significant number of comparisons to one statistical test, reducing the FAR while maintaining sensitivity.

As there is no substantial prior knowledge on the effect of habituation towards different visual stimuli in existing literature, this research chooses non-parametric CBPT for statistical analysis. Moreover, this test will be computed using the Field-trip toolbox, a plugin added to Matlab software (FIELDTRIP 2023). In the field trip, the Cluster-Based Test Statistic and significance probability are computed as follows.

Calculation of the Cluster-Based Test Statistic

- **Compute Sample-Level Statistics:** For each data point (e.g., a specific channel at a particular time), calculate a test statistic (such as a t-value) that quantifies the effect of interest between experimental conditions.

- **Apply a Threshold:** Identify data points where the test statistic exceeds a predefined threshold, determined by a chosen significance level (e.g., $\alpha = 0.05$). This step isolates candidate data points that may form clusters.
- **Form Clusters:** Group neighbouring data points that surpass the threshold into clusters based on their adjacency in time, space, or frequency.
- **Calculate Cluster-Level Statistics:** For each cluster, compute a summary statistic, typically the sum of the test statistics within the cluster, known as ”cluster mass.”
- **Determine the Maximum Statistic:** Identify the largest cluster-level statistic across all clusters. This maximum value serves as the test statistic for the dataset.

Calculation of the Significance Probability

To assess the significance of the observed clusters, a reference distribution is generated using the Monte Carlo method:

- **Combine Data:** Pool all trials from the different experimental conditions into a single dataset.
- **Randomly Partition Data:** Randomly assign trials to new subsets, maintaining the original number of trials per condition. This random reassignment simulates the null hypothesis where no condition effect exists.

- **Compute Test Statistic for Each Partition:** For each random partition, repeat the steps of calculating sample-level statistics, forming clusters, and determining the maximum cluster-level statistic.
- **Build Reference Distribution:** Repeat the random partitioning process many times (as specified by the number of permutations, e.g., 1000 or more) to create a distribution of maximum cluster-level statistics under the null hypothesis.
- **Calculate the p-Value:** Compare the observed maximum cluster-level statistic to the reference distribution. The p-value is determined by the proportion of random partitions that produced a test statistic equal to or greater than the observed one.

If this p-value is less than the chosen significance level (e.g., 0.05), the null hypothesis is rejected, indicating that the observed cluster is statistically significant. This methodology is implemented in the FieldTrip toolbox, specifically using functions like ft_timelockstatistics for time-locked data and ft_freqstatistics for frequency-domain data. These functions facilitate the execution of cluster-based permutation tests, allowing researchers to effectively control for multiple comparisons in complex neuroimaging datasets. For a comprehensive tutorial on performing cluster-based permutation tests using FieldTrip, refer to their official documentation (Oostenveld et al. 2011).

2.7 Craving Experience Questionnaire

The Craving Experience Questionnaire (CEQ) is a self-report questionnaire that is used to measure the subjective experience of craving in individuals with substance use disorders. The CEQ is based on the cognitive model of craving, which suggests that craving arises from an interaction between environmental cues, attentional biases, and cognitive appraisals (Carpenter et al. 2012; Marsden et al. 2017).

Sensory stimuli play a significant role in craving for food and drink addiction (May et al. 2008, 2004). Currently, there are lots of subjective measures to measure craving based on elaborated intrusion theory, such as Alcohol Craving Experience (ACE), CEQ, etc. ACE and CEQ share the same three-factor structure measure (intensity, imagery and intrusiveness), but CEQ is more of a generic measure over different consummatory targets, including food (May et al. 2014). This research sets out to measure only food craving intensity (only one factor - intensity) using a CEQ questionnaire.

Overall, the CEQ is a valuable tool for assessing craving in individuals with substance use disorders, and it has the potential to inform the development of effective interventions for reducing craving and preventing relapse (Carpenter et al. 2012; Aslan et al. 2023).

2.8 Literature Gaps and Research Motivation

While numerous studies have explored the neural and behavioural responses to food-related stimuli, important gaps remain in our understanding of how the brain adapts to repeated exposures to specific food cues over time. Much of the existing research has focused on momentary responses to food images or on comparing ERP amplitudes across food categories without systematically analysing how these responses change with repetition (Wolz et al. 2017; Lietti et al. 2012). This limits our understanding of neural habituation, a process that may play a crucial role in eating regulation and obesity.

One of the most common limitations across previous studies is the use of intermixed food stimuli within the same category. For example, rather than presenting the same image repeatedly, many experiments expose participants to different images of high-calorie or low-calorie foods, thereby introducing novelty and variety that can interfere with habituation processes (Epstein, Temple and Bouton 2009; Epstein, Paluch and Coleman 1996b). Given that food variety itself is known to delay habituation and increase consumption (Rolls et al. 1988; Raynor, Niemeier and Wing 2006), such designs may confound the ability to isolate neural markers associated with true habituation to a specific stimulus.

Another gap is the lack of consistent focus on dishabituation, the re-engagement of attentional and neural processes after a novel stimulus interrupts repeated exposure. Although some behavioural studies have examined dishabituation paradigms using taste or visual cues (Epstein, Mitchell and Caggiula 1993; Epstein et al. 1992), few EEG-based studies have implemented experimental designs that capture both habituation and dishabituation in the same paradigm, especially in relation to food images. This is a missed opportunity to examine the flexibility of attentional disengagement and re-engagement processes, which are critical in understanding eating behaviour.

Moreover, while ERP components such as P2, N2, and LPP have been frequently used to study food cue reactivity, their roles in tracking habituation over time remain underexplored. Most studies using ERP analysis focus on peak responses to single-trial presentations rather than analysing changes across multiple exposures (Nijs, Franken and Muris 2008; Asmaro et al. 2012). The integration of ERP with time–frequency and connectivity measures is also rarely attempted, even though such multimodal approaches could offer a more nuanced understanding of the temporal dynamics and inter-regional coordination underlying food-related cognitive processing.

Additionally, the influence of individual differences, particularly BMI, has not been systematically integrated into habituation studies. Although some research has shown that individuals with higher BMI may exhibit stronger and more prolonged responses to food cues (Nijs, Franken and Muris 2010; Temple et al. 2007a), it remains unclear whether these differences translate into altered habituation rates at the neural level. Understanding these individual differences could have significant implications for tailoring interventions aimed at eating behaviour and weight management.

Based on these gaps, this research aims to provide a detailed examination of neural habituation and dishabituation using repeated, controlled visual exposures to the same food and non-food stimuli. The study uniquely combines ERP component analysis (e.g., P2, N2, LPP) with time-frequency features (e.g., theta, alpha power) and inter-regional functional connectivity (WPLI) to capture both short-term patterns of attentional engagement. Additionally, by comparing high and low BMI groups, the study investigates how individual differences in body weight may modulate neural adaptation to food cues over time.

The overall motivation for this research is to bridge the disconnect between traditional behavioural models of food habituation and their neurophysiological underpinnings. By addressing the methodological gaps in prior literature, the study contributes to a deeper understanding of how the brain's response to food stimuli evolves with repetition and how this process differs across individuals. Such knowledge has practical relevance for developing targeted interventions to reduce overconsumption and promote healthier eating behaviours.

Finally, this literature review has provided a thorough exploration of the theoretical and empirical foundations of habituation, particularly in the context of food stimuli, while emphasising the role of EEG in studying neural response. This chapter establishes the importance of integrating these insights into the study of food habituation through EEG, laying the groundwork for investigating how neural and behavioural responses to repeated food stimuli contribute to overeating and obesity. By bridging the gaps in existing literature, this research aims to provide meaningful contributions to the understanding of eating behaviours and inform interventions for promoting healthier food consumption patterns.

Chapter 3

Methodology and Data Processing

3.1 Chapter Outline

This chapter provides an overview of the experimental design, detailing the procedures for data collection, the data pre-processing steps used to clean the data and the analytical methods used to study habituation in cognitive and sensory processes using EEG. It also delves into the data collection process, including participant selection, experimental session structure, EEG setup, and procedures followed to capture neural activity during the experiment. This chapter also details the various methods and techniques employed in EEG analysis, such as epoching, bad channel removal, independent component analysis (ICA), etc., for isolating and removing artefacts while preserving meaningful neural data. These methods form the foundation for analysing how the brain adapts to repeated stimuli over time. Overall, it bridges the gap between raw EEG data and valuable research findings, setting the stage for understanding the neural mechanisms underlying the habituation process.

3.2 Experimental Design and Procedure

This section outlines the experimental design and describes the procedures carried out during the experiment.

Ethical Approval

As this experiment involves human participants, ethical approval was obtained from the Faculty of Sciences Research Ethics Committee at the University of Kent (Ethics approval reference: 0471920). All participants provided written informed consent to participate in the experiment.

Experimental Design

In this research, the experiment was carefully designed to address all the research objectives (refer to Section 1.3). Two sets of experiments were conducted to explore the mechanisms underlying habituation, i.e., the habituation process and the dishabituation process. Habituation, which refers to the decrease in response to repeated stimuli, requires uninterrupted exposure to the visual stimulus to be accurately observed. On the other hand, dishabituation involves the recovery of the habituated response when a novel stimulus is introduced. Therefore, in the first part of the experiment, the same visual food stimuli were presented without any interruptions to ensure that the habituation process was measured without external influence. This group is referred to as the Habituation group in this study (experiment details given in subsection Habituation Experimental Design in Section 3.2).

In the second part of the experiment, a separate group of participants was exposed to the same food stimuli (as used in the Habituation group), followed by the introduction of a new stimulus. This group is referred to as dishabituation in this research. This approach allowed for the analysis of response recovery and the assessment of the ability to differentiate between familiar and novel stimuli (experiment details given in subsection Dishabituation Experimental Design in Section 3.2). Analysing both habituation and dishabituation within the same group could have interfered with the ongoing habituation process upon the introduction of a novel stimulus, potentially confounding the results and making it difficult to discern whether changes in response were due to genuine habituation, dishabituation, or merely the novelty of the new stimulus.

Also, existing research highlights that food variety significantly influences appetitive behaviour, motivation to eat, and overall energy intake (Epstein et al. 2009c; Epstein, Temple and Bouton 2009). This study focuses specifically on habituation to a single visual stimulus, selecting a single exemplar condition for this initial exploration. This approach enables a controlled investigation of the habituation process by eliminating the variability associated with multiple stimuli. Furthermore, this study is the first to examine food habituation using a single exemplar, offering valuable insights into the neural mechanisms underlying the comparison between food and non-food stimuli.

In this study, a pizza image was used as the high-calorie stimulus, an apple image represented the low-calorie stimulus, and a hammer image was used as the non-food stimulus for visual stimuli. The images used for this research are given in Appendix A. The visual stimuli used in this study were selected from the Food-Pics database, a publicly available and validated repository developed for research in eating behaviour and cognitive neuroscience (Blechert et al. 2014b). This image set includes a wide range of high-resolution pictures of food and non-food items, standardised for visual complexity, recognisability, and affective ratings. Although it is acknowledged that using pizza as a high-calorie food and apple as a low-calorie food may not represent the entire population, the findings are considered relevant for individuals who enjoy pizza and apples. Pizza was specifically selected as the high-calorie stimulus based on a YouGov survey (Smith 2019) of over 25,000 people in 24 countries, which identified pizza and pasta as among the most popular foods globally. Apples, widely regarded as a healthy option, were chosen to represent the low-calorie condition. Consequently, participants were selected based on their liking for pizza and apples, with those who indicated low preference excluded through a Likert scale questionnaire.

Participants' preferences for pizza and apples were evaluated using a Likert scale, where 0 = Not at all, 1 = Dislike a lot, 2 = Dislike a little, 3 = Like a little, 4 = Like a lot, and 5 = Like extremely. Scores from 0 to 2 were classified as negative, while scores from 3 to 5 were classified as positive. Based on Leung's findings (Leung 2011), a six-point Likert scale was utilised, as it tends to produce normally distributed data and encourages participants to express clear positive or negative preferences rather than remaining neutral (Apple liking: mean = 5.01±0.74, Pizza liking: mean = 5.41±0.79).

Participant Selection Criteria

Participants were recruited via university-wide announcements and were initially screened using an online questionnaire. The inclusion criteria required participants to:

- Self-reported liking scores of >=3 (on a 0–5 Likert scale) for both apple and pizza images, ensuring consistent food preference and affective salience.
- No history of neurological or eating disorders.

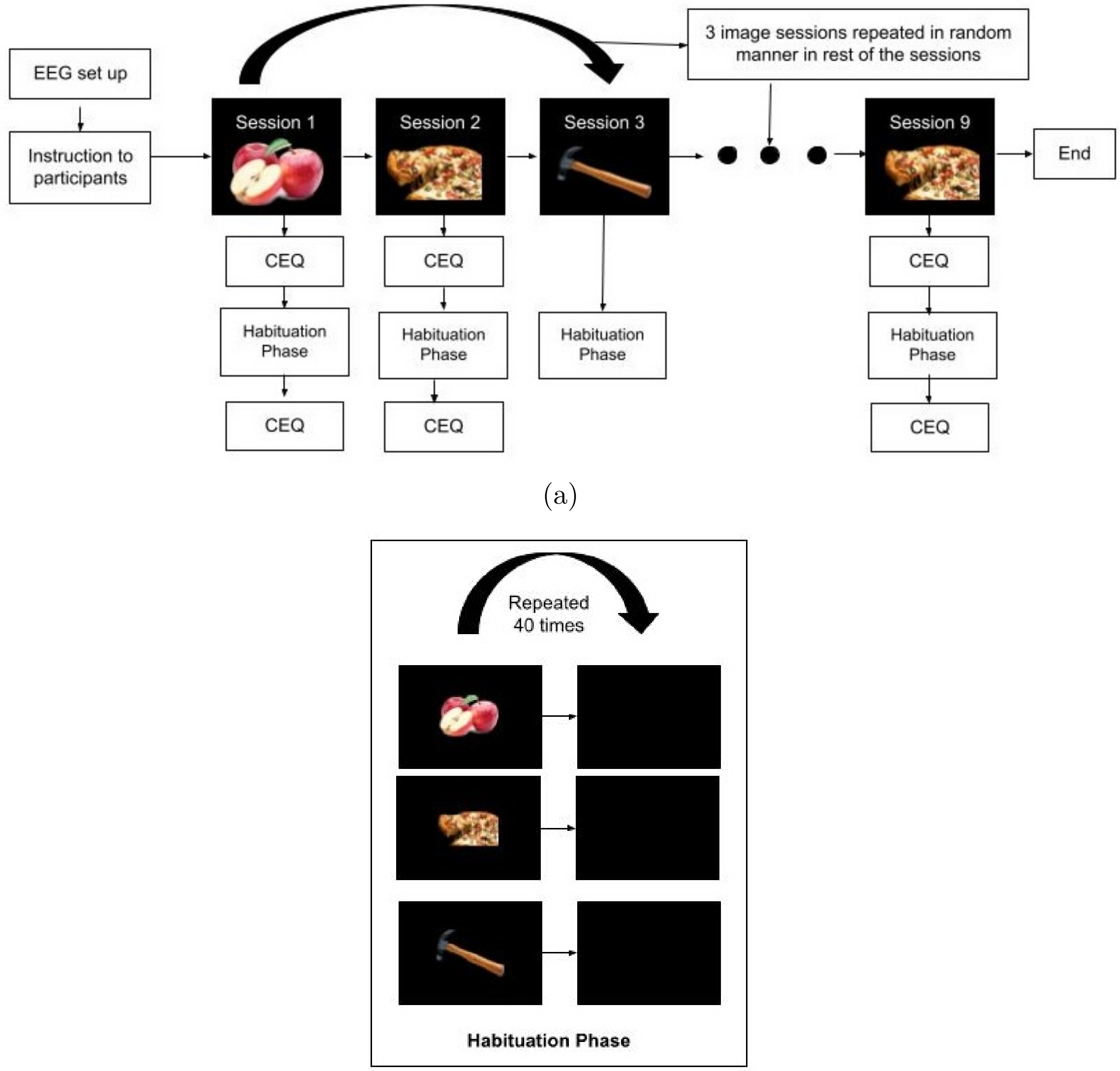
- Not taking medications that might affect cognitive or neural responses.

Overall, twenty-six participants (13 males and 13 females) were recruited via university announcements. Their ages ranged from 18 to 48 years, with an average age of 31.38 years and a standard deviation of 7.83. The participant's Body Mass Index (BMI) ranged between 17.21 and 39.15 kg/m^2, with an average BMI of 25.9 and a standard deviation of 5.0. Among these, 14 participants (eight females and six males) were classified as overweight or obese. Participants were randomly and equally assigned to two groups, with EEG data collected while they passively viewed either food or non-food images with their eyes open.

Habituation Experimental Design

This section outlines the experimental design for the habituation experiment. Thirteen participants were allocated to this study, during which they viewed three images displayed on a monitor positioned one meter away: an apple and a pizza (representing low and high-calorie foods, respectively), along with a hammer as a non-food image. In this group, participants' age ranged between 24 and 39 years (mean = 27.84±4.38). Body mass index (BMI) ranged from 19.72 to 28.67 kg/m^2 (mean = 24.54±2.80), with 7 participants (four females and three males) being overweight or obese.

Participants observed three distinct images displayed on a monitor positioned one meter away: an apple, a pizza, and a hammer as a non-food image. Each participant completed nine sessions in a single day, with each session featuring only one of these images. Each image was presented 40 times within a session, totalling 360 trials per participant across all sessions (9 sessions × 40 trials), with 120 trials for each image category. In each session, participants were repeatedly shown the same image (either



(a)

(b)

Figure 3.1: (a) Overall habituation experimental design, EEG - Electroencephalogram, CEQ - Craving Experience Questionnaire (participants record their current craving intensity). (b) Habituation phase for each image category: low-calorie, high-calorie, and non-food. All images were displayed for 4 seconds, followed by a 2-second inter-stimulus interval featuring a blank screen.

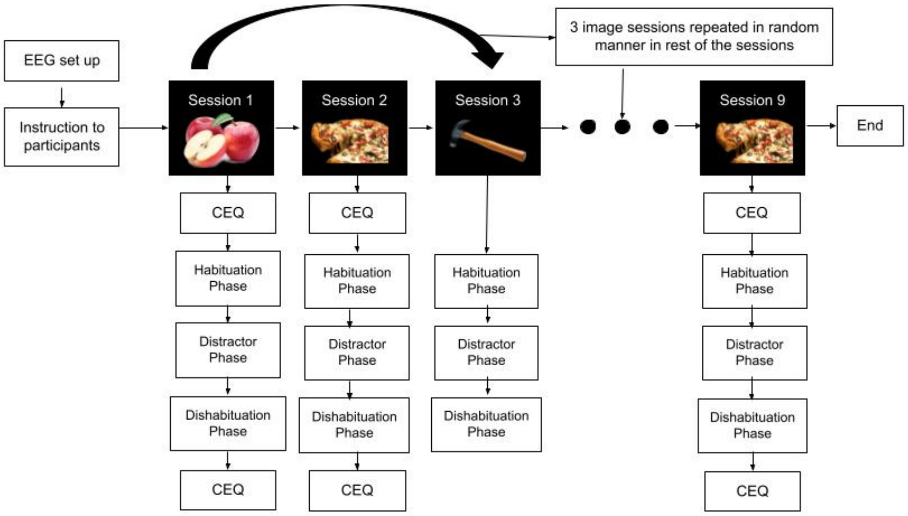
apple, pizza, or hammer). The image was displayed for four seconds, followed by a two-second inter-stimulus interval. The order of sessions was randomised to avoid predictable sequences and maintain participant engagement. Figure 3.1 provides a graphical representation of the experimental paradigm.

In order to evaluate participants' craving intensity during the experiment, participants were asked to provide their current food craving intensity score using the Craving Experience Questionnaire (CEQ) (May et al. 2014) at the beginning and end of each session. This questionnaire was administered exclusively for the food image group. Craving intensity was assessed through three questions (given below) on a 10-point Likert scale, ranging from ”Not at all” (0 points) to ”Extremely” (10 points):

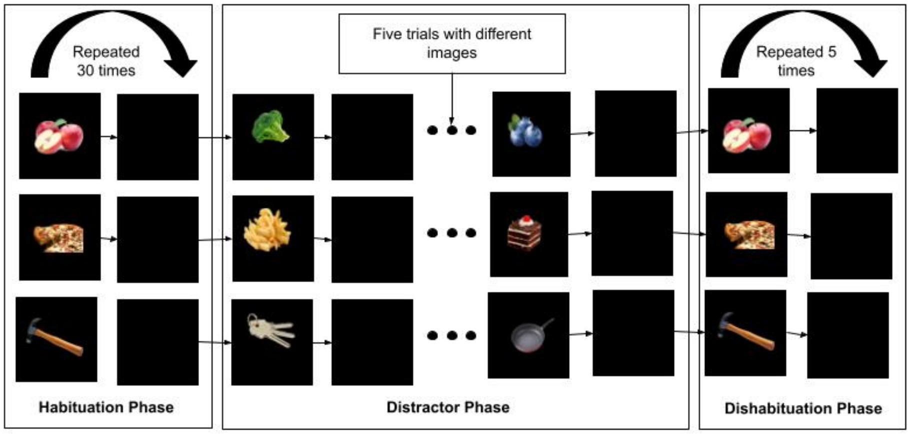
1. How much did you want it?
2. How much did you need it?
3. How strong was the urge to have it?

Dishabituation Experimental Design

This section describes the experimental design for the dishabituation experiment, which involved thirteen participants. In this group, the participants varied in age from 18 to 48 years (mean = 35.58±9.01). The BMI of the individuals ranged from 21.26 to 39.15 kg/m^2 (mean = 28.11±5.75), with seven people (four females and three males) being overweight or obese. The experiment is designed to be very similar to the habituation experiment as given in previous Section 3.2, except the experiment consisted of three phases: the habituation phase, the distractor phase, and the dishabituation phase. During the habituation phase, the same stimuli used in



(a)



(b)

Figure 3.2: (a) Overall dishabituation experimental design, EEG - Electroencephalogram, CEQ - Craving Experience Questionnaire (participants record their current craving intensity). (b) Habituation, Distractor, and Dishabituation phases for each image category: low-calorie, high-calorie, and non-food. All images were displayed for four seconds, followed by a two-second inter-stimulus interval featuring a blank screen.

the habituation experiment, images of pizza, apple, and a hammer, were presented. In the distractor phase, different high-calorie and low-calorie images were used as distractors, while various everyday objects served as distractors for the non-food category.

Participants were shown three images on a monitor placed one meter away: an apple (low-calorie food), a pizza (high-calorie food), and a hammer (non-food item). Each participant completed nine sessions in a single day. During each session, one image from the three categories was randomly displayed for four seconds, followed by a two-second inter-stimulus interval (ISI) showing a blank screen. This sequence was initially repeated 30 times per session (habituation phase - 30 trials). Next, a distractor phase occurred, consisting of five trials with different session-related images (distractor phase - five trials). The session then concluded with five trials of the original habituation stimuli (dishabituation phase - five trials), resulting in a total of 40 trials per session. The CEQ was administered to assess food cravings at the beginning and end of each session but only during sessions involving food stimuli. Participants were provided with a five-minute rest period between sessions. A graphical representation of the experimental paradigm is shown in Figure 3.2.

Data Extraction Summary Across Chapters

To maintain coherence and avoid repetition, this section outlines the general structure of EEG data extraction and usage across Chapters 4 to 9. Detailed participant demographics and recruitment criteria are provided in section 3.2, while this summary focuses on the shared aspects of data handling and segmentation used throughout the thesis.

For all chapters except Chapter 7, EEG data were collected from a consistent group of 24 participants. Each participant completed nine sessions, with each session dedicated to one image type, high-calorie food, low-calorie food, or non-food. Each session consisted of 30 trials, leading to a total of 270 trials per participant. To facilitate analysis of how brain responses evolve over time, the trials in each session were divided into five equal groups as given in Table 3.1, capturing progressive exposure to the stimuli. This segmentation was uniformly applied in 5, 6, 8 and 9, each of which applies specific analytical methods such as ERP analysis, frequency decomposition, or connectivity modelling to investigate different aspects of habituation.

Table 3.1: Time domain analysis - Trial groups and their corresponding trial ranges were defined as follows: 30 trials were divided into five groups, each containing six trials, for three images across three sessions

Group name	**Trial range**
Trial Group 1	1-6
Trial Group 2	7-12
Trial Group 3	13-18
Trial Group 4	19-24
Trial Group 5	25-30

Chapter 7, however, followed a distinct experimental design and used a separate participant group. Data from 12 participants were included in the analysis, and each of these participants also completed nine sessions involving the same three image categories. However, each session consisted of 40 trials structured into three sequential phases: habituation, distractor, and dishabituation. This resulted in 360 trials per participant, equally distributed across the image types. For data analysis, the trials were grouped into eight segments that corresponded to these experimental phases. Further details about the trial segmentation and the specific analysis performed is given in Table 3.2. This summary provides a unified view of the data extraction procedures applied across the thesis, while individual chapters elaborate on the tailored methodologies used to address their respective research questions.

Table 3.2: Dishabituation analysis – Trial groups and their corresponding trial ranges across three phases

Group Name	**Trial Range**	**Phase Type**
Trial Group 1	1–5	Habituation
Trial Group 2	6–10	Habituation
Trial Group 3	11–15	Habituation
Trial Group 4	16–20	Habituation
Trial Group 5	21–25	Habituation
Trial Group 6	26–30	Habituation (pre-distractor)
Trial Group 7	31–35	Distractor
Trial Group 8	36–40	Dishabituation

Experimental Procedure

Participants first provided written informed consent and completed a screening questionnaire via mail to check for inclusion and exclusion criteria. Then, those who were eligible to participate were invited for EEG data collection. To standardise ERP responses and minimise the influence of hunger, all participants were instructed to have a substantial breakfast and refrain from eating for at least three hours prior to data collection (Geisler and Polich 1992). All experiments were conducted at noon to maintain consistency. Upon arriving at the lab, participants completed the Dutch Eating Behaviour Questionnaire (DEBQ) (Wardle 1987) to assess their eating behaviours, including emotional, external, and restrained eating patterns. These constructs are commonly used to classify eating styles: emotional eaters consume food in response to feelings; external eaters react strongly to food-related cues in the environment; and restrained eaters consciously limit intake to control weight. Based on the results, the participants were categorised as follows: ten were identified as external eaters, eight as restrained eaters, and eight as emotional eaters. Following the completion of the DEBQ, participants were outfitted with EEG electrodes to prepare for data collection.

Before the experiment began, participants were provided with detailed instructions on the tools being used (EEG device and Graphical User Interface (GUI)) and the physical behaviour expected during the experiment. A test run was offered upon request, which was recommended for all participants. During the experiment, participants viewed one image per session, with each session lasting approximately five minutes while EEG data were recorded. The participants were instructed to sit comfortably and in a relaxed state with minimal tension. The participants were discouraged by excessive physical movements, especially blinking, excessive swallowing or any physical gestures during the experiment. They were instructed to focus on the tasks and not distract themselves during the experiment. Participants were ensured that the experimental procedure was harmless and that they could stop the experiment and leave at any time. Participants received £20 Amazon vouchers as compensation for their participation.

Tools Used in This Experiment

In this research, EEG data were collected using a research-grade Neuroelectric Instrumentation Controller's (NIC) Starstim device, a wireless 32-channel EEG monitor specifically designed for research studies (NEUROELECTRIC 2023). The collected EEG signals were processed and analysed using MATLAB (R2023a) (MATLAB 2023), along with its plugin EEGLAB (v2023.0) (EEGLAB 2023) and the FieldTrip toolbox (v20210212)(FIELDTRIP 2023). Additionally, a GUI desktop application was developed using the Psychtoolbox (PSYCHTOOLBOX 2023) to present the images and manage the experiment. The Lab Streaming Layer (LSL) library (LIBRARY 2023) was integrated into the desktop application to send event markers to the NIC system.

Presentation System

A GUI was created using the Psychtoolbox to present images to the participants. Markers were sent at the beginning and end of each visual stimulus using the LSL library. Participants were thoroughly briefed on how to use the GUI and were offered a test trial upon request, which was strongly recommended to all participants. This preparation helped prevent any issues during the actual experiment that could lead to unnecessary physical movement, which is discouraged. Both groups of participants viewed the images 40 times per session (each session lasting approximately five minutes) while EEG data were recorded.

Environmental Conditions

EEG data was recorded in a controlled environment within a closed room at the School of Computing, University of Kent, to minimise the impact of environmental noise on the results. The room was arranged to minimise external noise, maintain a comfortable temperature, and provide dim lighting, as illumination can influence alpha rhythms (Müller-Putz, Riedl and Wriessnegger 2015). To avoid disturbances, no one was allowed to enter the room during the experiment. Adequate breaks were provided during each trial to ensure the participants' well-being.

3.3 Data Pre-Processing

After data collection, the following pre-processing steps were undertaken to clean the raw EEG data to remove artefacts and extract relevant information to support the research objectives, as detailed in this section.

Data Pre-Processing Pipeline

EEG data comprises both signal and noise, making proper pre-processing crucial to minimise the noise and isolate the desired signals. Pre-processing involves a series of signal-processing steps performed before data analysis and interpretation. It is an essential process in EEG data analysis to remove noise and obtain a clear signal that reflects brain activity. The signals recorded from the scalp are inevitably a mix of brain-generated signals (desired data) and other signals from non-brain sources (undesired data). Since the skull is a poor conductor of electricity, the EEG signals recorded from the scalp are very weak. In contrast, noise signals, especially those from muscles and eyes, are often much more significant in amplitude. If these noise sources aren't removed, detecting brain activity becomes highly unlikely, and any interpretations made could be significantly compromised. Therefore, pre-processing is a critical step in EEG analysis.

Noise in EEG can come from both physiological and non-physiological sources. Physiological noise includes signals from muscles (particularly those in the face and neck, which generate electrical potentials during contraction and relaxation), the eyes (which produce distinct signals during blinks and eye movements), and sometimes the heart, breathing, which can introduce noise into the EEG data. Non-physiological noise sources include artefacts caused by electrode movement relative

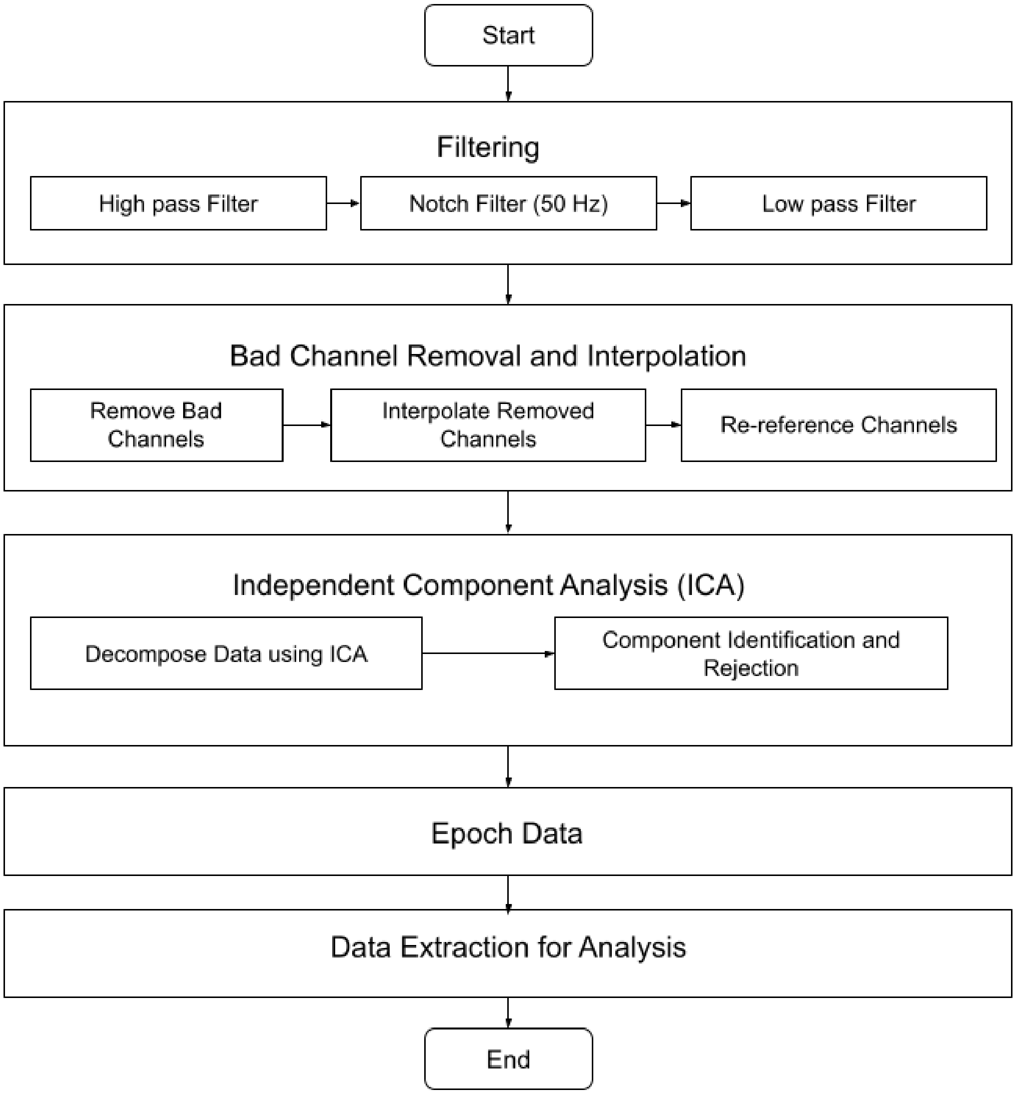


Figure 3.3: Data cleaning and extraction steps

to the scalp, movement of electrode wires, and ambient electromagnetic noise. Electromagnetic noise is generated by almost any device that uses electricity. In Europe and some other regions, line voltage, alternating current provided through electrical outlets—oscillates at 50 Hz (in the UK, 60 Hz in USA), which often appears as a distinct peak in the frequency spectrum. While line noise is the most common source of electromagnetic interference, noise at other frequencies can also come from nearby equipment, sometimes from another room or even another floor of the building.

The primary goal of pre-processing is to prepare the EEG data for analysis in a way that improves the quality and reliability of the results. Developing a pre-processing pipeline, particularly for artefact removal, is essential to ensure a standardised and automated process is consistently applied across all data sets. In this study, a specific pre-processing pipeline for artefact removal was established to enhance the signal-to-noise ratio. The steps involved in this pipeline are described in detail in this section, with a graphical overview provided in Figure 3.3.

Filtering

In EEG data analysis, digital filters are commonly used to improve the signal-to-noise ratio by reducing unwanted frequency components, such as low-frequency skin potentials, high-frequency electromyographic activity, or line noise at 50/60 Hz. Although many time-frequency decomposition methods, such as wavelet convolution, FFT, and filter-Hilbert, inherently apply temporal filters, digital filters can still be beneficial in some cases.

For instance, pre-filtering can be particularly useful when applying a high-pass filter with a cutoff frequency of 0.1 or 0.5 Hz to continuous EEG data, which is recommended to minimise slow drifts in the signal. It's important to note that high-pass filtering should be applied only to continuous data, not to epoch data, which has already been temporally segmented. Research by Winkler et al. (Winkler et al. 2015) suggests that using low cutoff frequencies between 0.5 Hz and 2 Hz yields excellent results for detecting and removing artefacts in ICA. They also indicate that pre-filtering at very low frequencies below 0.5 Hz may not be optimal for artefact removal in ICA based on dipolarity measures.

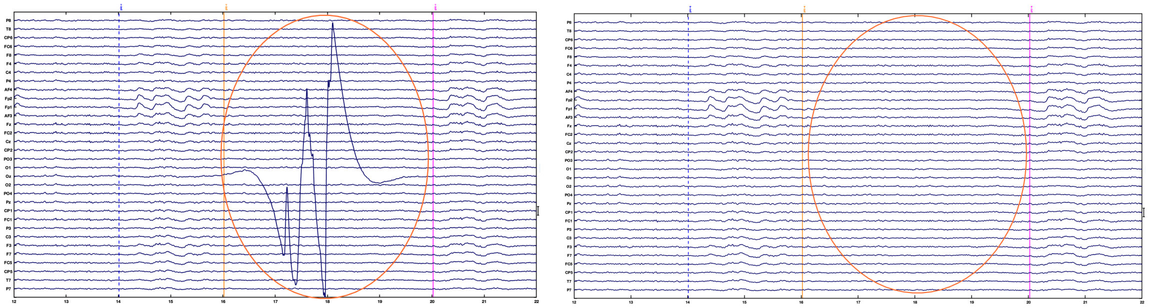
In this research, raw EEG data was filtered prior to epoching to improve the signal-to-noise ratio. Specifically, a high-pass filter at 0.5 Hz (-6 dB cutoff, Hamming-windowed sinc FIR filter) was applied using EEGLAB's filter. This approach ensures that the resulting epoched data is of high quality and ready for subsequent processing and analysis. Subsequently, a notch filter was applied to attenuate AC power line noise at 50 Hz and 100 Hz (for fluorescent lighting noise) with minimal impact on the EEG signals. Since frequencies above 60 Hz are likely to originate from external sources and muscle activity, they were filtered out. Therefore, EEG signals were low-pass filtered at 60 Hz using EEGLAB's Finite Impulse Response (FIR) filter. During analysis, the choice of the low-pass filter was based on the type of analysis: 30 Hz for time-domain analysis and 60 Hz for time-frequency analysis.

Bad Channels Removal And Interpolation

A channel (A) is considered abnormal or bad if the correlation between the channel (A) and its reconstruction based on other channels falls below a predefined threshold in EEGLAB. The reconstruction is typically performed using a spatial filtering method that estimates the expected signal of channel (A) from neighbouring channels. This process is crucial because low correlation indicates that the channel is behaving differently from the rest of the dataset, likely due to artefacts, noise, or electrode displacement.

Removing bad channels is essential, particularly before performing average referencing, which involves computing the mean signal across all channels and subtracting it from each electrode's signal. This ensures that the reference is spatially unbiased, allowing for better interpretation of neural activity. To identify and remove bad channels, the EEGLAB plugin clean_rawdata was used (Delorme and Makeig 2004; Bigdely-Shamlo et al. 2015). This function applies multiple criteria to detect noisy channels, including:

1. Correlation-based detection: Channels with low correlation to neighbouring channels are marked as bad.
2. High-frequency noise detection: Electrodes with excessive high-frequency power (e.g., muscle artefacts) are removed.
3. Flat-line detection: Channels with almost no variation over time are flagged.



(a) (b)

Figure 3.4: (a) Sample participant signal before bad channel removal (b) Sample participant signal after bad channel removal and interpolation

Once bad channels are identified and removed, they must be interpolated to maintain signal symmetry between the left and right hemispheres and prevent bias in the re-referencing step. Interpolation ensures that missing data points are estimated based on neighbouring electrodes rather than leaving gaps in the dataset. In EEGLAB, channel interpolation is done using spherical spline interpolation, a method that estimates the missing electrode's potential by considering the surrounding electrodes' signals in a weighted manner (Perrin et al. 1989). Spherical splines are particularly useful because they take into account the 3D spatial distribution of electrodes rather than relying on simple linear interpolation. This approach preserves the spatial structure of the EEG data and ensures smooth transitions in the reconstructed signals. After interpolation, average referencing was performed by subtracting the mean signal of all available channels from each individual channel. This step helps remove any global biases and approximates scalp potentials independently of their location.

Figure 3.4 gives an overview of before and after bad channel removal and interpolation. Figure 3.4 (a) shows the channel noise (circled in red) in the Oz electrode, which might be caused due to the participant's excessive movements. Once the bad channel was removed and interpolated, the channel noise was removed, as shown in Figure 3.4 (b).

Independant Component Analysis

ICA is a powerful computational technique that aims to extract independent sources of signals from EEG time series data. The main objective of ICA is to decompose the EEG signal into a set of independent components, each of which represents a distinct source of electrical activity in the brain. This technique provides a set of weights for all the electrodes in the EEG system, and the independent components are then computed as weighted sums of the activity at each electrode.

The use of ICA in EEG analysis can serve two purposes. Firstly, it can be used as a method for cleaning EEG data by identifying components that isolate artefacts and then subtracting them from the data. This helps to minimise the influence of extraneous signals on the analysis of brain activity. Secondly, ICA can be used as a data reduction technique by analysing the independent components' time series instead of the electrode time series. This can provide a more compact and informative representation of the EEG data, which can be helpful for certain types of analyses.

In conclusion, ICA is a valuable tool for EEG analysis, as it provides a flexible and effective way of identifying independent sources of electrical activity in the brain. By extracting independent components, it is possible to gain a better understanding of the underlying brain signals, which can help to improve the quality of EEG data and facilitate more accurate analysis. In this research ICA is performed using EEGlab using ”runica” technique.

The IC_label plugin in EEGlab is a valuable tool for EEG data analysis that provides a graphical user interface for annotating independent components (ICs) extracted from EEG data using ICA (Pion-Tonachini, Kreutz-Delgado and Makeig 2019). The aim of ICA is to separate a multi-channel EEG signal into independent sources, each of which represents an underlying neural or artifactual process. The resulting components, however, are often difficult to interpret and need to be labelled in order to indicate their functional significance.

The IC_label plugin allows users to inspect each component's topography, power spectrum, and activity over time and then assign a label to it, such as ”EOG,” ”Brain,” or ”Muscle.” This information can be used to reject components representing artifactual processes or to study components of interest in further analysis. The use of the IC_label plugin streamlines the process of manually annotating ICs, reducing the risk of human error and saving time in analysing large datasets.

In summary, the IC_label plugin provides a convenient and efficient solution for EEG data analysis by offering an intuitive interface for labelling ICA components, making it a valuable tool for EEG researchers and practitioners.

In this research this automated EEGLAB ICA component classifier was used to classify different components such as eye, muscle, channel noise, line noise and heart. If the generated probabilistic score of artifact components such as eye, heart, line noise and channel noise was more than 75%, then that artifact components were rejected. After this step, cleaned EEG data would be generated by discarding the rejected ICs.

Epoch Data

In EEG data recording, the continuous signal is represented as a two-dimensional matrix of time and electrodes. To analyse task-related changes in the EEG signal, this continuous data is segmented into portions known as epochs, which are centred around specific experimental events, typically the start of a trial. This process transforms the data into a three-dimensional matrix consisting of electrodes, time, and trials.

Determining the amount of time to include before and after the event of interest during epoching is crucial for ensuring the quality of the time-frequency decomposition, especially for lower frequencies. The length of these epochs varies depending on the specific experiment and the type of analysis being conducted. For example, when computing ERPs, epochs typically encompass the entire period of interest plus a baseline period. Conversely, for time-frequency analysis, longer epochs are often preferred to minimise edge artefacts.

In this research, the EEG data were epoched from -1 second before the stimulus

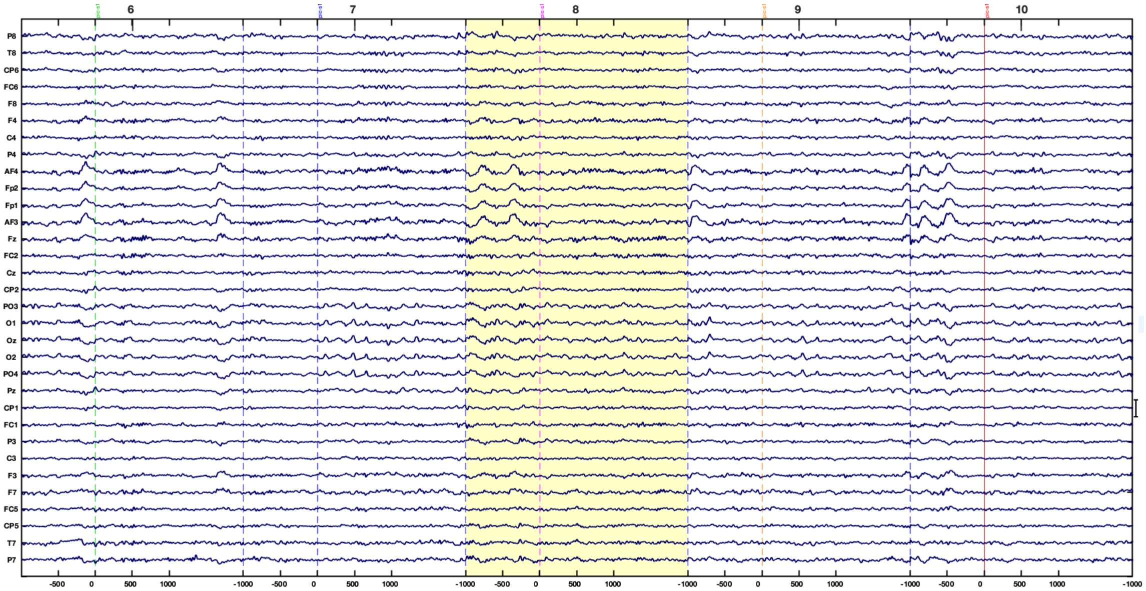


Figure 3.5: Sample epoched data of a participant.

onset to 2 seconds after the stimulus onset to investigate the dynamics associated with specific visual stimuli. After time-frequency decomposition, buffer zones at the beginning and end of the trial were discarded. A sample of the epoch data is shown in Figure 3.5, where all epochs from participants are combined for visualisation, with one epoch highlighted in yellow. The horizontal straight lines in the figure indicate the visual stimuli onset, and the blue dashed lines mark the pre- and post-stimulus thresholds.

Finally, ERP responses were extracted from the cleaned EEG data using different analysis procedures. This extraction process involved identifying and isolating specific ERP components that correspond to the experimental conditions under investigation. Due to too noisy data, two participant's data were removed (1 male and 1 female), and all the analyses were performed on 24 participants' data. The detailed results of these analyses, including any significant patterns, trends, or insights derived from the ERP data, are thoroughly presented and discussed in the subsequent chapters.

Chapter 4

Attentional Bias Towards Repeated Visual Stimuli: ERP Analysis

4.1 Chapter Outline

This chapter explores attentional bias in response to the repetition of identical high- and low-calorie food visual stimuli, contrasting with existing research that predominantly uses a variety of food images (Lietti et al. 2012; Wolz et al. 2017). By focusing on repeated exposure to the same image, this study uniquely contributes to understanding the influence of same-image repetition on attentional bias. This approach eliminates variability introduced by diverse stimuli as food variety influences human appetite (Epstein et al. 2009c), offering a more controlled context for investigating neural and cognitive processes. This study aligns with a part of the first research objective (refer to Section 1.3), examining how repeated high-calorie, low-calorie, and non-food images differ from the varied food images used in prior research. This novel perspective provides critical insights into repeated visual stimuli, laying the groundwork for identifying robust neural markers of food-related behaviours.

4.2 Introduction

Obesity can be seen as the inability to regulate food intake to maintain a healthy balance between food consumption and energy expenditure. This issue is largely driven by pre-ingestion choices influenced by the visual appearance of food, primarily through repeated exposure to food imagery. Multinational food industry chains often leverage repeated food exposure as a key marketing and advertisement strategy (Krajbich, Armel and Rangel 2010). In obesity-related research, developing effective treatment and intervention techniques is challenging. It is essential to gain deeper insights into the mechanisms regulating responses to food stimuli. Previous studies have shown that food images are easily distinguished based on their energy or calorie content (Temple et al. 2006).

The effect of variety in food consumption appears to be primarily related to sensory and potentially nutrient characteristics, supporting the hypothesis that this effect is due to habituation, a basic form of learning (Raynor, Niemeier and Wing 2006; Epstein et al. 2009a, 2013, 2010). Habituation occurs when repeated exposure to the same stimulus (such as food) leads to a decrease in behavioural and physiological responses (consumption) (Raynor, Niemeier and Wing 2006; Epstein et al. 2009a; Ernst and Epstein 2002). This process demonstrates stimulus specificity, meaning habituation happens more rapidly when the presented stimuli are more similar (i.e., foods with similar flavours, colours, and shapes) (Epstein et al. 2013, 2010) and slows down when varied stimuli are presented (i.e., foods with different flavours, colours, and shapes) (Epstein et al. 2013; Ernst and Epstein 2002; Temple et al. 2006).

Consequently, an eating occasion featuring only one type of food (as seen in non-variety conditions in previous research) or very similar sensory foods (such as chocolates of different colours but similar flavours and textures) results in a faster rate of habituation, causing consumption to end more quickly and leading to a lower intake. In contrast, eating occasions with a greater variety of foods slows the rate of habituation, resulting in more extended consumption periods and higher intake levels.

The impact of variety on the rate of habituation during an eating occasion has been studied in both children and adults, consistently showing that variety slows the rate of habituation and increases consumption within a single laboratory session (equivalent to an eating occasion) (Epstein et al. 2009a). Although limited, some evidence addresses long-term habituation (Epstein et al. 2013). One study investigated the effect of variety in high-energy-density (HED) main meal at dinner over five days on habituation and dinner energy intake in children with overweight and obesity in a laboratory setting (Epstein et al. 2013). When children were presented with different HED main meal compared to the same or sensory-similar HED main meal over the five days, those with greater variety habituated more slowly and consumed more on day five at dinner than those consuming the same or similar main meal.

While these studies focused on children who are overweight, previous research indicates that the rate of habituation to food stimuli also varies in lean children (Epstein et al. 2011). Factors such as HED main meal variety, which reduces habituation, increase the risk of excess weight gain in all children.

Several hemodynamic imaging studies, including fMRI and positron emission tomography (PET), have explored the neural networks involved in food categorisation and reward evaluation in both humans and animals. These studies have identified a prefrontal cortical and subcortical network that responds to various modes of food presentation. This network is activated not only by oral administration (De Araujo et al. 2003; Small et al. 2001) and viewing actual foods (Wang et al. 2004) but also by multisensory combinations (Small et al. 2001) and solely viewing food images (Killgore et al. 2003; Santel et al. 2006; Rothemund et al. 2007).

Furthermore, studies using visual stimulation have identified additional temporoparietal brain regions involved in food perception (Killgore et al. 2003; Santel et al. 2006; Rothemund et al. 2007). It has been found that visual cortex activity is more strongly modulated by food images compared to non-food images (Killgore et al. 2003; Santel et al. 2006), suggesting greater attentional and motivational salience for food.

Previous research studies demonstrate that food images are readily differentiated according to the energy/calorie content, and related motivation behaviour modulates the amplitude of late positive potentials (LPPs) measured over the centroparietal brain region (around 250 ms -500 ms); larger LPPs can be viewed for high-calorie food images than low-calorie food and neutral images Lietti et al. (2012), Wolz et al. (2017). Moreover, in the early ERP window (∼150 ms–200 ms), the research found increased negative amplitude (N2) for chocolate images more than neutral image in binge-eating individuals Wolz et al. (2017). This differentiation in early ERP component and LPP modulation can be interpreted as individuals' motivational significance towards external stimuli that might be mediated by the activation of cortico-limbic appetitive and defensive systems, supporting individuals' perception and action Bradley (2009). Research also suggests that these early and late alterations in behavioural and cognitive response patterns can be interpreted in terms of implicit memory processes De Lucia et al. (2010).

Previous research on repeated food stimuli mainly investigated individuals' cognitive responses and motivational behaviour by presenting different food class images based on varied calorie values to participants (presenting via varied, i.e. inter-mixed images in each class) Lietti et al. (2012), Wolz et al. (2017). Those research studies found that LPP's affective modulation appears less susceptible to repetition effects for high-energy content food images than responses to low-energy and neutral food images. This enhancement in LPPs could be caused by the influence of diverse food images (different presentations of the same food or different varieties of food) presented repeatedly, as appetite behaviour is strongly influenced by the variety of food Epstein, Temple and Bouton (2009), Epstein et al. (2009b). This differentiation in food variety might be highly related to food reward properties, initial cognitive encoding, and attentional allocation processes of different food images presented repeatedly Lietti et al. (2012), Wolz et al. (2017). This opens the question of whether repeated exposure to the same visual food image presented repeatedly shows any difference in the modulation of the cognitive process for different energy-value foods. However, this has not been investigated so far.

Therefore, this study investigates whether there is any differentiation in motivation behaviour and cognitive responses when the same food image is repeatedly presented (free viewing) and analysed in different brain regions. For this purpose, data were collected from participants when they passively viewed the same food (one high-calorie image and one low-calorie image) and non-food image repeatedly for 40 times each. The purpose of this study is to compare the behavioural responses to the repeated presentation of images using well-developed EEG signal analysis techniques.

4.3 Data Extraction and Analysis Method

This study was conducted and analysed during the early stages of the COVID-19 lockdown, with a focus on the habituation study group as described in Section 3.2. Due to noise-related quality concerns in the EEG data, one male participant's dataset was excluded following pre-processing. Consequently, the final analysis included data from 11 participants.

Each of these participants completed nine EEG recording sessions, with each session comprising 40 trials. Trials were organised by image session type, high-calorie food, low-calorie food, and non-food and subsequently averaged over time for further analysis. ERP measurements were concentrated on brain regions and time intervals previously implicated in visual repetition effects. The ROIs included the frontal (F8, F4, AF4, FP2, FP1, AF3, F3, F7), centroparietal (C3, Cz, C4, CP1, CP2, P3, Pz, P4), parietooccipital (PO3, PO4, O2, Oz, O1, Pz), and occipitotemporal (P8, T8, P4, PO3, O1, Oz, O2, PO4, P3, T7, P7) electrodes, following established protocols (Codispoti, Ferrari and Bradley 2007; Wolz et al. 2017; Ferrari et al. 2011).

To assess temporal dynamics, ERP amplitudes were extracted from two distinct time windows. Early negative peaks were measured between 150–300 ms post-stimulus onset, and Late Positive Potentials (LPP) were identified between 300–600 ms, both across all ROIs. This temporal segmentation enabled a fine-grained analysis of how repeated visual food cues engage attentional and emotional processing across different brain regions.

To explore overall differences in neural responses to repeated images, non-parametric Friedman tests were employed to examine main effects and interactions across image types (apple, pizza, and hammer) and brain regions. Additionally, to probe attentional differences between image categories, Wilcoxon signed-rank tests were used for pairwise comparisons. These comparisons tested hypotheses based on relative salience: high-calorie image > low-calorie image, high-calorie image > non-food image and low-calorie image > non-food image. To correct for multiple testing, a Bonferroni adjustment was applied, setting the significance threshold at $p < 0.017$ (i.e., 0.05/3). The outcomes of these statistical analyses are detailed in the sections that follow.

4.4 Results

Significant main effects and interactions for ERPs were analysed in early (150-300ms) and late time windows (300-600ms) in parietal, frontal, central and occipitotemporal areas of the brain, and the results are provided in this section.

Early ERP Interval (150–300 ms)

In the early time window (150–300 ms), the most pronounced effects were observed in the frontal, parietooccipital, and occipitotemporal regions (Table 4.1, with significant p-values highlighted in bold). These findings point to heightened early neural engagement in these regions when processing visual food cues. Interestingly, the centroparietal region did not yield statistically significant differences, suggesting that initial perceptual and evaluative processing is more localized to fronto-posterior visual circuits rather than being distributed across the entire cortical surface.

Further insights are provided by post-hoc pairwise comparisons (Table 4.2), which reveal that high-calorie food images (pizza) elicited significantly stronger ERP responses than both low-calorie (apple) and non-food (hammer) images in the frontal areas. These differences reflect early attentional and motivational biases toward

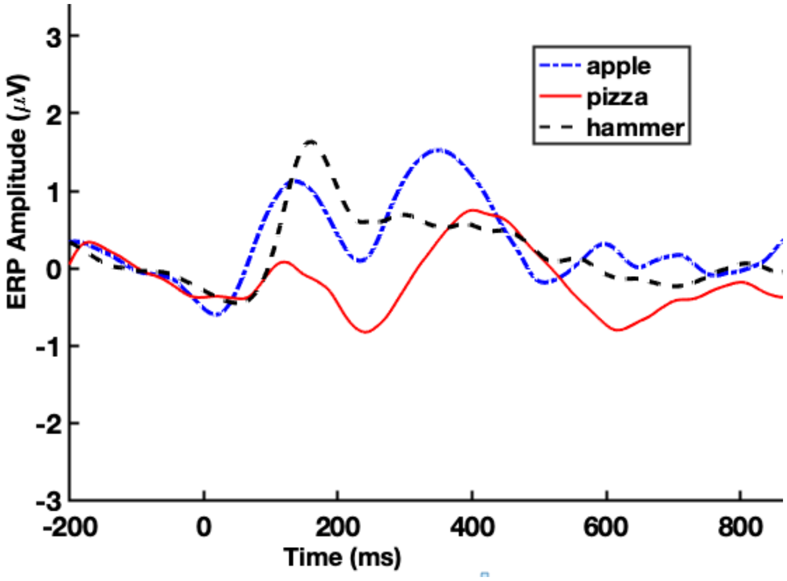


Figure 4.1: Grand averaged ERP over the frontal region for apple, pizza, and hammer images

Table 4.1: Early ERP Interval (150–300 ms): Main effect p-values across ROIs

Region of Interest (ROI)	**p-value**
Frontal	$\mathbf{4.28 \times 10^{-11}}$
Parietooccipital	$\mathbf{1.27 \times 10^{-5}}$
Occipitotemporal	$\mathbf{8.84 \times 10^{-7}}$
Centroparietal	0.121

energy-dense stimuli. While the parietooccipital and occipitotemporal region demonstrated a similar trend, not all pairwise comparisons reached significance after correction, indicating slightly lower discriminatory sensitivity in this region during early processing stages.

Table 4.3 presents the N2 component peak amplitudes for the frontal region. The data show that pizza images generated the most negative peak (-0.9 µV), compared to minimal responses for apple (0.1 µV) and hammer (0.6 µV), reinforcing the distinctiveness of high-calorie stimuli in early neural processing. These findings collectively underscore the role of early ERP components, particularly N2, in capturing rapid, evaluative responses to food-related visual cues.

Table 4.2: Early ERP Interval: Post-hoc comparisons (Wilcoxon W, p-values)

Pair	**Region**	**p-value (W)**
Pizza vs Apple	Frontal	$\mathbf{1.53 \times 10^{-5}}$ ($\boldsymbol{W = -3.91}$)
Pizza vs Hammer	Frontal	$\mathbf{1.18 \times 10^{-12}}$ ($\boldsymbol{W = -6.85}$)
Apple vs Hammer	Frontal	$\mathbf{3.21 \times 10^{-4}}$ ($\boldsymbol{W = -3.10}$)
Pizza vs Apple	Parietooccipital	$\mathbf{9.85 \times 10^{-12}}$ ($\boldsymbol{W = 6.54}$)
Pizza vs Hammer	Parietooccipital	$\mathbf{3.04 \times 10^{-7}}$ ($\boldsymbol{W = 4.77}$)
Apple vs Hammer	Parietooccipital	0.22 ($W = -0.44$)
Pizza vs Apple	Occipitotemporal	0.065 ($W = 6.31$)
Pizza vs Hammer	Occipitotemporal	$\mathbf{5.15 \times 10^{-11}}$ ($\boldsymbol{W = 6.29}$)
Apple vs Hammer	Occipitotemporal	$\mathbf{1.9 \times 10^{-3}}$ ($\boldsymbol{W = 2.52}$)

Table 4.3: Mean peak amplitudes (µV) for frontal N2 component across stimuli

Image	**Peak value (µV)**
Apple	0.1
Pizza	-0.9
Hammer	0.6

Late ERP Interval (300–600 ms)

In the later ERP window, significant neural responses were most pronounced in the occipitotemporal region, followed by the parietooccipital and centroparietal areas (Table 4.4). The frontal region did not show statistically significant differences ($p = 0.163$), indicating a transition from early perceptual processing, typically associated with rapid stimulus detection, to later-stage evaluative and attentional mechanisms concentrated in posterior cortical regions. This shift suggests that initial processing gives way to more sustained attention and motivational evaluation in response to salient visual stimuli.

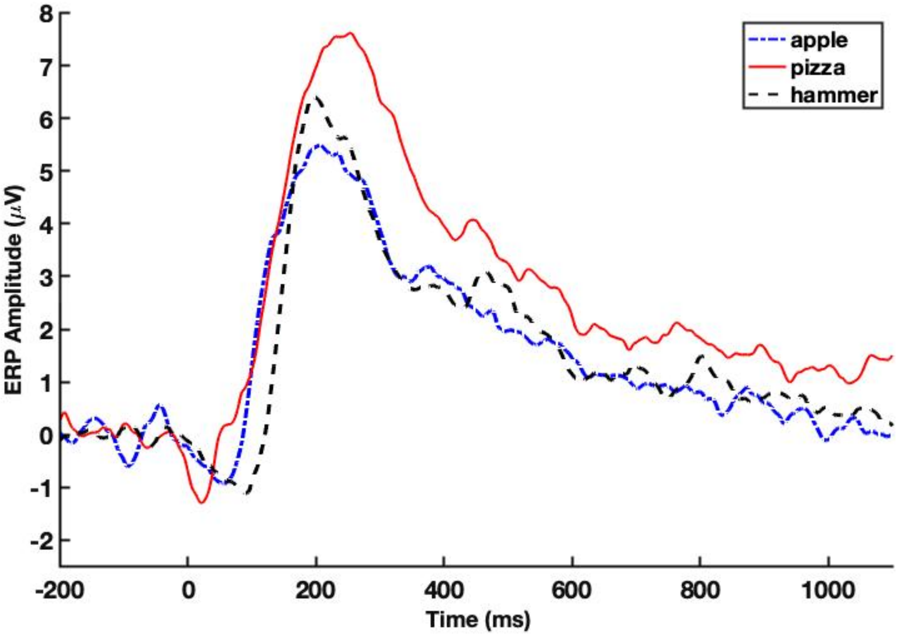


Figure 4.2: Grand averaged ERP over the occipitotemporal region for apple, pizza, and hammer images

Table 4.4: Late ERP Interval (300–600 ms): Main effect p-values across ROIs

Region of Interest (ROI)	**p-value**
Frontal	0.163
Parietooccipital	$\mathbf{6.53 \times 10^{-12}}$
Occipitotemporal	$\mathbf{6.50 \times 10^{-17}}$
Centroparietal	$\mathbf{1.57 \times 10^{-4}}$

Post-hoc comparisons (Table 4.5) confirmed that high-calorie stimuli, particularly pizza, elicited the highest LPP amplitudes in occipitotemporal region. These results align with theories of motivated attention, where stimuli with high biological relevance, such as energy-dense foods, are more likely to capture and maintain neural engagement. The elevated LPP responses reflect the brain's prioritization of stimuli that signal potential reward or nutritional value.

Mean peak amplitudes in the occipitotemporal region were highest for pizza (7.6 µV), followed by hammer (6.5 µV) and apple (5.3 µV) (Table 4.6), demonstrating a graded pattern of neural activation consistent with the relative salience and motivational value of the stimuli.

Table 4.5: Late ERP Interval: Post-hoc comparisons (Wilcoxon W, p-values)

Pair	**Region**	**p-value (W)**
Pizza vs Apple	Parietooccipital	$\mathbf{1.63 \times 10^{-15}}$ $\boldsymbol{(W = 7.74)}$
Pizza vs Hammer	Parietooccipital	$\mathbf{2.49 \times 10^{-11}}$ $\boldsymbol{(W = 6.41)}$
Apple vs Hammer	Parietooccipital	0.20 $(W = -0.27)$
Pizza vs Apple	Occipitotemporal	$\mathbf{3.35 \times 10^{-20}}$ $\boldsymbol{(W = 9.01)}$
Pizza vs Hammer	Occipitotemporal	$\mathbf{6.9 \times 10^{-22}}$ $\boldsymbol{(W = 9.42)}$
Apple vs Hammer	Occipitotemporal	$\mathbf{2.79 \times 10^{-4}}$ $\boldsymbol{(W = 3.14)}$
Pizza vs Apple	Centroparietal	$\mathbf{2.43 \times 10^{-3}}$ $\boldsymbol{(W = 2.44)}$
Pizza vs Hammer	Centroparietal	$\mathbf{5.27 \times 10^{-6}}$ $\boldsymbol{(W = 4.16)}$
Apple vs Hammer	Centroparietal	0.063 $(W = 2.64)$

Table 4.6: Mean peak amplitudes (µV) for occipitotemporal LPP component across stimuli

Image	**Peak value (µV)**
Apple	5.3
Pizza	7.6
Hammer	6.5

Taken together, these findings demonstrate that high-calorie food images consistently elicit enhanced neural responses across both early and late ERP time windows.

Early-stage effects were most evident in frontal regions, indicating rapid perceptual detection, while later-stage effects, particularly the LPP, were strongest in posterior regions, reflecting sustained attentional and evaluative processing. This spatiotemporal pattern underscores the motivational salience of high-calorie stimuli and highlights the dynamic engagement of both anterior and posterior brain regions in the visual and cognitive appraisal of food-related cues.

4.5 Discussion

This study explored the effects of repeated exposure to the same food and non-food images on the modulation of early and late ERP windows. This study focuses primarily on comparing the evoked potentials and behavioural reaction to the repeated presentation rather than on technological design issues; standard data processing techniques were employed for this purpose. In the early and late ERP windows, food images were associated with greater amplitude than non-food images, particularly the high-calorie pizza image. This suggests that ERP components linked to attention and motivation may follow a consistent pattern, highlighting sustained attentional engagement with food images, particularly those high in calories.

In research examining food processing via image viewing tasks, N2 is associated with conflict response and cognitive inhibitory control in the early ERP window Baker and Holroyd (2011). Existing research indicates that frontal negativity (also known as ”Anterior Negativity”) is elevated among binge eaters in response to chocolate imagery compared to neutral images Wolz et al. (2017) suggested that the decline in the frontal region of the brain may be associated with a cognitive control mechanism that exerts a top-down influence on the desire to consume chocolate in non-cravers Asmaro et al. (2012).

Regarding the processing of food stimuli, however, existing research has shown that more anterior negative deflections in the N2 are associated with a stronger response to food stimuli Asmaro et al. (2012). Identical findings can also be observed in affective-related investigations, where emotion pictures exhibit greater negativity than neutral pictures in the early ERP window Codispoti, Ferrari and Bradley (2007). When the same image was repeatedly presented to participants, high-calorie food was associated with an increase in negativity relative to low-calorie food and non-food images. This interaction effect may suggest that there was a relative increase in cognitive control in response to images with a high-calorie content relative to other images. This demonstrates that in the early ERP window, a person's appetitive behaviour and motivational attention do not differ between identical or intermixed presentations identified in other studies Asmaro et al. (2012); Wolz et al. (2017).

In late positive potential over occipitotemporal channels, however, food images, particularly high-calorie food images, continue to elicit greater positive potentials than neutral images. This indicates that compelling food visuals continue to attract attention despite the previous presentation. These findings complement the findings of earlier ERP research indicating that the repetition of a variety of food images has a high motivational impact, particularly for high-calorie food images compared to non-food images Lietti et al. (2012).

Moreover, repeated exposure to the same food images may continue to engage brain circuits involved in processing motivation and attention, particularly for high-calorie foods. This suggests that, despite increased familiarity with the images over time, the brain may still allocate resources to process their significance. The findings indicate that initial encoding and attention to these images remain active and may potentially influenced by their hedonic value. Also, in the early ERP window, the results of this study (high negativity for food images) parallel those of affective studies in which emotional images elicit greater negativity than neutral images Codispoti, Ferrari and Bradley (2007). This shows that emotion towards food images modulates the LPP window more than emotion towards non-food images, with strong emotion being related more to high-calorie food than to low-calorie food and non-food. This shows that emotion towards food images modulates the LPP window more than emotion towards non-food images, with strong emotion being related more to high-calorie food than to low-calorie food and non-food images.

Previous studies have found that food images tend to elicit longer latency ERP responses compared to non-food images, highlighting a connection between long-latency ERPs and the motivation to eat (Nijs, Franken and Muris 2008; Stoeckel et al. 2009). Our study supports this observation, showing that food images—particularly high-calorie ones—produce higher latencies than non-food images across both BMI groups. High-energy foods are known to carry greater reward and motivational salience, making them more resistant to habituation, even when presented purely as visual stimuli (Rosburg et al. 2006; Frömer, Maier and Abdel Rahman 2018). Disruptive factors such as increased dietary variety, divided attention, and environmental cues like watching television have also been shown to interfere with habituation, leading to increased energy intake and a higher risk of obesity.

Our findings further indicate that high-calorie food images, such as pizza, consistently elicited greater amplitudes in both early and late ERP components compared to non-food images. This suggests that these ERP responses are modulated by both attentional and motivational processes, and that the brain processes food and non-food images in notably different ways. For example, early ERP components like the N2 are linked to conflict monitoring and cognitive inhibitory control. Notably, increased frontal negativity has been observed in binge eaters in response to chocolate imagery, reflecting greater cognitive effort to inhibit the urge to consume. In our study, high-calorie images also evoked stronger frontal negativity than low-calorie or non-food images, indicating enhanced cognitive control engagement in response to more tempting stimuli.

In the later ERP window, high-calorie food images continued to produce stronger positive potentials over occipitotemporal areas, suggesting sustained attentional engagement even after repeated exposures. These prolonged LPP responses are widely interpreted as markers of motivational relevance, particularly in emotionally salient contexts.

The patterns observed in our ERP data suggest that different neural mechanisms underpin motivational behaviour and cognitive processing. Specifically, sustained LPP activity in response to high-calorie images points to motivational engagement, whereas early components like N1 and P2—more prominent in low-calorie and non-food conditions—are indicative of early-stage cognitive evaluations. These findings align with previous research (Lietti et al. 2012; Wolz et al. 2017) that demonstrated ERP modulation based on food type and its associated motivational salience.

Altogether, our results complement earlier ERP literature by reinforcing the idea that high-calorie food images exert a particularly strong motivational impact. Repeated visual exposure to the same high-calorie image appears to activate brain circuits associated with appetitive and defensive motivation more intensely than non-food images. Even though the images become familiar over time, processes involved in initial encoding and attentional allocation remain active, influenced by the hedonic value of the stimulus. Notably, emotional responses to food images seem to amplify the LPP response far more than non-food stimuli, underscoring the persistent attentional capture and motivational pull of high-calorie foods.

4.6 Conclusion

In conclusion, this study evaluated the impact of manipulation of early and late ERP windows under repeated exposure to identical food and non-food images. In both the early and late ERP windows, high-calorie foods continued to draw more attention than low-calorie foods and non-food images. In the early ERP window, subjects exhibit more negative amplitude for high-calorie images in the frontal region than with other images. This negative deflection may be attributable to cognitive control processes that exert a top-down influence on the urge to consume high-calorie foods. In the occipitotemporal area, participants exhibit sustained positive amplitude for high-calorie images more than low-calorie or non-food images during the late ERP window. This demonstrates that high-calorie foods continue to attract more attention than other visuals. In conclusion, the early and late ERP component results of this study can be compared to those of other studies Lietti et al. (2012); Wolz et al. (2017) in which a variety of images are used, suggesting that the effect of repetition of food and non-food images can be obtained by repeatedly presenting a single image rather than a variety of images. This could be useful for planning future repeated experiments that employ a single image of food rather than a combination of images to have the same effect.

In the next chapter, this analysis will be extended by exploring time-domain analysis and habituation effects between high-calorie, low-calorie and non-food images, providing further insight into how neural responses to repeated visual stimuli evolve over time.

Chapter 5

Habituation Towards Repeated Visual Stimuli: Time Domain ERP Analysis

5.1 Chapter Outline

This chapter explores whether attentional and motivational responses, as measured by ERPs, differ during repeated presentation of high-calorie, low-calorie, and non-food images. It also examines the consistency and pattern of habituation observed across these stimulus types. This investigation addresses two of the research objectives outlined in Section 1.3: to determine whether ERP measures reflect food-related habituation, and whether these responses vary between high-calorie, low-calorie, and non-food stimuli.

5.2 Introduction

Time domain analysis is a commonly used method in EEG research to study the dynamics of brain activity over time. In EEG research, time domain analysis is typically used to extract features from raw EEG signals that are relevant to the study of cognitive processes and brain functioning. For example, ERPs are time-locked signals that are generated in response to specific stimuli, such as visual or auditory stimuli. Time domain analysis can be used to calculate the latency and amplitude of ERPs, which can provide insights into the timing and strength of neural processes related to the stimuli. ERP time domain analysis is a widely used technique in EEG research that enables the investigation of electrical brain activity related to specific events or stimuli. ERP analysis is a powerful tool for examining the time-locked responses to specific stimuli, such as visual, auditory, or somatosensory, and can reveal valuable insights into the underlying neural processes that lead to observable behavioural changes.

One of the key features of ERP analysis is the ability to examine the changes in the EEG signal over time, which can reveal valuable insights into the timing of the underlying neural processes. The ERP waveform is typically displayed in a time-domain plot, where the y-axis represents the amplitude of the EEG signal and the x-axis represents time, with each tick mark corresponding to a specific time point in the waveform. One of the most important aspects of ERP analysis is the identification of the specific components of the ERP waveform that are of interest. These components can be characterised by their latency, timing, and amplitude and can provide valuable information about the underlying neural processes that are occurring.

In neurophysiological studies, ERPs are used to understand how the brain processes food-related cues. ERPs are changes in brain activity that occur in response to a stimulus, recorded using electrodes placed on the scalp. The strength (amplitude) of these signals varies depending on how a person perceives and reacts to a stimulus (Luck 2014). Different ERP components are linked to specific brain functions, such as visual perception, emotional responses, and higher-level thinking. Previous research suggests that the way food is visually processed can influence whether it captures attention and affects eating behaviour (Müller-Putz, Riedl and Wriessnegger 2015). Some ERP components reflect early sensory attention, such as P1 (P100), N1 (N100), P2 (P200), and posterior N2 (N200). Others, like P3 (P300) and Late Positive Potential (LPP), are associated with higher-order attention processes related to emotions and motivation.

Research has shown that certain brain signals, known as ERP components, respond more strongly to food images than to neutral images. For example, studies on early sensory processing components like P2, N2, and anterior negativity have found that food-related stimuli produce higher amplitudes compared to neutral stimuli (Asmaro et al. 2012; Nijs et al. 2010a; Leland and Pineda 2006). Additionally, food images with strong sensory appeal or those linked to health and survival tend to elicit greater P1, N1, and P2 amplitudes, starting around 150 milliseconds after the stimulus appears (Becker et al. 2016; Schwab et al. 2017).

In individuals with binge eating tendencies, research has found that chocolate images trigger stronger negative amplitudes (N2) in the early ERP window (150–200 ms) compared to neutral images (Wolz et al. 2017). This difference in brain response suggests that food images hold greater motivational importance, possibly due to the activation of brain areas linked to reward and survival (Bradley 2009). These neural reactions may influence how people perceive and interact with food stimuli.

The way the brain and behaviour adapt to repeated exposure has also been studied using familiar and unfamiliar objects and faces (Dolan et al. 1997; Grill-Spector, Henson and Martin 2006). Behaviourally, people tend to recognise and classify repeated items more quickly and accurately. Brain responses, measured through visual evoked potentials (VEP), show early changes in amplitude around 150–200 ms after the stimulus appears (Guillaume et al. 2009; Tacikowski et al. 2011). Researchers suggest that implicit memory plays a role in these changes, as repeated exposure influences both behavioural and neural responses over time (De Lucia et al. 2010; Schacter, Dobbins and Schnyer 2004).

In conclusion, ERP time domain analysis is a powerful tool in EEG research that provides valuable insights into the underlying neural processes that are associated with specific events or stimuli. By examining the changes in the EEG signal over time, researchers can identify the specific components of the ERP waveform that are of interest and can provide valuable information about the underlying neural mechanisms that are responsible for the observed behavioural changes.

So far, studies on the effects of habituation on behavioural and neural responses to repeated object presentation have compared visual evoked potentials and behavioural reactions to initial and repeated display of a varied energetically valued food and non-food items (Lietti et al. 2012). These authors discovered that activations seen in response to high-energy foods were consistent and did not habituate. Furthermore, earlier studies on repetition of food stimuli mainly examined individuals' cognitive reactions and motivated behaviour by showing distinct food class images based on varying calorie values to participants (presented via diversified, i.e. inter-mixed images in each class) (Wolz et al. 2017). Those research studies found that LPP's affective modulation appears less susceptible to repetition effects for high-energy content food images than responses to low-energy and neutral food images. This enhancement in LPPs could be caused by the influence of diverse food images (different presentations of the same food or different varieties of food) presented repeatedly, as appetite behaviour is strongly influenced by the variety of food (Epstein, Paluch and Coleman 1996a). This differentiation in food variety might be highly related to food reward properties, initial cognitive encoding, and attentional allocation processes of different food images presented repeatedly (Epstein, Paluch and Coleman 1996a).

One key finding in food habituation research is that it helps explain eating that is not driven by hunger. Studying habituation across different types of food is important for designing better intervention strategies. Previous research has used measures like salivation, facial muscle movements, and reinforcement responses to study food habituation (Epstein et al. 1992; Epstein and Paluch 1997; Temple et al. 2006). However, these methods can be costly, invasive, and difficult to apply in real-world settings. This study provides new insights into neural habituation by examining brain responses through ERP when the same food and non-food images are repeatedly shown.

The primary aim of this study was to explore how neural habituation unfolds over time within a session when food and non-food images are repeatedly presented. By measuring ERP responses, we focused on short-term habituation effects. We aimed to determine whether repeated exposure to high-calorie, low-calorie and non-food images influences attention and motivation, with the expectation that high-calorie foods would elicit the strongest responses. Additionally, we examined whether high-calorie foods show slower habituation rates compared to low-calorie and non-food images, assessing the reliability of this effect.

5.3 Data Extraction and Analysis Method

This chapter investigates the dynamic neural mechanisms underlying habituation using time-domain ERP analysis. While the general procedures for participant recruitment, trial design, EEG recording, and preprocessing have been detailed in Chapter 3 and the overview section in Chapter 3, this section highlights the specific elements relevant to this experiment.

The analysis focused exclusively on the habituation phase, defined as trials 1 to 30 across both habituation and dishabituation groups. Each participant completed nine sessions, each corresponding to one image category (high-calorie, low-calorie, or non-food), resulting in 270 trials per participant. For this ERP analysis, only the first 30 trials per session were used, yielding 90 trials per image type.

To investigate within-session habituation effects, trials were grouped based on image type and further divided into five consecutive trial groups of six trials each. These groupings allowed for the temporal tracking of ERP amplitude changes and the examination of neural adaptation over repeated stimulus exposure. Please refer Chapter 3, Section 3.2 for more details on trial group structure.

ERP waveforms were computed by averaging trials within each image condition and trial group. Statistical comparisons between conditions were carried out using non-parametric cluster-based permutation testing, as implemented in FieldTrip's `ft_timelockstatistics` function. This approach enabled the identification of significant effects without assumptions of normality, ensuring robust statistical inferences.

Statistical Analysis

The main effects and interactions of ERP responses to the three images during the first 1000 ms after cue onset (the beginning of visual stimulus presentation) were analysed across various time windows and regions of interest (ROIs). These ROIs included parietal regions (P7, P3, Pz, P4, P8), frontal regions (Fp1, Fp2, F7, F3, Fz, F4, F8), central regions (C3, Cz, C4), temporal regions (T7, T8), and occipital regions (O1, Oz, O2). To explore habituation effects within a session (across four trial groups) for the three images, a mass-univariate analysis (MUA) was conducted using a cluster-based statistical approach. The analysis was carried out with the EEGLAB and FieldTrip toolboxes, employing a non-parametric cluster-based permutation test with Monte Carlo randomisation (Maris and Oostenveld 2007). The methodology followed FieldTrip documentation (Oostenveld et al. 2011) and was further informed by established research (Maris and Oostenveld 2007; Rodriguez-Larios et al. 2020; Quiroga-Martinez et al. 2020).

To avoid assuming a normal data distribution, a non-parametric statistical test was chosen over parametric alternatives. The cluster-based permutation approach used for statistical testing assumes that actual neural activity induces changes in signals over contiguous time points. A reference distribution for mean cluster magnitude was generated by performing random permutation testing (1,000 iterations) on each subject-specific trial group for each condition.

To evaluate the hypothesised linear decrease in ERP amplitude (indicating habituation, i.e., trial group 1 > trial group 2 > trial group 3 > trial group 4 > trial group 5), linear regression analysis for dependent samples was applied. The regression analysis used the *ft_statfun_depsamplesregrT* function in FieldTrip, which computes t-statistics for regression coefficients on EEG data (dependent variable) based on the independent variable (trial groups as predictors). Clusters in the observed data were deemed significant if their magnitude exceeded the 2.5th or 97.5th percentile thresholds (corresponding to a 5% significance level in a two-tailed test). The p-value reported in this study corresponds to the overall regression model, assessing the significance of the relationship between trial groups and ERP amplitudes.

5.4 Results

To investigate habituation effects in ERP responses across repeated exposures, linear regression analysis was conducted on ERP amplitudes recorded over five trial groups for three image categories: low-calorie (apple), high-calorie (pizza), and non-food (hammer). The analysis considered multiple regions of interest (ROIs), including frontal (Fp1, Fp2, F7, F3, Fz, F4, F8), central (C3, Cz, C4), parietal (P7, P3, Pz, P4, P8), temporal (T7, T8), and occipital (O1, Oz, O2) channels. A non-parametric cluster-based permutation test with 1,000 iterations was applied to assess the statistical significance of linear amplitude reductions indicative of habituation. This approach avoids assumptions of normality and identifies clusters of electrodes and time windows where ERP amplitudes decrease consistently across trials.

A comparison of p-values across all ROIs is provided in Table 5.1. The results show that statistically significant habituation effects were observed only in the parietal region for the apple and hammer conditions. All other regions yielded non-significant values. Given this outcome, the parietal region was selected for focused analysis and visualisation, ensuring that reported findings are statistically robust and relevant. This decision also aligns with the literature, as the parietal region is frequently implicated in attention-related ERP components such as P200, which is sensitive to stimulus salience and repetition.

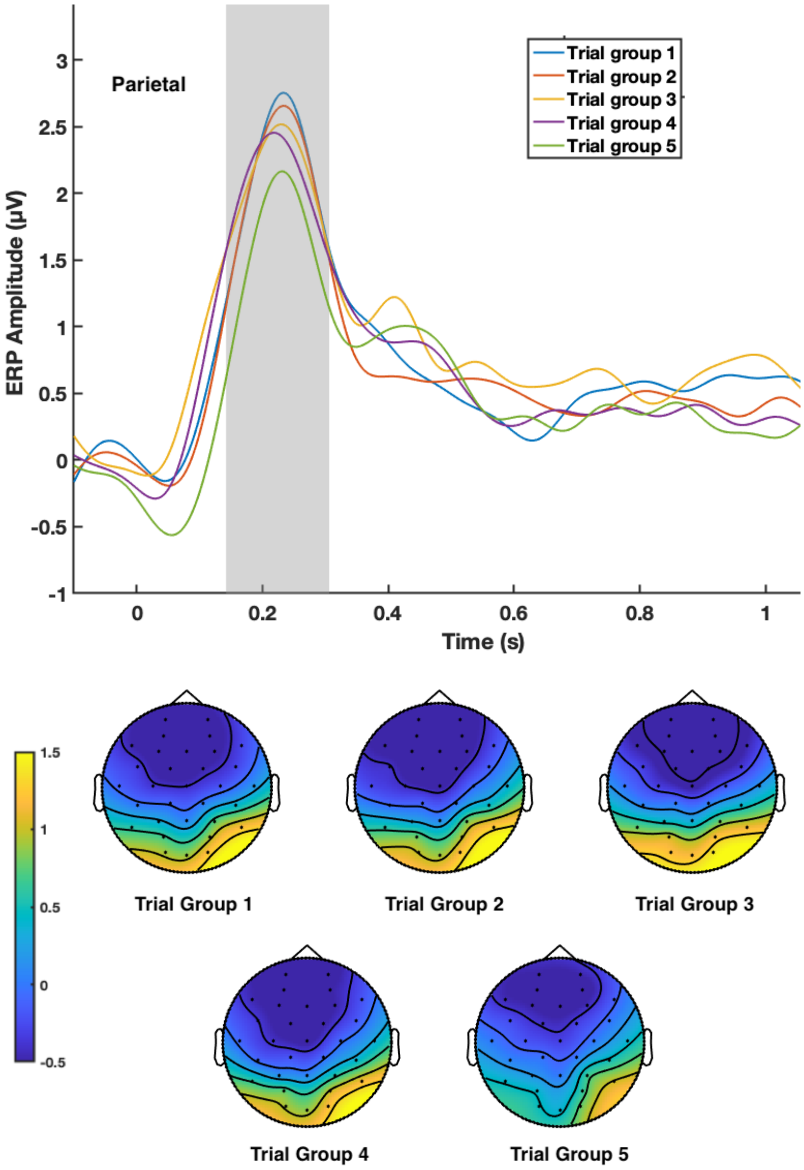


Figure 5.1: Apple - (a) Mean ERP amplitude of different images and trial groups over parietal brain region. (b) Topographical view of different images and trial groups over parietal brain region

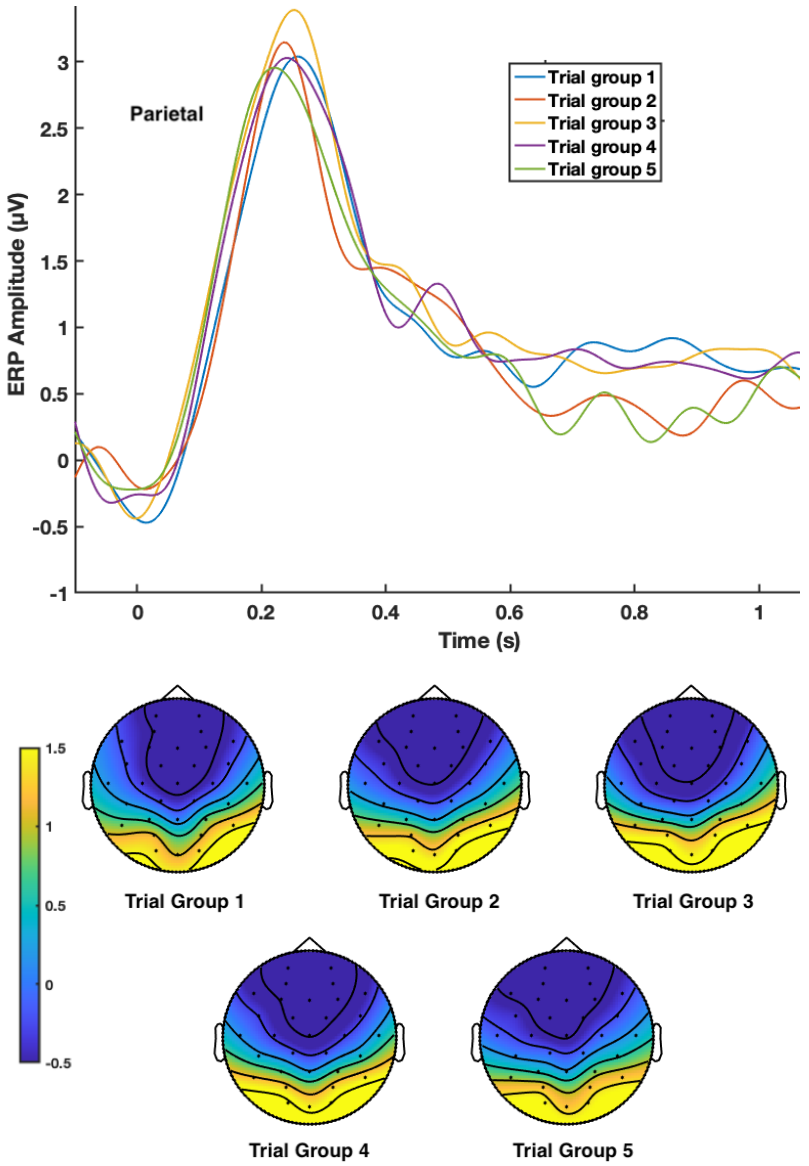


Figure 5.2: Pizza - (a) Mean ERP amplitude of different images and trial groups over parietal brain region. (b) Topographical view of different images and trial groups over parietal brain region

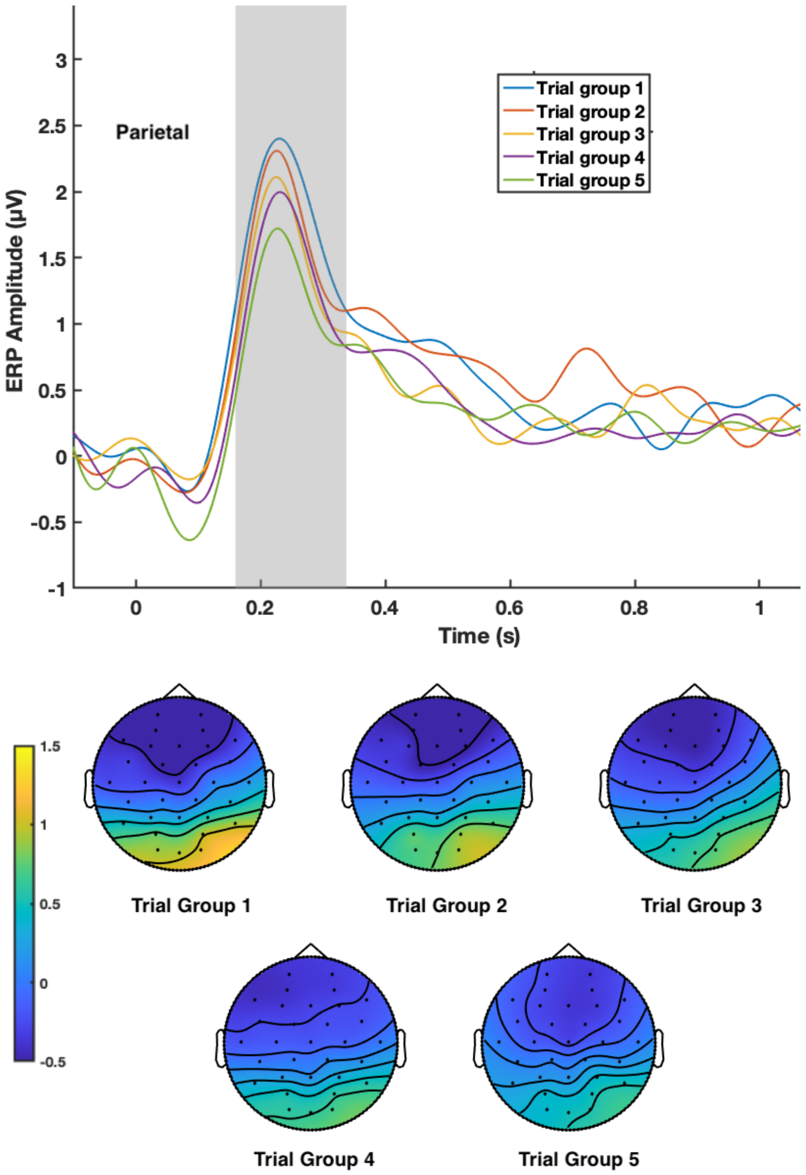


Figure 5.3: hammer - (a) Mean ERP amplitude of different images and trial groups over parietal brain region. (b) Topographical view of different images and trial groups over parietal brain region

Table 5.1: ROI p-values across different image conditions from linear regression analysis. Significant p-values are in bold.

ROI	Apple	Pizza	Hammer
Frontal	0.241	0.382	0.196
Central	0.198	0.457	0.273
Temporal	0.324	0.511	0.209
Occipital	0.275	0.398	0.287
Parietal	**0.016**	0.213	**0.011**

Figure 5.1 shows the ERP waveforms and corresponding topographical maps over the parietal region for apple images. A prominent linear decline in ERP amplitude was observed, with Trial Group 1 showing the highest amplitude and a gradual decrease in subsequent groups. The significant habituation trend occurred within the 170–300 ms time window, which corresponds to the P200 component ($p = 0.016$). This finding reflects a reduction in attentional engagement over repeated exposures to low-calorie stimuli.

In contrast, ERP waveforms for pizza images, illustrated in Figure 5.2, did not show a statistically significant decline across trial groups ($p = 0.213$). Although a visual inspection reveals a mild downward trend, the effect did not reach significance. This suggests that high-calorie food images maintain their attentional salience across repeated exposures, potentially due to their heightened motivational relevance.

Figure 5.3 presents ERP amplitudes for the non-food (hammer) condition. Similar to the apple image, this condition demonstrated a significant linear decrease in ERP amplitude across trials ($p = 0.011$), particularly within the 180–330 ms window. This pattern reinforces the hypothesis that neutral stimuli are more susceptible to rapid habituation than highly salient or motivationally charged images.

A broader comparison of habituation rates across image types is shown in Table 5.2. The slope of the linear trend was steepest for the hammer condition ($-0.19\,\mu$V per group), followed by apple ($-0.18\,\mu$V), while pizza showed the slowest decline ($-0.06\,\mu$V). These values reflect how quickly ERP amplitudes diminish across repeated exposures, serving as a neural index of habituation.

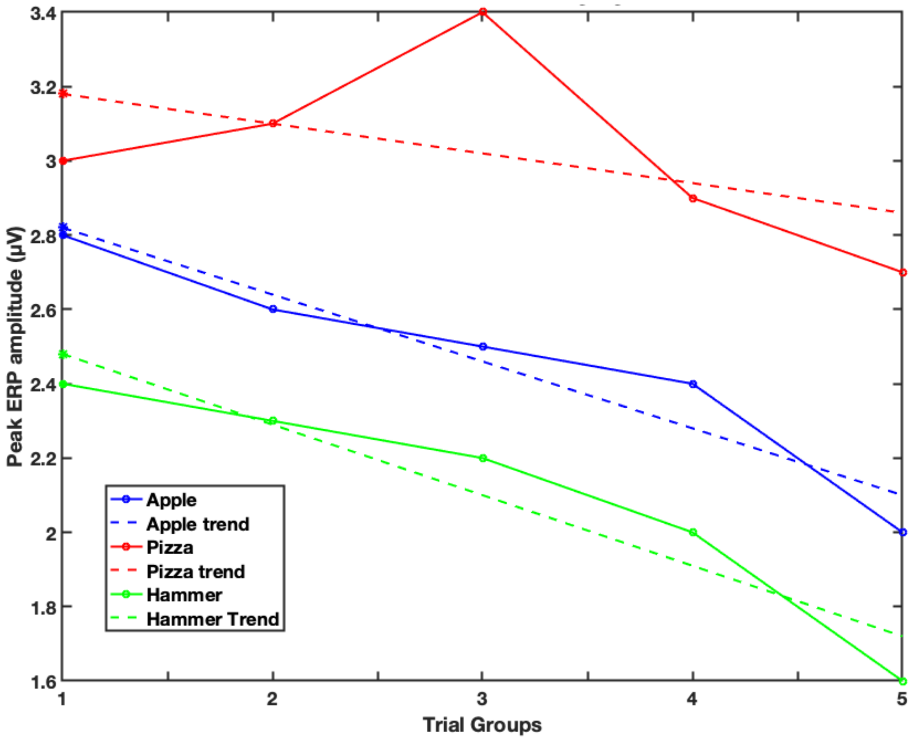


Figure 5.4: ERP peak amplitudes and linear trends across trial groups for different images.

The linear trends across trial groups are visually represented in Figure 5.4. These trends further confirm that non-food and low-calorie food images exhibit stronger habituation effects than high-calorie food images. The slower rate of decrease in ERP amplitude for pizza suggests a sustained attentional or motivational response that resists adaptation. This differential habituation pattern supports the theoretical

Table 5.2: Habituation trend details for different images (ERP slope and intercept values).

Image	**Slope (μV per group)**	**Intercept (μV)**
Apple	-0.18	3.01
Pizza	-0.06	3.22
Hammer	-0.19	2.67

framework that caloric density influences neural engagement and attention over time.

5.5 Discussion

This study is the first to examine how habituation affects different time windows within a session when the same food and non-food images are presented repeatedly. The aim was to compare the evoked potentials (using processed EEG data) of within-session trial groups to repeated presentations of various energy-value food and non-food images.

Habituation effect

In the first part of the analysis, ERP responses to repeated presentations of the same image were examined to evaluate cognitive processes and motivational responses towards high-calorie and low-calorie images and to assess how repetition influences the habituation of these images within a session. To achieve this, the 30 trials for each image were divided into five groups, and comparisons were made regarding motivation and attention across these trial groups for each image. The findings generally support the hypothesis that repeated food presentations lead to habituation. Specifically, significant effects were observed for low-calorie and non-food images in the

170 ms-300 ms and 180 ms-320 ms range, respectively, in the parietal brain area. In contrast, no significant effects were noted for high-calorie images. Figures 5.1 and 5.3 illustrate a significant decreasing trend over time for low-calorie and non-food images, while Figure 5.2 (representing pizza) does not exhibit a similar habituation effect (no significance). These results align with previous studies on food habituation observed through salivation responses in both children and adults (Epstein et al. 1992, 2003; Wisniewski et al. 1997), facial muscle responses in adults (Epstein and Paluch 1997), and motivational behaviours related to food (Epstein et al. 2009a; Temple et al. 2006, 2008a). Additionally, the ERP results from this study are consistent with earlier neurophysiological research on food habituation using diverse images (Lietti et al. 2012), indicating that high-energy food activations remained consistent and did not show habituation. This suggests that rather than using multiple images, the effects of habituation and motivation might be more effectively studied by repeatedly presenting the same image.

This study suggests that repeated exposure to the same food image, particularly high-calorie ones, may continue to engage brain circuits involved in appetitive or defensive motivation more than non-food images. It is well-documented that high-energy foods significantly impact homeostatic balance, provoke stronger hedonic responses compared to low-energy foods, and are linked to greater reward and motivational salience (Rosburg et al. 2006; Frömer, Maier and Abdel Rahman 2018). These attributes likely contribute to the greater mnemonic effectiveness and persistence of high-energy foods, making them more resistant to changes induced by repeated visual exposure, even when these foods are only appraised for potential consumption.

Neuroimaging research has shown that viewing food images activates brain regions associated with taste, reward, and memory (Toepel et al. 2009; Lietti et al.

2012). These responses help individuals evaluate the significance of the stimulus and, if sufficiently motivated, trigger eating behaviours. Once these behaviours are established, the brain's reaction to food stimuli becomes habitual (Holsen et al. 2005). Our findings suggest that the habituation of neural responses to food also leads to a reduction in behavioural responses to food, even without actual consumption. This implies that engagement with food images continues to attract attentional resources despite previous exposure. These results align with earlier ERP studies (Wolz et al. 2017; Lietti et al. 2012), which show that repeating food images, especially high-calorie ones, generates a strong motivational response compared to non-food images.

Additionally, the habituation effect may be influenced by top-down processes such as visual imagery. Morewedge et al. (Morewedge, Huh and Vosgerau 2010) demonstrated that imagining the repeated consumption of M&Ms can reduce the desire for actual chocolate, reflecting habituation behaviour. Since both perceptual and mental imagery activate similar brain regions, prolonged mental exposure to a stimulus might lead to habituation and diminished responses to the food cue(Kosslyn, Ganis and Thompson 2001). However, Zorjan et al. (Zorjan, Schwab and Schienle 2020) found that pretending to eat M&Ms did not affect reactivity, contradicting Morewedge et al.'s results. This suggests that habituation might not occur with repeated mental imagery of high-calorie foods, similar to the lack of habituation observed in this study for high-calorie images. As there is currently no literature supporting this observation, further research is needed to explore how visual imagery impacts habituation across different food types and energy values.

Habituation rate

The rate at which habituation occurs with food stimuli may be a critical factor in the development of obesity. Research indicates that various factors, including dietary variety (McCrory et al. 1999), attentional allocation (Temple et al. 2008b), and television watching (Temple et al. 2007a), can disrupt habituation and lead to increased energy intake. These factors have been linked to obesity (Epstein and Paluch 1997), likely due to their influence on energy consumption. This study examined how calorie content affects the rate of habituation in adults by analysing changes in habituation rates across different trial groups within a session, using motivational ERP responses. The trials were compared based on how motivation and attention declined over time for each image. While participants did show habituation to both food and non-food images, the data revealed that attention and motivation contributed to a faster decrease in response rates. As illustrated in Figure 5.4, the linear decrease observed can be attributed to habituation. Low-calorie and non-food images reflected this process, but high-calorie food images did not, possibly due to their ability to maintain sustained attention. Notably, the habituation rate for the high-calorie pizza image was slower compared to the low-calorie apple and non-food hammer images. The ERP responses indicate that high-calorie foods have a more pronounced effect on attention and motivation than other types of images.

Wagner's initial priming model posits that habituation occurs when repeated stimulus presentations become predictable and no longer surprising (Wagner 1981). According to this model, if a stimulus, such as a food item, is encountered again and matches the information already stored in short-term memory, the processing and response to the stimulus decrease. For instance, when a food is tasted and then tasted again, if the second tasting corresponds to what is already remembered, the response will be less intense. Variables that disrupt or remove the stimulus from short-term memory can delay or hinder this habituation process (Epstein et al. 2009a). This concept is supported by research on visual paradigms, which shows that top-down control and attention can influence how information is retained in visual short-term memory (Kuo, Stokes and Nobre 2012). Consequently, sustained attention to high-calorie images may slow down or inhibit habituation, unlike low-calorie or non-food images.

The results of this study align with previous research showing that high-calorie foods slow down habituation and contribute to increased energy intake in children (Temple et al. 2008a). If habituation acts as a mechanism for limiting eating, then a slower habituation rate, meaning responses remain heightened for a longer period, would be linked to higher calorie consumption. This concept has been supported by studies on motivated behaviour, which find that variety in food offerings can reduce the rate of habituation. When individuals are presented with a diverse range of foods rather than the same food repeatedly, they tend to consume more energy (Temple et al. 2008b). Moreover, a slower habituation rate in eating responses is consistently associated with greater energy intake.

This study primarily examined attentional peaks and chose to analyse the rate of habituation rather than the actual amplitude of responses to normalise the saliency effect of the images. Normalising response amplitudes can be challenging due to individual differences in preferences, as well as variations in the colour or intensity of the images.

5.6 Conclusion

In conclusion, this study discovered differences in the approximate 170 ms - 330 ms time range associated with cognitive processing for low-calorie and non-food images, respectively. Also, the rate of habituation was analysed rather than the actual amplitude, normalising the impacts of colour and intensity. Existing research indicates that individuals with disordered eating exhibit greater amplitudes in the 220 ms-310 ms range on posterior electrodes for both high-calorie and low-calorie food compared to neutral pictures (Blechert et al. 2011). Obese patients show more significant early electrophysiological processing (e.g., P200) of high-calorie food stimuli than normal-weight individuals (Nijs et al. 2010a). This suggests that obese persons have more automatic, preconscious attentional processing of food-related stimuli, contributing to overeating in a food-abundant environment. Chocolate-craving individuals also show greater P200 amplitudes in response to chocolate than neutral stimuli (Asmaro et al. 2012).

This study extrapolated that early attention processing (P200) demonstrated sustained attention to high-calorie pizza images and habituation to low-calorie apple and non-food images. The results indicated that the habituation effect occurs in the 170 ms-300 ms and 180 ms-330 ms range (from Figure 5.4) in the parietal regions of the brain for low-calorie and non-food images respectively, but not for high-calorie images. High-calorie images show sustained attention, while low-calorie and non-food images show decremental attention, reflecting the habituation process. The habituation rate was slower for high-calorie images than for low-calorie and non-food images in the parietal region. Summarising, the results of this study using EEG and ERP measures are consistent with previous studies on food habituation that measure individuals' salivation response through self-reported questionnaires Epstein et al. (2009a).

In the next chapter, this investigation will be extended by exploring time-frequency domain analysis, which provides a more detailed examination of neural oscillatory activity in response to repeated exposure to food and non-food images. Unlike time-domain ERP analysis, which focuses on stimulus-locked responses, time-frequency analysis allows us to investigate how different frequency bands (e.g., theta, alpha, beta) contribute to the habituation process. This will enable us to assess changes in neural power over time, revealing how attentional and motivational engagement with food-related stimuli through repeated exposure.

Chapter 6

Habituation Towards Repeated Visual Stimuli: Time Frequency ERP Analysis

6.1 Chapter outline

This chapter delves into the examination of the connection between time and frequency in regard to the adaptation to repetitive exposure to identical high-calorie, low-calorie, and non-food visual stimuli. The research aims to explore the temporal frequency response in the cortex when exposed to changes in habituation effects between high-calorie, low-calorie, and non-food images. In order to achieve this, EEG data gathered from 24 subjects will be analysed using time-frequency analysis techniques such as wavelet transform. The data were processed using Matlab, with the help of EEGLAB and Fieldtrip plugins, and the results will be interpreted in line with the research objectives. This study satisfies two of the research objectives given in Section 1.3, i.e. to find whether the ERP measure reflects food habituation in the time-frequency domain and shows variations between high/low calorie and non-food images.

6.2 Introduction

Time-frequency analysis is a powerful method for examining how the frequency content of signals changes over time. It decomposes a time-domain signal into its frequency components, revealing its dynamic variations. Two widely used approaches for this analysis are Fourier transforms and wavelet transforms. The Fourier transform mathematically represents a signal as a sum of sinusoidal functions of varying amplitudes, frequencies, and phases:

$$F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-i\omega t} dt \tag{1}$$

where $F(\omega)$ is the complex-valued Fourier transform of the function $f(t)$, ω is the angular frequency and $e^{-i\omega t}$ acts as a basis function for decomposing the signal into different frequency components.

However, the Fourier transform does not capture how frequency components change over time, limiting its use for non-stationary signals like EEG. To address this, wavelet transforms are used, which decompose signals into localised waveforms with finite duration, preserving both time and frequency information.

The wavelet transform overcomes the limitations of Fourier analysis by allowing multi-resolution analysis, where low-frequency components are captured over long durations and high-frequency details over short intervals. The continuous wavelet transform (CWT) is defined as:

$$CWT_x(a,b) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt \tag{2}$$

Where a is the scale parameter that controls the dilation of the wavelet, and b is the translation parameter that determines its shift in time, $x(t)$ represents the original signal and $\psi\left(\frac{t-b}{a}\right)$ represents the scaled and shifted function used to analyse different parts of the signal at different time locations and frequencies. By varying a and b, the wavelet transform enables multi-resolution analysis, capturing both high-frequency details over short durations and low-frequency components over longer intervals.

In EEG research, time-frequency analysis has been extensively used to investigate the temporal dynamics of neural oscillations in response to various stimuli or tasks. For instance, studies have shown that approach and avoidance tendencies play a significant role in everyday food choices between high-caloric and low-caloric options. On a neuronal level, these motivations have been associated with asymmetrical activity of the frontal cortex, often quantified by alpha power in EEG recordings. Time-frequency analyses have revealed that low-caloric foods can elicit relatively stronger left-hemispheric frontal activity, indicating a stronger approach tendency compared to high-caloric foods (Kirsten, Seib-Pfeifer and Gibbons 2022).

Furthermore, research has demonstrated that electrophysiological responses to food-related stimuli can vary based on individual differences. For example, individuals with higher food neophobia exhibit increased attention toward food-related stimuli, as evidenced by larger LPP amplitudes in EEG recordings. This heightened attentional processing is observed not only for unfamiliar foods but also for familiar food images, suggesting that food neophobia affects attention more broadly (Stuldreher et al. 2023)

Another study explores how the brain responds to food cues in overweight/obese and normal-weight adolescents using event-related potentials (ERPs) and frequency analysis, specifically looking at alpha-band activity (Biehl et al. 2020). The results show that overweight/obese adolescents process high- and low-calorie foods similarly, whereas normal-weight adolescents show a stronger focus on high-calorie foods. Interestingly, brain activity in the alpha band suggests that low-calorie food cues may influence later snack consumption in overweight/obese individuals.

Furthermore, time-frequency analysis has been instrumental in investigating the temporal dynamics of neural oscillations in response to various stimuli or tasks. For instance, studies have shown that frontal-midline theta (FMT) oscillations increase in amplitude during cognitive control tasks, indicating their role in cognitive effort and control processes (McFerren et al. 2021). Recent studies have also explored the relationship between frontal theta activity and food-related decision-making. For example, individual differences in LPP amplitude and theta power have been found to predict cue-induced eating behaviours, highlighting the significance of frontal theta oscillations in regulating responses to food cues (Gibney, Kypriotakis and Versace 2023). Moreover, research has shown that alpha and theta oscillations contribute to attribute regulation in food choice, with frontal and occipital theta power representing food tastiness more strongly during regulation efforts (HajiHosseini and Hutcherson 2020).

The primary objective of this study was to determine whether attentional and motivational responses, measured using ERP-based time-frequency analysis, differ when repeatedly presented with high-calorie, low-calorie, and non-food images. This study examines oscillatory activity in different frequency bands over time to test the hypothesis that food images will evoke greater motivational responses than non-food images and that high-calorie food images will elicit stronger motivation than low-calorie food images. The secondary objective was to assess the reliability of habituation rates across high-calorie, low-calorie, and non-food images, testing the hypothesis that food images, particularly high-calorie ones, exhibit slower habituation rates compared to non-food images. This was investigated through time-frequency analysis of ERP data, which examines oscillatory activity in different frequency bands over time, capturing the dynamic neural responses over repeated exposures.

6.3 Data Extraction and Analysis Method

This chapter investigates within-session habituation effects using time-frequency analysis. While the general participant demographics, trial structure, and EEG recording procedures are outlined in Chapter 3 and summarised in the data extraction overview section, the focus here is on methods specific to this experiment.

The analysis considered trials 1 to 30 across both habituation and dishabituation groups, totalling 90 trials per image type (high-calorie, low-calorie, and non-food) per participant. These trials were selected to evaluate neural adaptation during repeated exposure and were analysed using time-frequency methods to capture oscillatory dynamics over time.

The time-frequency analysis in this study was performed using a wavelet transformation method, allowing for the examination of how neural oscillatory activity evolves over time in response to different stimuli. The analysis was designed to extract power spectral density (PSD) information across multiple frequencies, with normalisation applied to ensure consistency across trials. Morlet wavelets with a width of five cycles per frequency were used, providing a balance between temporal and frequency resolution. This choice ensures sufficient time resolution to capture rapid changes in neural activity while maintaining adequate frequency resolution for distinguishing different oscillatory components. A width of five cycles per frequency allows for a compromise between capturing transient neural responses and accurately identifying spectral components.

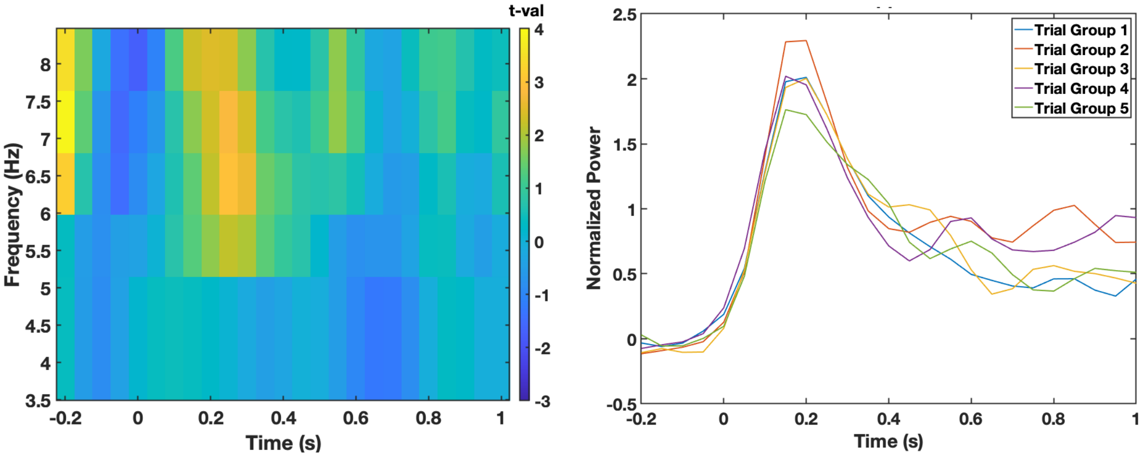
To ensure accurate estimation of neural power and reduce any distortion in the frequency domain, a Hanning taper was applied to the EEG signals, effectively minimising spectral leakage. The EEG recordings were then segmented to include a window from 500 milliseconds before the stimulus to 1000 milliseconds after it, with baseline correction performed using the pre-stimulus period. After normalisation, the spectral data were averaged across all trials to obtain a stable representation of brain activity. To capture how these neural responses evolved over time, trials were first sorted by image type and then grouped into five sequential sets, each containing six trials. This grouping allowed for the tracking of temporal patterns in brain dynamics. Statistical comparisons were carried out using a cluster-based permutation approach, offering robust insight into any significant trends. Further details on how the trial groups were structured can be found in Chapter 3, Section 3.2.

Statistical Analysis

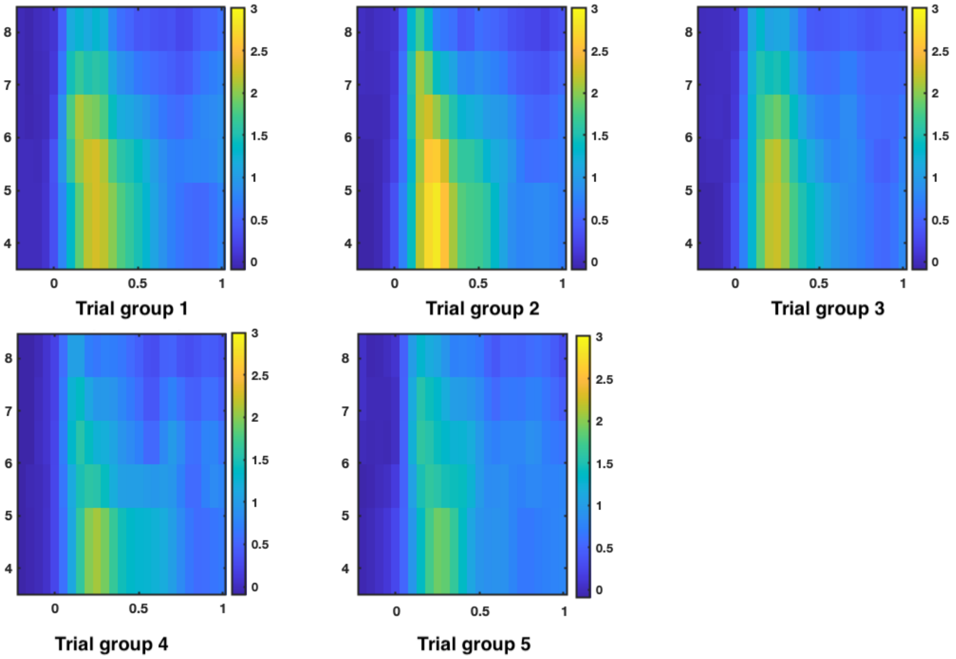
This study analysed significant main effects and interactions for different time and frequency bands in various brain areas, including the parietal (P7, P3, Pz, P4, P8), frontal (Fp1, Fp2, F7, F3, Fz, F4, F8), central (C3, Cz, C4), temporal (T7, T8), and occipital (O1, Oz, O2) areas, using a cluster-based permutation test. The purpose of this test was to examine the difference between groups of trials in response to visual stimuli such as apple, hammer, and pizza in different frequency bands, based on linear regression analysis of the habituation effect in different time windows, frequency and channel pairs within the first 1000 ms after cue onset. The study focused on key frequency bands—Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–14 Hz), Beta (15–30 Hz) and Gamma(30–60 Hz), which are associated with various cognitive and attentional processes. To assess within-session habituation effects, the ERP responses across four trial groups were analysed using a mass-univariate approach with a cluster-based statistical method. Specifically, EEGLAB and FieldTrip were used to conduct a non-parametric cluster-based permutation test with Monte Carlo randomisation (Maris and Oostenveld 2007) to identify significant clusters of activity.

To ensure statistical rigour and avoid assumptions of normality, a non-parametric approach was chosen instead of parametric tests. The cluster-based permutation method assumes that genuine neural activity produces sustained signal changes over contiguous time points, allowing for the identification of significant clusters across trials. A random permutation test (1,000 iterations) was applied to subject-specific trial groups for each condition, generating a reference distribution of the mean cluster magnitude.

To test the hypothesised linear decrease in amplitude (i.e., a habituation effect where trial group 1 > trial group 2 > trial group 3 > trial group 4 > trial group 5), a linear regression analysis for dependent samples was conducted using the *ft_statfun_depsamplesregrT* function in FieldTrip. A cluster in the observed data was considered statistically significant if its magnitude exceeded the 2.5th and 97.5th percentile thresholds (corresponding to a 5% significance level in a two-tailed test). This approach ensured that statistically meaningful habituation effects were identified while controlling for multiple comparisons across time and frequency domains.

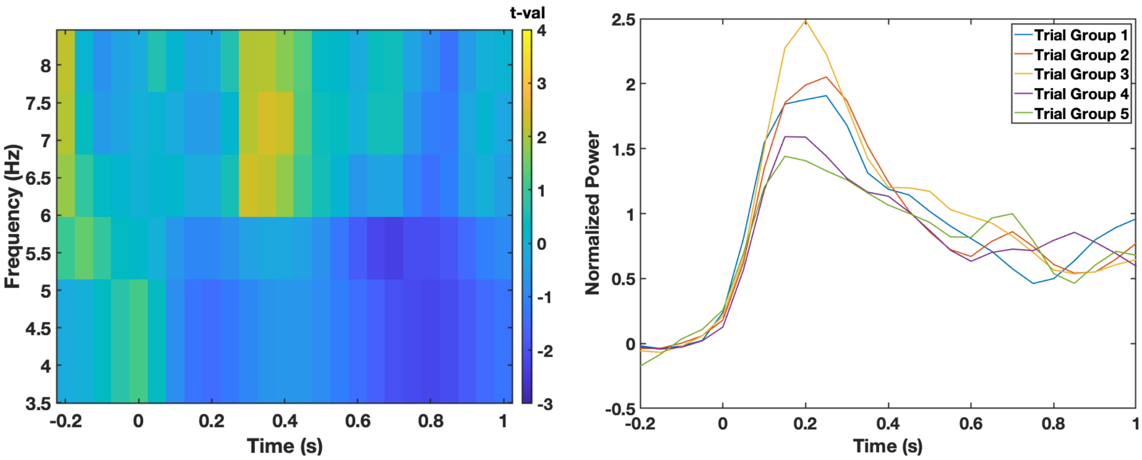


(a) t-val distribution within cluster (b) Power distribution

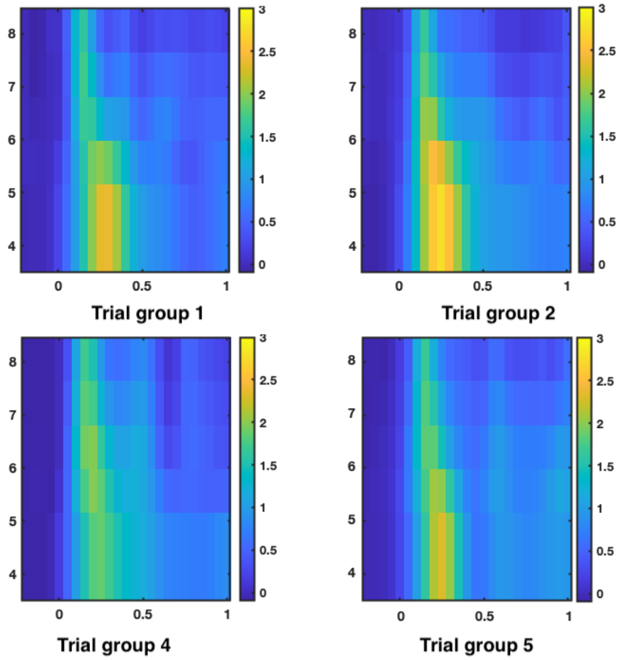


(c) Time frequency power changes over trial groups

Figure 6.1: Apple - t-value distribution within the cluster, power distribution, and time-frequency power changes in the frontal theta band.

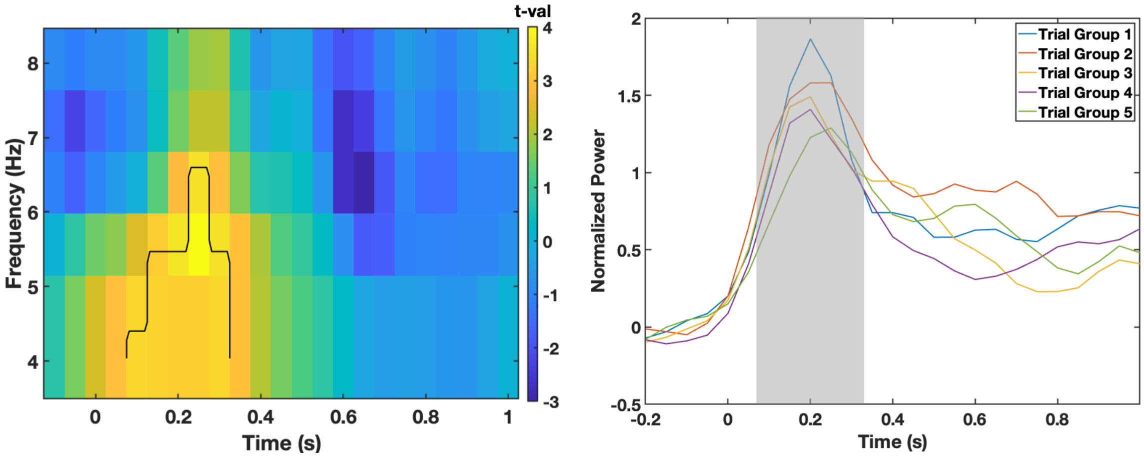


(a) t-val distribution within cluster (b) Power distribution



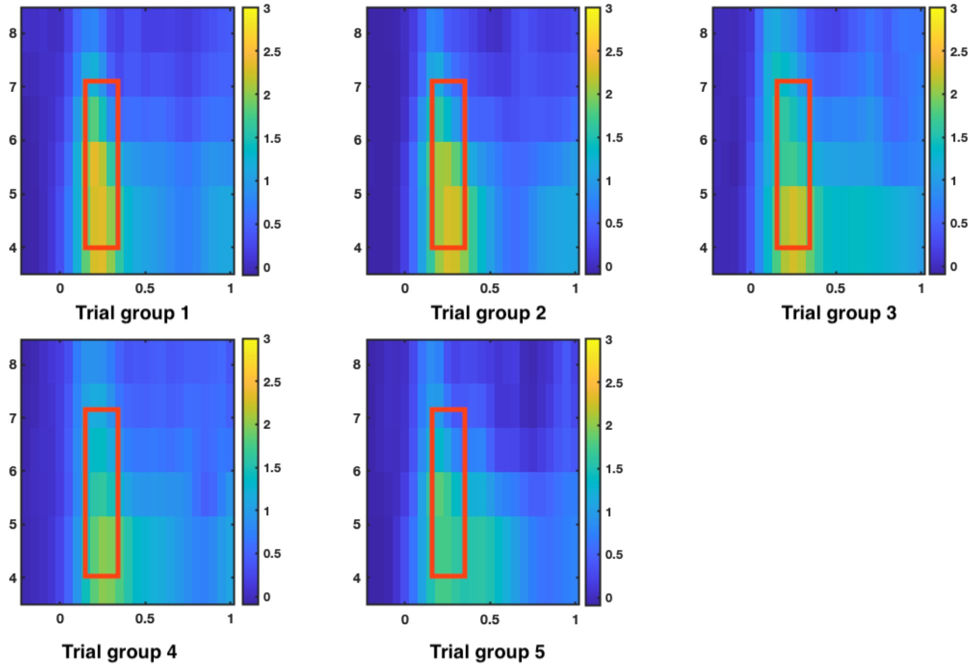
(c) Time frequency power changes over trial groups

Figure 6.2: pizza - t-value distribution within the cluster, power distribution, and time-frequency power changes in the frontal theta band.



(a) t-val distribution within cluster

(b) Power distribution



(c) Time frequency power changes over trial groups

Figure 6.3: hammer - t-value distribution within the cluster, power distribution, and time-frequency power changes in the frontal theta band.

6.4 Results

Significant main effects and interactions of normalised power were analysed across time windows, brain regions, and frequency bands using a cluster-based permutation test to compare within-session trial groups' responses to visual stimuli (apple, hammer, and pizza). Figures 6.1, 6.2, and 6.3 illustrate the time-frequency analysis results. From these visualisations, it is evident that a habituation effect is observed only for the non-food image (hammer), while both high-calorie (pizza) and low-calorie (apple) food images did not show a significant reduction in power over repeated exposures. This suggests faster neural adaptation to non-food images, whereas food stimuli, particularly high-calorie foods, sustain attentional and cognitive engagement for a longer duration.

The statistical analysis using a cluster-based permutation test revealed a significant habituation effect for the hammer image in the frontal theta band (4–7 Hz). Figure 6.3a illustrates the distribution of t-values within the cluster, Figure 6.3b presents the power distribution, and Figure 6.3c displays the time-frequency normalised power changes. The results indicate a statistically significant main effect between trial groups within the 110 ms–330 ms time window, highlighted in red in Figure 6.3c (p-val = 0.011). A clear habituation effect is observed, where trial group 1 shows the highest amplitude, which progressively decreases in subsequent trial groups.

The selective presentation of the frontal theta band results was based on the statistical outcome that this region and frequency band were the only ones to show significant habituation effects, as shown in Table 6.1. Frontal theta is also well-established in literature as a marker of cognitive control and attentional engagement.

Since no other regions or frequency bands met the statistical threshold, their exclusion from the results ensures clarity and avoids overinterpretation of non-significant data.

Table 6.1: Summary of p-values across brain regions and frequency bands for each image type. Only frontal theta showed statistically significant effects.

Image	**Region**	**Delta**	**Theta**	**Alpha**	**Beta**	**Gamma**
Apple	Frontal	0.431	0.196	0.388	0.476	0.512
	Parietal	0.506	0.378	0.442	0.219	0.397
	Central	0.693	0.301	0.216	0.055	0.787
	Temporal	0.368	0.292	0.403	0.489	0.072
	Occipital	0.491	0.326	0.134	0.521	0.693
Pizza	Frontal	0.411	0.059	0.372	0.855	0.478
	Parietal	0.283	0.334	0.419	0.497	0.088
	Central	0.162	0.289	0.108	0.269	0.376
	Temporal	0.074	0.308	0.417	0.453	0.163
	Occipital	0.491	0.314	0.422	0.288	0.495
Hammer	Frontal	0.392	**0.011**	0.366	0.451	0.169
	Parietal	0.189	0.328	0.109	0.506	0.278
	Central	0.972	0.294	0.201	0.283	0.165
	Temporal	0.468	0.312	0.412	0.571	0.179
	Occipital	0.287	0.341	0.127	0.093	0.789

For the low-calorie food image (apple), no significant habituation effect was observed in the frontal theta band. Figure 6.1a illustrates the distribution of t-values within the cluster, Figure 6.1b presents the power distribution, and Figure 6.1c displays the time-frequency normalised power changes. The results indicate no statistically significant main effects between trial groups (p-val = 0.196). Although a slight decrease in power over trial groups is visible, the change does not reach statistical significance, suggesting that low-calorie food images maintain moderate neural engagement over repeated exposures.

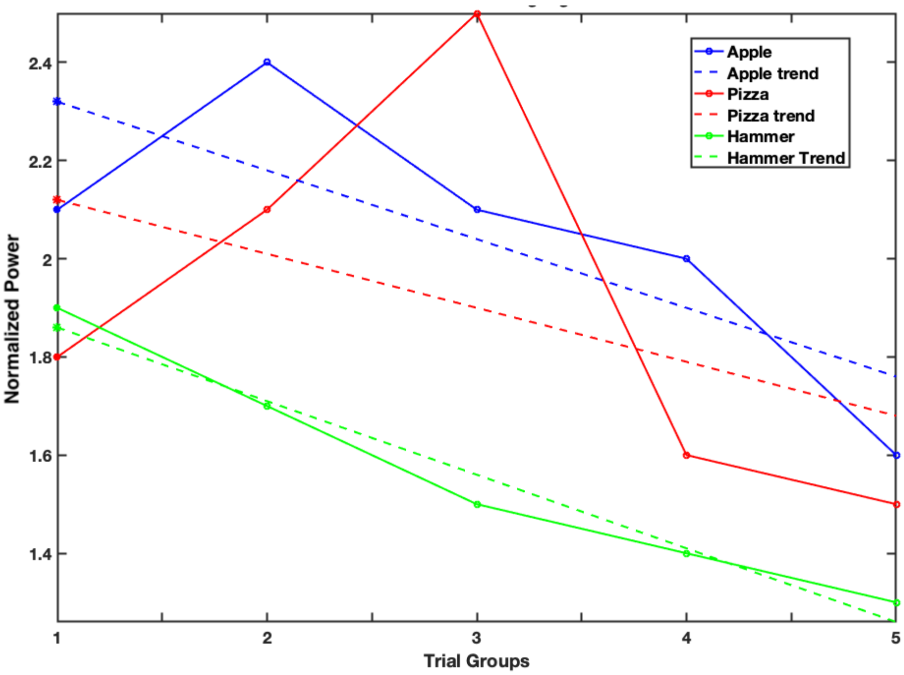


Figure 6.4: Line plot displaying the peak normalised mean power and its linear trend for different images and trial groups in the frontal theta band.

Similarly, the high-calorie food image (pizza) did not exhibit significant habituation effects in the frontal theta band. Figure 6.2a illustrates the illustrates the distribution of t-values within the cluster, Figure 6.2b presents the power distribution, and Figure 6.2c displays the time-frequency normalised power changes. While a slight downward trend is observed, no statistically significant differences were found between trial groups (p-val = 0.059). These results suggest that high-calorie food images sustain attention over repeated exposures.

Additionally, Figure 6.4 illustrates the peak amplitude and linear trends for all three image categories: apple (highlighted in blue), pizza (highlighted in red), and hammer (highlighted in green) across all trial groups. Table 6.2 provides the slope and intercept values for each image category, quantifying the rate of habituation.

The findings reveal that the non-food image exhibits the most rapid habituation among the three categories. This is reflected in the slope coefficient of -0.15, indicating a decrease of 0.15 in normalised mean power per trial group throughout the session and an intercept of 2.07.

Table 6.2: Time-frequency analysis - Habituation rate details for different images.

Image	**Slope**	**Intercept**
Apple	-0.14	2.46
Pizza	-0.11	2.23
Hammer	-0.15	2.07

For the low-calorie image, the results suggest a moderate habituation rate faster than the high-calorie image but slower than the non-food image. With a slope coefficient of -0.14, indicating a decrease of 0.14 in normalised mean power per trial group throughout the session and an intercept of 2.46 .

In contrast, the high-calorie image exhibited the slowest habituation rate among the three categories. The slope coefficient of -0.11 reflects a minimal reduction in normalised mean power by 0.11 per trial group and an intercept of 2.23. This suggests that high-calorie food stimuli maintain attentional and cognitive engagement longer than low-calorie and non-food images.

6.5 Discussion

This study is the first to explore how habituation occurs over different time windows and frequency bands within a session when the same food and non-food images are repeatedly shown. Using time-frequency analysis, the research aimed to compare brain responses (measured through processed EEG data) across different trial groups exposed to repeated presentations of food and non-food images in different frequency bands with varying energy values. This approach helped to understand how the brain adapts to repeated visual exposure to food-related stimuli over time.

Habituation effect

In the first part of the analysis, ERP responses to repeated presentations of the same image were examined to understand cognitive processes and motivational responses toward high-calorie and low-calorie images. The study also explored how repetition influences habituation over time across different frequency bands, including delta, theta, alpha, beta, and gamma. To achieve this, the 30 trials for each image were divided into five groups, and comparisons were made regarding motivation and attention across these trial groups in the time-frequency domain. The results revealed a significant habituation effect in the frontal theta band (4–7 Hz) within the 110 ms–330 ms time window for the non-food image (hammer), showing a clear decrease in power with repeated exposures (refer to Figure 6.3). However, no significant habituation effects were observed for high-calorie (pizza) or low-calorie (apple) images in any frequency band, suggesting that food images sustain attentional engagement and do not follow the same neural adaptation pattern as non-food stimuli (refer Figures 6.1 (representing apple) and 6.2 (representing pizza)).

Theta oscillations in the frontal cortex are widely recognised for their role in cognitive control, attentional modulation, and working memory (Cavanagh and Frank 2014). The observed reduction in frontal theta power suggests that non-food stimuli elicit rapid disengagement of attentional and cognitive resources, leading to faster neural adaptation. This aligns with previous research indicating that frontal theta activity is strongly associated with sustained attention and stimulus evaluation, particularly in tasks that require active engagement and decision-making (Mitchell et al. 2008). The rapid decline in theta power suggests that the brain processes non-food stimuli as less salient or motivationally relevant, resulting in faster habituation.

Previous studies have demonstrated that frontal theta oscillations are crucial for processing novel and salient stimuli, particularly in situations requiring goal-directed attention (Cohen and Donner 2013). However, the brain quickly reduces attentional allocation when stimuli lack motivational significance, such as non-food images in the current study. This is supported by research on visual habituation, where decreased frontal theta activity corresponds with diminished attentional engagement over time (Klimesch 1999). This research investigates the effects of go/no-go training on frontal midline theta oscillations in response to food stimuli, highlighting the role of cognitive control in modulating responses to such cues (van de Vijver et al. 2018).

The findings also align with studies on stimulus-driven vs goal-directed attention, which suggest that theta-band oscillations are critical for maintaining attention to stimuli deemed relevant for behaviour (Başar, Erol, Schürmann, Martin and Sakowitz, Oliver 2001). Non-food stimuli, such as the hammer image, lack inherent affective or reward-related significance, leading to faster habituation as reflected by the decreasing theta-band power. In contrast, food-related stimuli activate reward-related neural pathways that are resistant to habituation, a phenomenon observed in studies examining food motivation and craving (Gearhardt et al. 2011). This distinction between food and non-food stimuli highlights the importance of frontal theta activity in determining attentional persistence and stimulus disengagement.

This pattern is consistent with findings from studies examining the role of frontal theta oscillations in attention and cognitive control. Research indicates that frontal theta power increases during tasks requiring heightened attention or conflict monitoring and decreases as stimuli become predictable or less relevant (Cohen and Donner

2013). The rapid decline in frontal theta activity in response to the non-food image suggests that participants allocated fewer cognitive resources to process these stimuli over time, reflecting efficient neural adaptation mechanisms.

Moreover, the decrease in frontal theta power may indicate a reduction in the need for top-down cognitive control as the non-food stimulus becomes familiar. This aligns with the dual-process theory of habituation, which posits that repeated exposure to a stimulus leads to decreased neural responsiveness due to diminished novelty and reduced attentional demands (Groves and Thompson 1970). The non-food image, lacking inherent motivational significance, likely prompted a swift decline in attentional engagement, as evidenced by the reduction in frontal theta activity.

Habituation Rate

The results further demonstrate distinct habituation rates for high-calorie, low-calorie, and non-food stimuli, reinforcing the idea that the brain adapts differently to repeated exposures depending on the motivational and cognitive salience of the stimuli. The non-food image exhibited the fastest habituation rate, followed by the low-calorie image, while the high-calorie image demonstrated the slowest habituation rate. These findings are consistent with neurophysiological research on food cue processing, where high-energy food stimuli sustain attention longer than other types of visual stimuli (Schmidt et al. 2018). The slower habituation rate for high-calorie foods suggests that these images maintain their salience, possibly due to their rewarding nature, which aligns with findings in obesity research that show enhanced neural responsiveness to energy-dense foods (Imperatori et al. 2015a).

The varying rates of habituation observed across stimulus categories in our study provide insight into the neural mechanisms underlying attentional allocation. The non-food image exhibited the fastest habituation rate, as indicated by a significant reduction in normalised mean power with a slope coefficient of -0.15. This suggests that stimuli lacking inherent motivational or emotional significance are processed more efficiently, leading to quicker neural adaptation.

In contrast, the low-calorie food image demonstrated a moderate habituation rate, with a slope coefficient of -0.14. This indicates a decrease in neural engagement over time, albeit at a slower rate than the non-food image. The sustained attention to the low-calorie food image may reflect its moderate motivational relevance, which maintains cognitive engagement longer than non-food stimuli but not as persistently as high-calorie food images.

The high-calorie food image showed the slowest habituation rate, with a slope coefficient of -0.11, indicating a minimal reduction in normalised mean power across trials. This finding aligns with research suggesting that high-calorie foods possess greater motivational salience, potentially due to evolutionary factors that prioritise energy-dense foods (Stoeckel et al. 2008). The prolonged neural engagement with high-calorie food images may reflect sustained attentional and reward-related processing, contributing to their resistance to habituation.

These differential habituation rates underscore the influence of stimulus salience and motivational relevance on neural adaptation processes. The rapid habituation to non-food stimuli suggests efficient neural mechanisms for filtering out irrelevant information, while the sustained engagement with high-calorie food images highlights the role of inherent reward value in modulating attention and cognitive control. Understanding these dynamics is crucial for developing interventions targeting maladaptive attentional biases, particularly in the context of eating behaviours and disorders.

6.6 Conclusion

In conclusion, this study provides valuable insights into the neural mechanisms underlying habituation to food and non-food stimuli by analysing frontal theta band activity and habituation rates. The findings indicate that non-food images exhibit the fastest rate of habituation, suggesting that the brain rapidly adapts to stimuli lacking motivational significance. In contrast, high-calorie food images sustain attentional and cognitive engagement for a longer duration, as evidenced by the slowest habituation rate and persistent frontal theta activity. This prolonged neural response to high-calorie foods aligns with previous research suggesting that energy-dense foods activate reward-related brain regions, potentially reinforcing food cravings and influencing eating behaviours. The results also emphasise the role of frontal theta oscillations in attentional control, particularly in response to non-food stimuli, where rapid habituation may indicate efficient neural adaptation.

The differential habituation rates observed in this study highlight the significance of food-related attentional biases in regulating eating behaviours. High-calorie foods may continue to engage cognitive and reward-processing circuits even with repeated exposure, reinforcing their salience and potentially contributing to overconsumption in individuals prone to obesity. These findings underscore the importance of developing targeted interventions that address attentional biases and reduce sustained engagement with high-calorie food stimuli. Understanding these mechanisms can inform strategies to promote healthier eating habits by modifying how individuals respond to food cues over time.

Compared to the time-domain ERP analysis in Chapter 5, which focused on stimulus-locked potentials like P200 in parietal regions, the time-frequency analysis presented in this chapter uncovered different patterns of habituation. Specifically, only the non-food image (hammer) showed a significant reduction in frontal theta power over repeated exposures, while food-related stimuli (apple and pizza) did not show such changes. This divergence suggests that while ERP and spectral analyses both capture habituation, they may reflect distinct cognitive mechanisms, time-domain ERPs indexing early sensory and attentional responses, and time-frequency dynamics capturing sustained cognitive control and engagement.

A novel technical contribution of this chapter is the identification of frontal theta power as a neural marker of habituation using a cluster-based permutation approach on time-frequency data. This method enabled the detection of trial-wise power reductions without relying on fixed windows or Gaussian assumptions. Moreover, whole-brain p-value mapping confirmed that only the frontal theta band consistently reached significance across conditions, justifying the focused reporting. These findings demonstrate that time-frequency analysis offers added value beyond classical ERP measures, providing new insights into the temporal and spectral dynamics of cognitive adaptation to repeated food and non-food stimuli.

In the next chapter, we will explore dishabituation towards repeated visual stimuli in the time domain, examining how neural responses recover when a novel stimulus follows repeated exposure to high-calorie, low-calorie, and non-food images. This analysis will provide insights into the dynamics of attentional engagement and the mechanisms underlying habituation and dishabituation in food-related visual processing.

Chapter 7

Dishabituation Towards Repeated Visual Stimuli

7.1 Chapter Outline

This chapter explores the differences in attentional and motivational responses, as measured by ERP, to the repeated presentation of high-calorie, low-calorie, and non-food images, particularly when novel visual stimuli are introduced between habituation trials. The study aims to determine how these responses vary with the introduction of new stimuli and to assess the reliability of the habituation and dishabituation processes for different image types. Importantly, this investigation ensures that observed habituation effects are not merely due to mental fatigue but rather reflect genuine neural adaptation. Specifically, it examines whether the introduction of novel stimuli disrupts the habituation process, leading to measurable dishabituation, or if the observed effects are simply a response to stimulus novelty.

7.2 Introduction

Habituation, a fundamental learning process characterised by a reduced response to a repeated stimulus, is observed across a wide array of organisms, from single-celled entities to primates. This mechanism enables organisms to instinctively ignore irrelevant information. Unlike other processes that result in response reduction, such as fatigue or refractory periods, habituation is unique because it can be interrupted by a change in the stimulus (Thompson et al. 2021). According to Thompson and Spencer (Thompson and Spencer 1966), and more recently, Rankin et al. (Rankin et al. 2009), for a response decrement to be accurately classified as habituation, several criteria must be met: response recovery, an increased reaction to a novel stimulus (referred to as a deviant), and dishabituation, which is a renewed increase in response to the previously habituated stimulus following the introduction of a deviant.

Early studies identified several hallmark features of habituation, including its effects on other stimuli (stimulus generalisation), the spontaneous recovery of the habituated response after a period of rest, and the revival of the habituated response when a novel stimulus is presented (dishabituation) (Rankin et al. 2009; Thompson and Spencer 1966). Dishabituation is considered nearly as pervasive as habituation itself (Thompson and Spencer 1966), implying that any response capable of habituation can also undergo dishabituation (Hinde 1970). Dishabituation is defined as the restoration of a habituated response following the introduction of a strong, distinct, or additional stimulus (Groves and Thompson 1970). This typically occurs when a new stimulus briefly interrupts the habituation process, resulting in a renewed response to the original stimulus. However, the response does not need to revert entirely to its initial pre-habituation levels (Wiel and Weeks 1996). Instead, dishabituation is demonstrated when response levels match or exceed those immediately prior to the introduction of the dishabituating stimulus, provided that the response was diminishing before the novel stimulus was presented (Petrinovich and Widaman 1984). In the scientific literature, dishabituation refers both to the process of response recovery and to the outcome, encompassing the novel stimulus that triggers this recovery as well as the reinstated response.

Dishabituation is essential as it provides a key method to confirm that habituation has indeed occurred. It is frequently used to determine whether a reduction in response is genuinely due to habituation rather than other factors like fatigue or satiation (Thompson and Spencer 1966). However, the literature on dishabituation is fraught with challenges, including confusion with other features of habituation, inconsistent demonstration across various experimental conditions, and limited investigation within the context of operant conditioning.

One of the common confusions in the literature is between dishabituation and stimulus specificity, another feature of habituation (Petrinovich and Widaman 1984). Both involve the introduction of a novel stimulus and lead to a recovery in response, but they are controlled by different stimuli. For an increase in response to be classified as dishabituation, it must occur after the novel stimulus is removed and the original stimulus is reintroduced (McSweeney 2004). On the other hand, stimulus specificity refers to an increase in response when the novel stimulus itself is presented (Thompson et al. 1973), and this increase is not necessarily an instance of dishabituation.

For instance, if a bright light is introduced between tone presentations and a person turns their attention to the light, this indicates stimulus specificity. Dishabituation, however, would be shown if the person starts responding to the tone again once the tone presentations resume. Clear procedural distinctions are crucial for accurately describing these phenomena, but confusion between these concepts has led to studies mistakenly identifying stimulus specificity as dishabituation (Rankin et al. 2009).

Temple et al. (Temple et al. 2006) emphasised the importance of habituation and dishabituation in the context of food intake. They suggested that any stimulus that shifts attention can interrupt habituation and consequently affect eating behaviours, whether the stimulus is related to food or involves audiovisual cues. Signs of dishabituation during eating include increased food consumption and renewed motivation to eat, which can be observed through both salivary responses to food and a heightened interest in eating.

In studies on food intake, dishabituating stimuli can be either food-related or non-food-related. For instance, Epstein et al. explored salivary habituation by repeatedly presenting lemon or lime juice, using the alternate juice as the dishabituating stimulus. Initially, salivation increased slightly, then gradually decreased over 10 trials. However, when the dishabituating juice was introduced on trial 11, salivation increased, and by trial 12, there was a recovery in response to the original habituating stimulus (Epstein et al. 1992). In contrast, a control condition with repeated lemon juice showed a consistent decline in salivation across all trials.

A range of experimental findings highlights the impact of habituation and dishabituation on eating behaviour. Research has demonstrated that humans tend to habituate to repeated food cues, but their responses can recover when exposed to a new food cue. This pattern is evident in studies focused on salivary habituation and motivational responses to food (Epstein and Paluch 1997; Epstein et al. 1992, 2003; Temple et al. 2006). Additionally, food intake often increases when individuals are distracted by activities such as watching TV or engaging with other environmental stimuli (Brunstrom and Mitchell 2006; Stroebele and de Castro 2006; Bellisle and

Dalix 2001; Bellisle, Dalix and Slama 2004). Moreover, introducing pauses during a meal can lead to greater overall consumption compared to continuous eating of the same food (Yeomans et al. 1997). Renewing sensory stimulation for a particular food during intake, such as by adding seasoning, can also boost consumption, likely due to the disruption of habituation (Brondel et al. 2009).

Since habituation in the parietal region has already been established (refer to chapter 5), this study focuses on overall habituation and dishabituation, particularly response recovery after a novel stimulus. The primary objective was to investigate how attention and motivational responses, measured through ERP, vary with repeated presentations of high-calorie, low-calorie, and non-food images and whether these responses show a habituation/dishabituation process within the session. It was hypothesised that food images, especially high-calorie ones, would elicit stronger motivational responses than non-food images. Additionally, this study assessed whether novel stimuli induce dishabituation, expecting a recovery in neural responses for both food and non-food images. By analysing ERP response recovery post-distractor, this study provides insights into neural mechanisms underlying attentional shifts in food-related decision-making.

7.3 Data Extraction and Analysis Method

This study aimed to investigate the dynamic neural mechanisms underlying both habituation and dishabituation processes using an adapted experimental design. As outlined in Chapter 3, trials from both the habituation and dishabituation phases were analysed, with a specific focus on how the brain responds to novel stimuli following repeated exposure.

This analysis draws on data from 12 participants, with one excluded due to excessive EEG noise. Each participant completed nine sessions featuring high-calorie, low-calorie, or non-food images. From each session, 40 trials were analysed—spanning habituation, distraction, and dishabituation phases—resulting in a balanced dataset of 360 trials per participant.

To capture how neural responses evolved across these phases, the trials were organised into eight sequential bins of five trials each. This temporal segmentation enabled a nuanced exploration of dynamic brain activity over the course of repeated and novel stimulus exposure. Full details of the trial structure are provided in Chapter 3, Section 3.2.

EEG data were preprocessed and analysed to extract event-related potentials (ERPs) for each trial condition. Data were segmented from -200 ms pre-stimulus to 1000 ms post-stimulus and baseline-corrected using the pre-stimulus interval. ERP waveforms were averaged within condition and subjected to non-parametric cluster-based permutation tests to assess statistical differences across phases and stimulus types.

To investigate both habituation and dishabituation processes, ERP responses were analysed across a structured sequence of trial groups. The first five trial groups (1–5) were used to examine the within-session habituation effects of repeated stimuli. Trial groups 6–8, which followed the introduction of a novel stimulus, were analysed to assess dishabituation, i.e., the recovery of neural responses due to stimulus novelty. This approach allowed for a systematic examination of both the reduction in ERP amplitude due to repetition and the extent to which a novel stimulus could re-engage attention. These analyses were conducted separately for each image category (high-calorie, low-calorie, and non-food) to explore whether dishabituation effects vary across stimulus types.

Statistical Analysis

Significant main effects and interactions were analysed to investigate ERP responses to three types of images during the initial 1000 ms after cue onset. Habituation and dishabituation effects within sessions for the three image categories were examined using mass-univariate analysis with a cluster-based statistical approach. The analysis employed non-parametric cluster-based permutation tests with Monte Carlo randomisation, using EEGLAB and FieldTrip plugins (Maris and Oostenveld 2007). This method was guided by FieldTrip documentation (Oostenveld et al. 2011) and related studies (Rodriguez-Larios et al. 2020; Quiroga-Martinez et al. 2020). A non-parametric approach was chosen to avoid assumptions about normal distribution, reflecting changes in neural activity across contiguous time points.

For each subject-specific trial group, random permutation testing was conducted 1,000 times to generate a reference distribution for the mean cluster magnitude. The hypothesised habituation and dishabituation effects were assessed by testing whether neural responses followed a decreasing trend across trial groups 1 to 6, indicating habituation (i.e., trial group 1 > trial group 2 > trial group 3 > trial group 4 > trial group 5 > trial group 6). Additionally, the analysis examined whether responses increased following the introduction of a distractor, confirming dishabituation (i.e., pre-distractor phase [trial group 6] <distractor phase (trial group 7) > dishabituation phase (trial group 8)). This approach enabled the evaluation of how neural activity changed with repeated exposure and whether a novel stimulus influenced response recovery. Specifically, the analysis tested whether neural responses in the pre-distractor phase were significantly lower than in both the distractor and dishabituation phases. The t-values for this analysis were computed using the *ft_statfun_depsamplesregrT* function in FieldTrip. Clusters were deemed significant if their magnitudes fell outside the 2.5th and 97.5th percentiles, corresponding to a 5% significance level in a two-tailed test.

To further examine the dishabituation effect separately, a cluster-based ANOVA test was performed with the conditions: pre-distractor phase (trial group 6) < distractor phase (trial group 7) and pre-distractor phase (trial group 6) < dishabituation phase (trial group 8). This analysis determined whether neural responses in the pre-distractor phase were significantly lower than in both the distractor and dishabituation phases, confirming the occurrence of dishabituation. The test statistic (t-value) was obtained using the *ft_statfun_depsamplesT* function. Clusters in the observed data were considered significant if their magnitude exceeded the 95th percentile threshold, following a right-tailed test with a 5% significance level. This additional analysis ensured that the observed dishabituation effects reflected meaningful neural response patterns rather than random fluctuations.

7.4 Results

Significant main effects and interactions for ERP responses were analysed across various time windows and regions of interest (ROIs), including the parietal (P7, P3, Pz, P4, P8), frontal (Fp1, Fp2, F7, F3, Fz, F4, F8), central (C3, Cz, C4), temporal (T7, T8), and occipital (O1, Oz, O2) regions. A cluster-based permutation test was conducted to assess habituation and dishabituation effects across trial groups. The results revealed a significant difference in ERP responses for non-food (hammer) images but not for low-calorie (apple) or high-calorie (pizza) images (refer to Figure 7.1). Among the three stimuli, only hammer images showed significant habituation and dishabituation effects, with the strongest differences observed in the parietal region, justifying its selection for focused reporting. A complete summary of p-values across brain regions and stimuli is presented in Table 7.1.

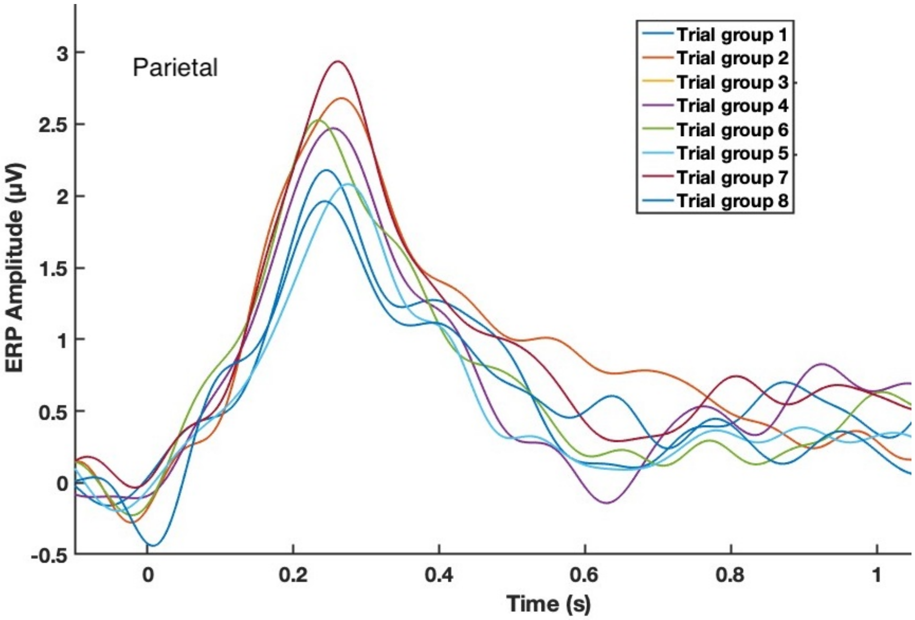
Table 7.1: ERP p-values across ROIs for each image category

ROI	**Apple (p-val)**	**Pizza (p-val)**	**Hammer (p-val)**
Parietal	0.058	0.090	**0.001**
Frontal	0.134	0.163	0.112
Central	0.215	0.229	0.179
Temporal	0.186	0.193	0.148
Occipital	0.207	0.218	0.191

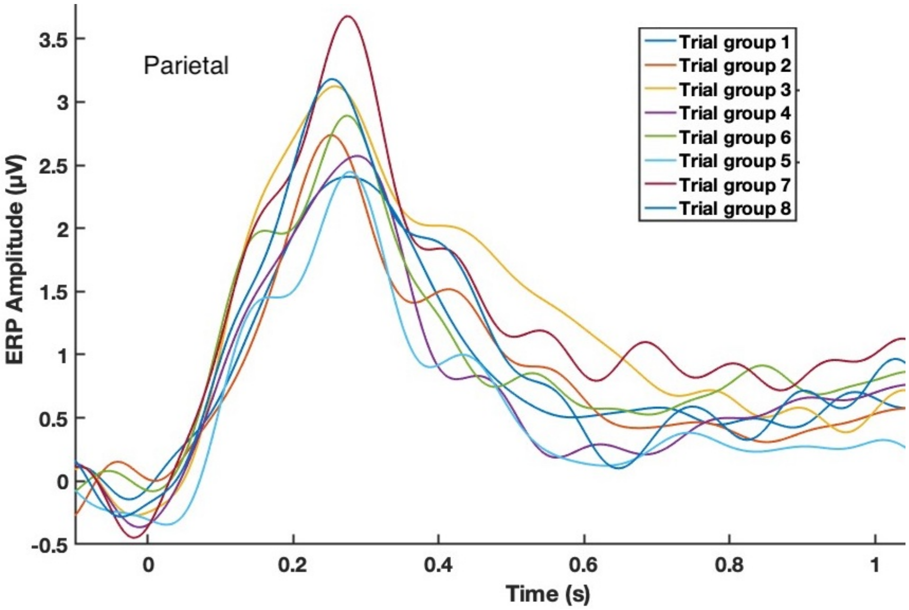
Figure 7.1c illustrates the mean ERP amplitudes across trial groups for the hammer image in the parietal region. A statistically significant main effect was observed within the 160 ms - 290 ms time window (p-val= 0.001), highlighted in grey, indicating a clear habituation pattern followed by a response recovery during dishabituation.

Figures 7.1a and 7.1b display the mean ERP amplitudes across trial groups for low-calorie and high-calorie images, respectively, over the parietal region. However, these images did not show significant overall habituation and dishabituation effects, with p-values of 0.058 for apple and 0.09 for pizza, suggesting a more sustained attentional response to food images.

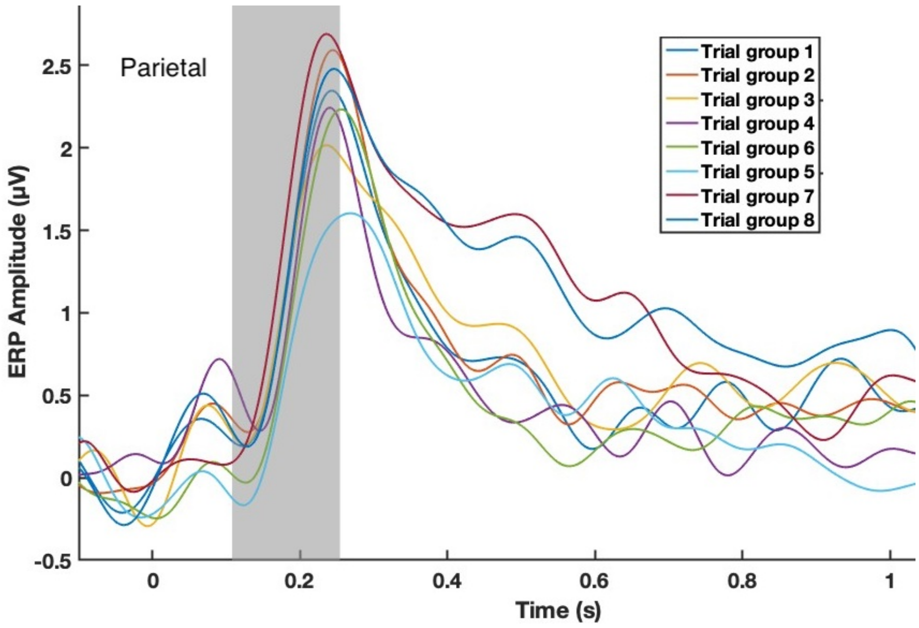
Since the apple and pizza images did not show overall significance in the habituation phase, further analysis was conducted to examine potential effects in the dishabituation phase. Specifically, significant main effects and interactions for ERP responses were assessed across various time windows in the parietal region using a cluster-based ANOVA test. The results indicate that all image categories, high-calorie, low-calorie, and non-food, exhibited significant response recovery during the dishabituation phase ($p < 0.05$) (refer to Figure 7.2). This suggests that despite the absence of strong habituation effects for food images, the introduction of novel



(a) Apple



(b) Pizza



(c) Hammer

Figure 7.1: Figures show the mean ERP amplitudes for different images in different trial groups. Figure (a) depicts the ERP amplitude for the low-calorie image (apple) over the parietal region, with no habituation/dishabituation effect observed. Figure (b) shows the ERP amplitude for the high-calorie image (pizza), where the habituation/dishabituation effect was also absent. However, Figure (c) reveals a significant habituation/dishabituation effect for the non-food image (hammer) in the same parietal region.

stimuli was sufficient to elicit a neural response recovery across all conditions.

7.5 Discussion

This study is the first to explore how habituation and dishabituation affect different time windows within a session when the same food and non-food images are repeatedly shown. The aim was to compare the evoked potentials derived from processed EEG data among within-session trial groups exposed to repeated presentations of

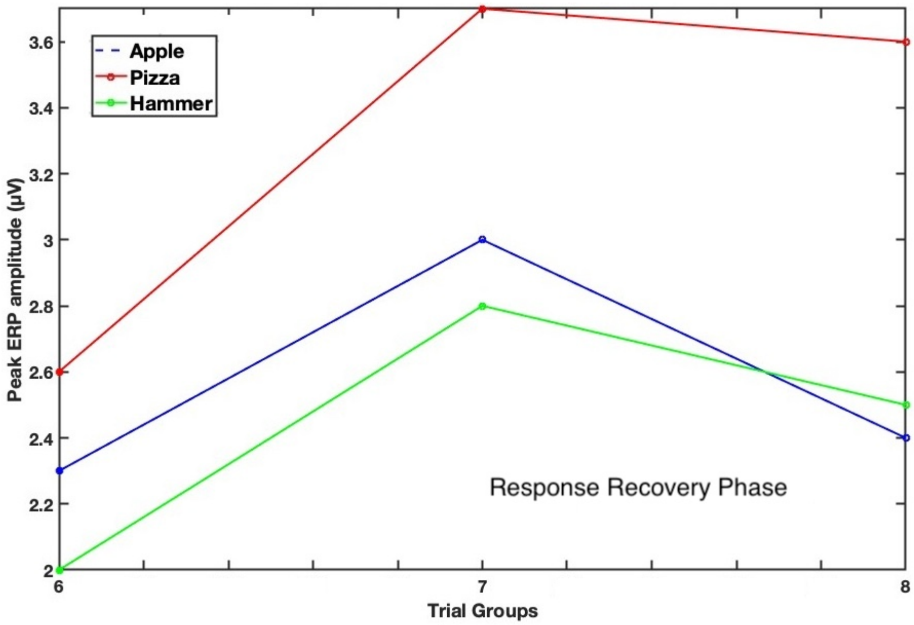


Figure 7.2: Display the peak ERP amplitude and its linear trend for different images and trial groups during the dishabituation phase, from trial groups 6 to 8.

food and non-food images with varying energy values. Initial analyses focused on ERP responses to these repeated images to assess cognitive processes and motivation related to high- and low-calorie foods and to examine how repetition influences habituation and dishabituation within each session.

The study's results generally support the idea that repeated presentations of food images may lead to habituation and dishabituation when novel stimuli are introduced. The findings confirm that habituation occurs in the parietal region, as previously discussed in Chapter 5. This study extends those findings by assessing the overall habituation/dishabituation process and evaluating response recovery following the introduction of a novel stimulus. A key objective was to determine whether food images elicit stronger motivational responses than non-food images and whether high-calorie foods generate the highest attentional engagement compared to low-calorie foods. The secondary objective was to assess whether novel stimuli would trigger dishabituation, leading to a recovery of neural responses.

The cluster-based permutation analysis confirmed that non-food images exhibited significant habituation and dishabituation effects within the parietal region, particularly within the 160 ms–290 ms time window. This suggests that food images, regardless of their caloric content, may sustain attentional engagement over repeated presentations. These ERP results align with previous research on food habituation, which observed similar patterns through salivation responses in children and adults (Epstein et al. 1992, 2003; Wisniewski et al. 1997), facial muscle responses in adults (Epstein and Paluch 1997), and motivational behaviours related to food in both adults and children (Epstein et al. 2009a; Temple et al. 2006, 2008a).

This is consistent with prior studies indicating that parietal regions play a key role in processing attentional shifts and stimulus salience (Corbetta and Shulman 2002). In contrast, the high-calorie and low-calorie food images did not demonstrate clear habituation effects. This suggests that the brain maintains an increased level of attention and motivation towards food images, possibly due to their relevance in survival and reward processing (Blechert et al. 2011; Stoeckel et al. 2009).

The lack of a significant habituation effect for food images is particularly interesting given previous studies showing that food cues elicit sustained neural engagement, especially for high-calorie options (Nijs et al. 2010b; Castellanos et al. 2009). One possible explanation for this sustained attentional engagement is that food stimuli inherently carry greater motivational salience, making them resistant to habituation. This aligns with findings from behavioural studies, which suggest that individuals are more likely to exhibit prolonged interest in high-calorie foods due to their association with pleasure and energy intake (Temple et al. 2007a; Brunstrom and Mitchell

2006). These results highlight the need for further research into the differences in attentional processing between food and non-food stimuli, particularly in individuals with varying dietary habits and weight profiles.

While habituation was not strongly evident for food images, all image categories showed significant response recovery during the dishabituation phase, suggesting that the introduction of a novel stimulus was sufficient to reinstate neural responses. This finding supports the classical definition of dishabituation, which posits that a novel stimulus can interrupt habituation and restore responsiveness (Rankin et al. 2009; Thompson and Spencer 1966). The ability of non-food images to elicit strong habituation and subsequent response recovery indicates that novelty plays a crucial role in maintaining attentional engagement. This has important implications for understanding how individuals respond to repeated exposure to food stimuli in real-world settings, such as advertisements, digital food cues, and dining environments.

The results also indicate that food images, particularly high-calorie foods, maintain prolonged attentional engagement, preventing complete habituation. This suggests that the sustained neural activity observed for food images may be attributed to their motivational significance rather than general cognitive fatigue. If mental fatigue were the primary driver of habituation, a uniform decline would be expected in neural responses across all stimuli, including non-food images. However, the observed differential habituation patterns, faster for non-food images and slower for food images, suggest that the process is stimulus-specific rather than a consequence of general fatigue or adaptation (Epstein and Paluch 1997; McSweeney 2004). This is further supported by the response recovery seen in the dishabituation phase, where ERP amplitudes increased following the introduction of a novel stimulus, demonstrating that the observed habituation was reversible and not due to participant exhaustion or neural desensitisation (Thompson and Spencer 1966).

The significant ERP differences observed in the parietal region reinforce the role of this area in modulating attentional shifts. The parietal cortex is known to be involved in the allocation of attentional resources and the processing of stimulus relevance (Posner, Petersen et al. 1990; Petersen and Posner 2012; Corbetta, Patel and Shulman 2008). The results of this study suggest that parietal activation may be crucial in tracking the habituation and dishabituation processes, particularly in response to non-food stimuli.

Another key consideration is the potential role of external factors, such as cognitive load and environmental distractions, in modulating habituation. Studies have shown that factors like television watching and multitasking can disrupt habituation, leading to increased food consumption (Temple et al. 2007a; Epstein et al. 2009a). The findings of this study suggest that while non-food stimuli follow a classical habituation pattern, food images maintain sustained neural engagement, potentially influencing eating behaviours. This may have implications for dietary interventions, as modifying exposure to food cues and introducing novel stimuli may help regulate food intake and prevent overeating.

7.6 Conclusion

Overall, this study contributes to the growing body of literature on food-related attentional biases and habituation processes. The results demonstrate that non-food stimuli undergo clear habituation and dishabituation effects, while food images maintain attentional engagement over repeated exposures. The findings reveal that non-food images exhibit significant habituation and dishabituation effects within the parietal region, particularly within the 160 ms–290 ms time window, whereas food images, regardless of caloric content, sustain attentional engagement over repeated presentations. This suggests that while non-food stimuli follow a classical habituation pattern, food images maintain prolonged neural activation, likely due to their relevance to attention and motivation. The absence of significant habituation effects for food images aligns with previous research showing that high-calorie foods elicit sustained attention and motivation due to their hedonic value.

Additionally, the response recovery observed in the dishabituation phase confirms that the reduced neural engagement seen during habituation was not due to mental fatigue but rather a dynamic neural process modulated by stimulus novelty. The significant ERP differences in the parietal region emphasise its role in tracking attentional shifts and stimulus relevance. These findings have important implications for understanding food-related attentional biases and their potential impact on eating behaviours.

In the next chapter, this investigation will be extended by analysing functional connectivity and examining how different brain regions interact during habituation processes. Using measures such as the WPLI, the study will explore patterns of neural synchronisation across key regions to determine whether functional connectivity changes in response to repeated exposure to high-calorie, low-calorie, and non-food images. This analysis will provide deeper insights into the underlying neural mechanisms of attentional engagement and how different stimuli influence inter-regional brain communication.

Chapter 8

Examining Functional Connectivity to Assess Food Habituation Through Repeated Visual Stimuli

8.1 Chapter Outline

This chapter explores the use of EEG signals as a tool to study functional connectivity and its role in food habituation through repeated visual stimuli. By applying advanced methods like the Weighted Phase Lag Index (WPLI), this pilot study investigates changes in cortical functional connectivity across different brain regions in response to low-calorie, high-calorie, and non-food images. The analysis focuses on clustering algorithms previously identified as relevant to connectivity measures, particularly those associated with WPLI (Vinck et al. 2011). This pilot study aligns with the third research objective (refer to Section 1.3) that aims to provide preliminary insights into the neural mechanisms underlying food habituation and the dynamic connectivity patterns that emerge during this process, laying the groundwork for future, more comprehensive research.

8.2 Introduction

Neuroscience seeks to understand brain communication, where multiple brain regions coordinate even in simple tasks. Even during rest, the default mode network (DMN) remains active (Buckner, Andrews-Hanna and Schacter 2008). Effective interaction between function-specific regions is essential for cognitive processes (Abrams et al. 2013). Connectivity can be assessed using neuroimaging (MRI) for anatomical connections (Rasero et al. 2017; Ercan et al. 2016) or EEG for statistical dependencies, measuring temporal coupling between spatially distant brain regions (O'Reilly, Lewis and Elsabbagh 2017).

Connectivity measures fall into functional connectivity (FC) and effective connectivity (EC). FC quantifies statistical dependence without causality, while EC detects directional influences. Based on statistical dependencies, connectivity measures are categorised into coherence-based, phase synchronisation, generalised synchronisation, and Granger causality (Niso et al. 2013). EEG-based studies have expanded our understanding of brain function in both standard and pathological conditions, revealing how factors such as age, gender, cognitive processes, and neurological disorders affect connectivity (Abrams et al. 2013; Duann et al. 2009; Huster et al. 2014; Heise et al. 2014).

In this study, FC measures were used to evaluate the statistical dependencies between neural activities across different brain regions to investigate food habituation.

FC captures temporal correlations in EEG signals, providing insight into how neural units interact during cognitive tasks. Unlike structural connectivity, which maps anatomical links, FC emphasises dynamic functional relationships without implying direct neural pathways. This method is particularly useful for understanding brain network dynamics, especially when exploring regional co-activation during cognitive tasks or external stimuli.

In EEG research, FC measures are broadly categorised into undirected and directed types. Undirected measures, such as coherence and phase-locking value (PLV), assess the degree of synchronisation between EEG signals without specifying the direction of influence (Chiarion et al. 2023). Directed measures aim to determine the directionality of interactions between brain regions. Common directed measures include Granger causality, which evaluates whether one time series can predict another, and the phase-slope index (PSI), which assesses the direction of information flow based on phase differences. These directed measures are crucial for understanding the causal relationships in neural networks, providing deeper insights into the directional flow of information within the brain.

In this study, WPLI is a directed FC measure that quantifies the consistency of phase lead or lag between EEG signals. The WPLI is particularly advantageous over other measures as it reduces the influence of volume conduction and common sources, which can artificially inflate connectivity estimates. By focusing on phase leads and lags, WPLI provides a more accurate representation of true neural interactions, making it a preferred choice in EEG studies investigating functional connectivity. This approach enhances the reliability of our findings by ensuring that the detected connections reflect genuine neural synchrony rather than artefacts.

Phase synchronisation is a fundamental concept in nonlinear dynamics and has been widely utilised in EEG-based neurophysiological research to assess functional connectivity between brain regions (Yu 2013). Functional connectivity refers to statistical dependencies between neural signals and is particularly useful in understanding neural communication during cognitive processes. Phase synchronisation occurs when the phase difference between two oscillatory signals remains constant over time, indicating a stable neural interaction.

Given two EEG signals, $X(t)$ and $Y(t)$, their respective phase time series $\phi_x(t)$ and $\phi_y(t)$ define their instantaneous phase difference as:

$$\Delta\phi_{xy}(t) = |\phi_x(t) - \phi_y(t)| <= constant \tag{3}$$

If this phase difference remains stable over time, phase synchronisation is present. However, in practical analysis, the phase difference is typically wrapped within the interval $[0, 2\pi)$ using modular arithmetic to avoid phase ambiguity:

$$\Delta\phi_{rel}(t) = \Delta\phi_{xy}(t) mod 2\pi \tag{4}$$

To compute phase synchronisation measures, the instantaneous phase of EEG signals must first be extracted. This is achieved using classical frequency domain transformation methods, such as band-pass filtering followed by the Hilbert transform, short-time Fourier transform (STFT), or continuous/discrete wavelet transform (CWT/DWT). Once the phase time series is obtained, various phase synchronisation indices can be computed to quantify the degree of neural connectivity.

Phase Synchronisation Measures

Several phase-based synchronisation indices have been developed to quantify functional connectivity, each with distinct advantages and limitations. The most widely used indices in EEG-based research include the Phase Locking Value (PLV), Phase Lag Index (PLI), and WPLI.

Phase Locking Value

The PLV measures the consistency of phase differences between two EEG signals across multiple trials or time points (Lachaux et al. 1999). It is defined as:

$$PLV_{xy} = |\frac{1}{N}\sum_{n=1}^{N} e^{i\Delta\phi_{\mathrm{rel}}(t_n)}| \tag{5}$$

Where N is the total number of time points. A higher PLV value indicates strong phase synchronisation, meaning the phase difference remains relatively stable over time. PLV has been extensively used in EEG studies on cognitive processes, sensory processing, and motor coordination (Stam, Nolte and Daffertshofer 2007). However, a key limitation of PLV is its susceptibility to volume conduction artefacts, as it does not distinguish between true neural interactions and artifactual coupling caused by common reference signals.

Phase Lag Index (PLI)

To overcome the limitations of PLV, the PLI was introduced by Stam et al. (Stam, Nolte and Daffertshofer 2007). PLI quantifies the asymmetry in the phase difference distribution, thereby reducing false connectivity estimates caused by volume conduction. It is computed as:

$$PLI = |\frac{1}{N}\sum_{n=1}^{N} \mathrm{sign}(\Delta\phi_{\mathrm{rel}}(t_n))| \tag{6}$$

PLI values range from 0 to 1, where 0 indicates no phase locking, and 1 indicates perfect phase synchronisation at a nonzero phase lag. PLI is particularly effective in detecting true neural interactions, as it eliminates instantaneous phase synchronisation that may arise from common sources. However, PLI has a discontinuity issue, as small fluctuations in phase can lead to drastic changes in connectivity estimates (Vinck et al. 2011).

Weighted Phase Lag Index (WPLI)

To address the limitations of PLI, the WPLI was introduced by Vinck et al. (Vinck et al. 2011). Unlike PLI, which relies on the sign of the phase difference, WPLI weights the phase differences using the magnitude of the imaginary component of the cross-spectrum, making it more robust to low-magnitude noise. WPLI is calculated as:

$$WPLI = \frac{|\langle |I(S)| \mathrm{sign}(I(S)) \rangle|}{\langle |I(S)| \rangle} \tag{7}$$

Where, S denotes the cross-spectrum between two EEG signals, computed as $S = X(f) \cdot Y(f)$, where $X(f)$ and $Y(f)$ are the Fourier transforms of the signals. The term $I(S)$ refers to the imaginary part of the cross-spectrum, which reflects phase differences between signals and is used in WPLI to assess true connectivity while minimising the effects of volume conduction.

WPLI has two primary advantages over other measures:

- Reduced sensitivity to volume conduction – By ignoring zero-phase lag interactions, WPLI minimises the effects of common sources, making it a more reliable indicator of true neural connectivity.

- Higher statistical power – WPLI provides greater sensitivity in detecting connectivity changes, making it particularly useful in clinical and cognitive neuroscience studies (Vinck et al. 2011).

Existing neurophysiological research has demonstrated the utility of WPLI in various contexts. For instance, a study on overweight and obese patients with food addiction utilised EEG functional connectivity measures, including WPLI, to assess neural network alterations. The findings indicated modifications in EEG power spectra and functional connectivity patterns, suggesting that food addiction shares neurophysiological correlates with other forms of substance-related and addictive disorders (Imperatori et al. 2015b).

Another study investigated food-induced brain activity in children with overweight or obesity using EEG frequency band analysis. The results demonstrated elevated beta band activity in response to high-calorie food stimuli, indicating increased attentional processing towards these cues. This heightened neural reactivity may contribute to overeating behaviours observed in this population (Kösling et al. 2022).

Furthermore, research examining neuropsychological and neurophysiological indicators of impulsivity in children with overweight and obesity found alterations in EEG resting-state activity. Specifically, increased frontal beta-band activity was observed, which may reflect heightened impulsivity and reduced inhibitory control in these individuals. These findings underscore the importance of assessing functional connectivity measures, such as WPLI, to better understand the neural mechanisms underlying obesity and related eating behaviours (Schmidt et al. 2018).

This pilot study aims to explore the dynamic neural mechanisms underlying within-session habituation to repeated high-calorie, low-calorie, and non-food visual stimuli. It specifically examines inter-regional brain connectivity during this process, focusing on patterns of functional connectivity using WPLI measures. By analysing phase synchronisation between different brain regions, this study seeks to provide insights into how neural networks adapt to repeated exposure to food and non-food stimuli, shedding light on the mechanisms of habituation.

8.3 Data Extraction and Analysis Method

This analysis focused on the neural dynamics of habituation using functional connectivity in the frequency domain. Building upon the experimental design outlined in Chapter 3, EEG data from trials 1 to 30 of each session were used, as these represent the habituation phase across both habituation and dishabituation groups.

To capture temporal changes in brain connectivity during repeated exposure, the 30 trials per session were divided into five sequential trial groups of six trials each. This structure enabled the investigation of evolving connectivity patterns in response to repeated stimuli across three image categories. The trial grouping is summarised in Chapter 3 under Section 3.2.

Frequency analysis was conducted using the Fourier method (*mtmfft*) with a Hanning taper. This method was chosen for its ability to minimise spectral leakage and enhance the precision of frequency estimates, which is crucial for accurately characterising neural oscillatory patterns associated with habituation. The analysis focused on key frequency bands: Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–14 Hz), Beta (15–30 Hz) and Gamma (30-60 Hz), which are linked to different cognitive and attentional processes. These frequency bands provided a framework for exploring how repeated exposure to food and non-food stimuli modulates functional connectivity in the brain.

Functional connectivity analysis was performed using FieldTrip's *ft_connectivityanalysis* function with the *wPLI_debiased* method, which quantifies the consistency of phase differences between neural signals while mitigating the effects of volume conduction and sample size bias. This approach provided a robust measure of genuine neural interactions. The analysis specifically focused on midline EEG channels (Fz, Cz, Pz, Oz), examining connectivity between channel pairs (e.g., Fz-Cz, Fz-Pz, Fz-Oz, Cz-Pz, Cz-Oz, Pz-Oz). These regions are critical for understanding cognitive and attentional mechanisms, as they play a key role in the neural processing of visual stimuli.

Statistical Analysis

Statistical analyses were conducted to examine habituation effects and functional connectivity changes across trial groups (T1–T5) and image categories (high-calorie, low-calorie, and non-food) with a focus on midline EEG channels (Fz, Cz, Pz, Oz). These channels were analysed in combinations (Fz-Cz, Fz-Pz, Fz-Oz, Cz-Pz, Cz-Oz, Pz-Oz) to explore connectivity changes between key regions associated with sensory processing, attentional regulation, and cognitive integration. The analysis covered multiple frequency bands, including Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–14 Hz), Beta (15–30 Hz) and Gamma (30-60 Hz), each linked to distinct neural processes.

A repeated-measures Friedman test, a non-parametric alternative to repeated-measures ANOVA, was used to evaluate overall differences in functional connectivity across the five trial groups. This test was chosen as it does not assume the normality of the data, making it well-suited for EEG-derived connectivity measures, which often exhibit non-normal distributions. The Friedman test provided a global assessment of whether significant differences existed in functional connectivity across trial groups, indicating the presence of habituation effects.

To further investigate specific changes between trial groups and gain a more detailed understanding of the habituation process, pairwise comparisons were conducted using Wilcoxon signed-rank tests. These tests examined connectivity changes between consecutive trial groups (T1 $>$ T2, T2 $>$ T3, T3 $>$ T4, T4 $>$ T5). Bonferroni correction was applied to control for multiple comparisons, setting the significance threshold at $p - val < 0.0125$ (0.05/4). By focusing on consecutive trial group comparisons, the analysis captured the progression of habituation and identified when significant reductions in connectivity occurred.

This integrated approach provided a comprehensive analysis of the neural dynamics underlying habituation. The Friedman test identified whether significant overall differences existed between trial groups, while the Wilcoxon signed-rank test pinpointed specific transitions contributing to the observed effects.

The statistical analysis began with data preparation, where WPLI values were extracted as measures of functional connectivity, representing the strength of phase consistency between specific channel pairs (e.g., Fz-Cz, Fz-Pz, etc.) in different frequency bands. These values were calculated for each participant, trial group, frequency band, and image category, providing a detailed dataset for connectivity analysis. Additionally, condition labels were created as numeric identifiers for the trial groups, ensuring each WPLI value was linked to its corresponding trial group (T1, T2, T3, T4, or T5). Lastly, the channel pair combinations were defined for the midline EEG channels (Fz, Cz, Pz, Oz), allowing the test to evaluate connectivity across these key regions.

The Friedman test was applied independently to each channel pair, image category, and frequency band. For example, the test was first conducted for the high-calorie image category with the Fz-Cz channel pair in the theta band, then repeated for other channel pairs, image types, and frequency bands. This stepwise approach enabled a granular analysis, uncovering specific connectivity patterns and differences between trial groups for various stimuli.

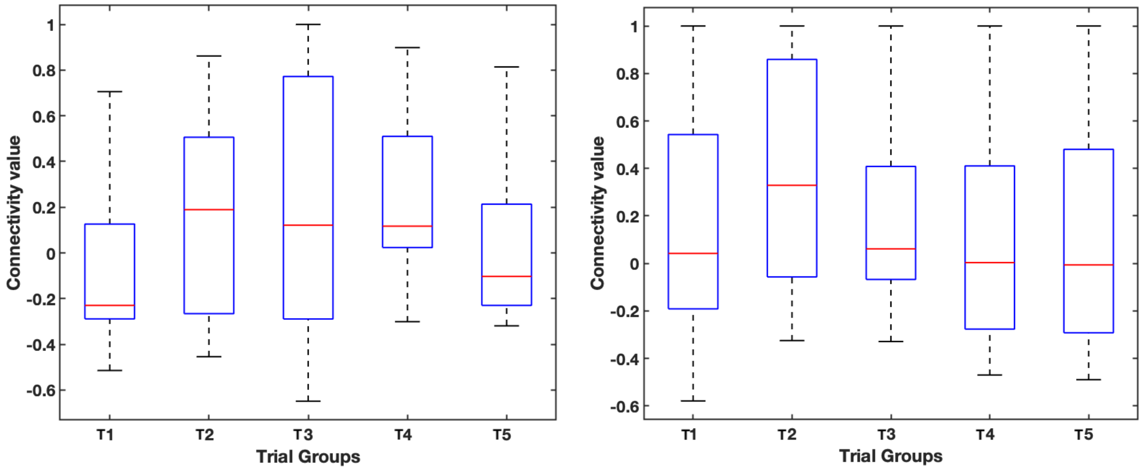
After the Friedman test, dependent-sample Wilcoxon signed-rank tests were conducted between consecutive trial groups (e.g., T1 vs. T2, T2 vs. T3). These tests examined connectivity changes between specific trial groups and provided detailed insights into the temporal progression of habituation.

8.4 Results

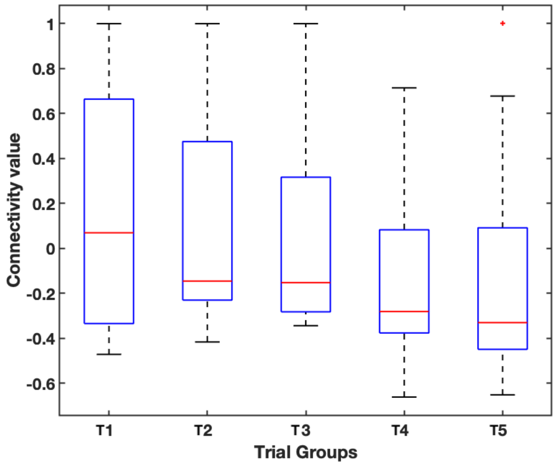
The repeated-measures Friedman test was conducted to analyse differences in functional connectivity (WPLI values) across the trial groups (T1–T5) for the three image categories: apple (low-calorie), pizza (high-calorie), and hammer (non-food) and different frequency bands. Figure 8.1 refers to the boxplot of functional connectivity values (WPLI) across trial groups (T1, T2, T3, T4, and T5) in the theta band for different image categories.

The result revealed that significant differences were observed in the theta band, with overall differences found for the low-calorie apple image and non-food hammer image but not for the high-calorie pizza image. The pairwise comparison between consecutive trial groups (T1/T2, T2/T3, T3/T4, T4/T5) revealed that the habituation effect was present for non-food hammer images in the frontal (Fz) and parietal (Pz) brain regions in the theta band, but not for the low-calorie apple or high-calorie pizza image. Figures 8.2, 8.3 and 8.4 refer to the connectivity matrix for different trial groups across midline channels (Fz, Cz, Pz and Oz) combinations in the theta band.

For the apple image, the Friedman test yielded p-val = 0.0160, indicating a

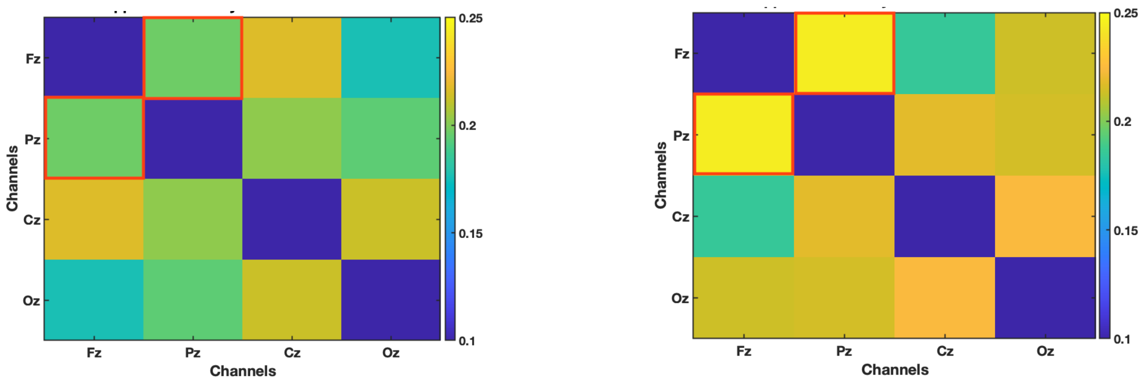


(a) Apple (b) Pizza

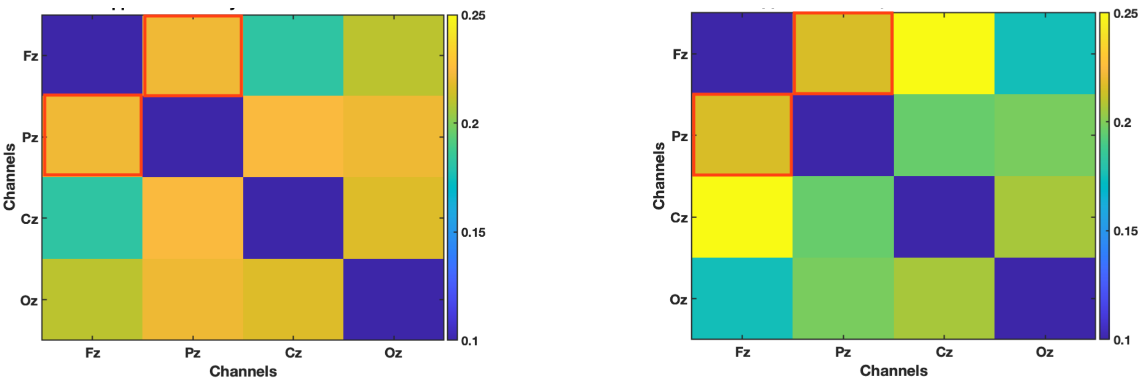


(c) Hammer

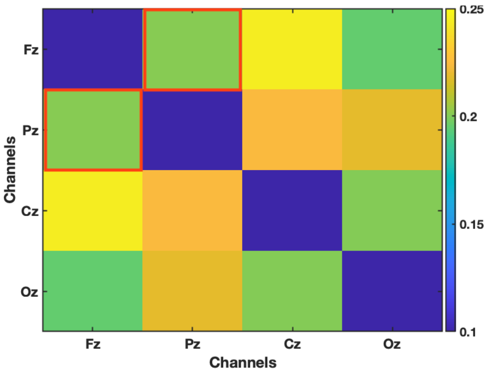
Figure 8.1: Boxplot of functional connectivity values (WPLI) across trial groups (T1, T2, T3, T4 and T5) in theta band for different image categories



(a) Trial Group 1 (b) Trial Group 2

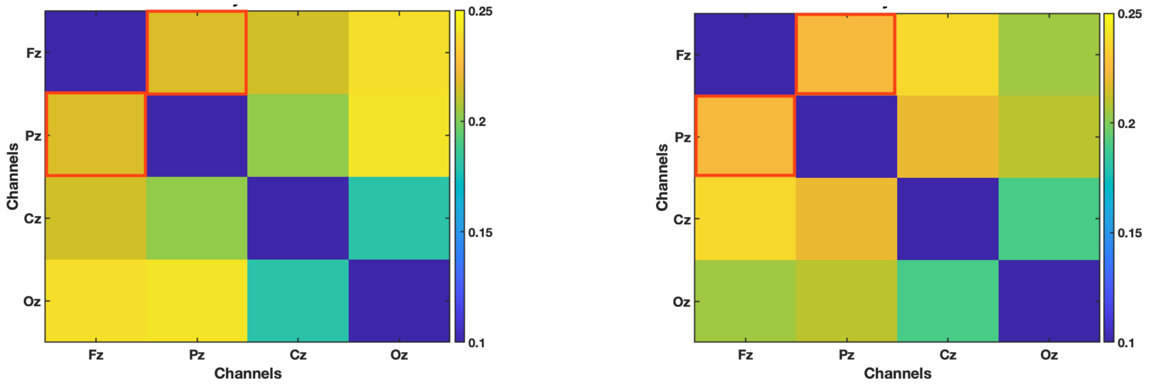


(c) Trial Group 3 (d) Trial Group 4



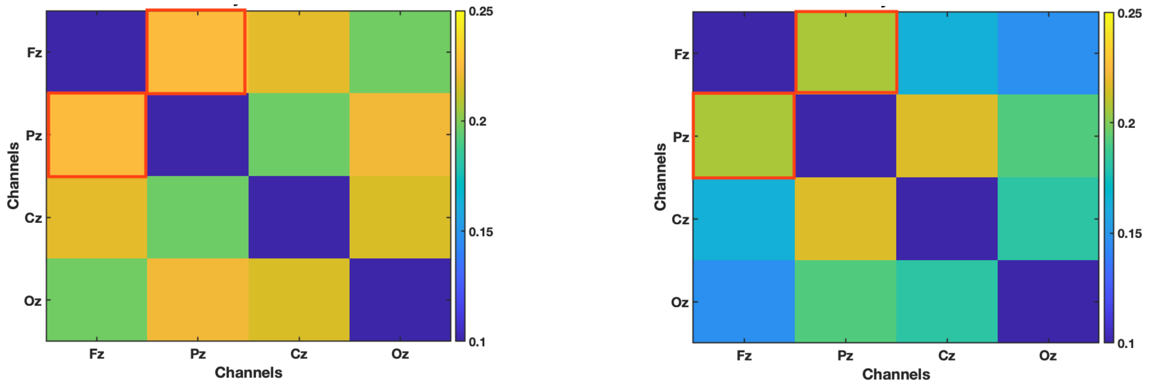
(e) Trial Group 5

Figure 8.2: Apple - Connectivity matrices for trial groups across midline channel (Fz, Cz, Pz, and Oz) combinations in theta band



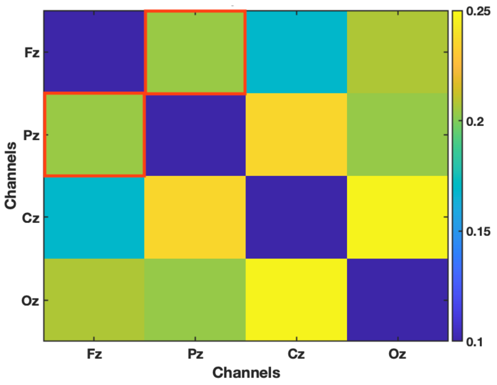
(a) Trial Group 1

(b) Trial Group 2



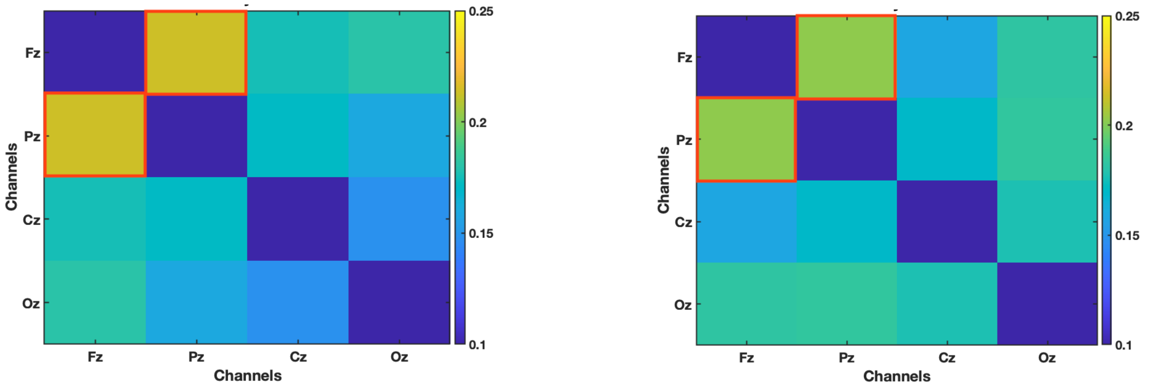
(c) Trial Group 3

(d) Trial Group 4



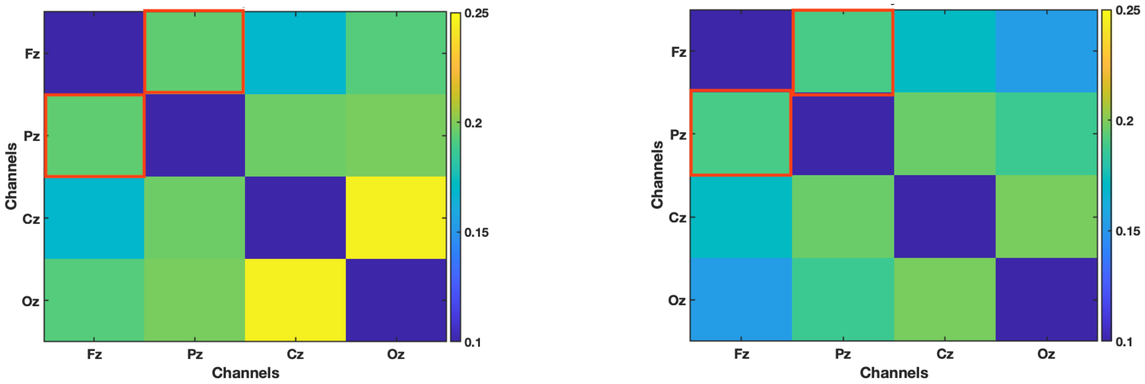
(e) Trial Group 5

Figure 8.3: Pizza - Connectivity matrices for trial groups across midline channel (Fz, Cz, Pz, and Oz) combinations in theta band



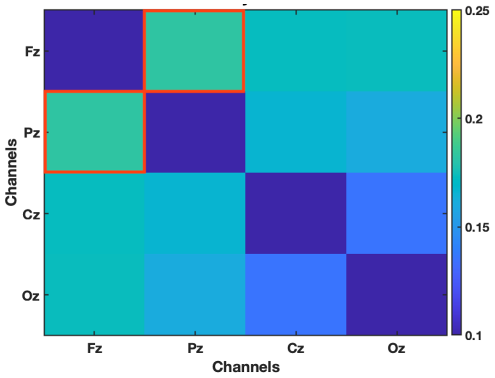
(a) Trial Group 1

(b) Trial Group 2



(c) Trial Group 3

(d) Trial Group 4



(e) Trial Group 5

Figure 8.4: Hammer - Connectivity matrices for trial groups across midline channel (Fz, Cz, Pz, and Oz) combinations in theta band

Table 8.1: Functional Connectivity - Pairwise comparison between consecutive trial groups

Compare Trial Groups (p-Value)	**Apple**	**Pizza**	**Hammer**
Trial Group 1 /Trial Group 2	0.626	0.774	**0.0012**
Trial Group 2 /Trial Group 3	0.250	0.323	**0.0094**
Trial Group 3 /Trial Group 4	0.987	0.314	**0.0104**
Trial Group 4 /Trial Group 5	0.276	0.997	**0.0119**

statistically significant difference in functional connectivity across the trial groups. However, pairwise comparisons between consecutive trial groups (T1/T2, T2/T3, T3/T4, T4/T5) did not show significant changes, with p-values of 0.626, 0.250, 0.987, and 0.276, respectively (see Table 8.1). These results suggest that while there is an overall habituation effect for the apple image, it is not driven by specific transitions between trial groups.

For the pizza image, the Friedman test resulted in p-val = 0.2138, indicating no significant overall differences in functional connectivity across the trial groups. Pairwise comparisons also did not show significant changes, with p-values of 0.774, 0.323, 0.314, and 0.997 for T1/T2, T2/T3, T3/T4, and T4/T5, respectively. These results suggest no evidence of habituation in response to the high-calorie pizza image.

For the hammer image, the Friedman test yielded p-val = 0.011, indicating a significant overall difference in functional connectivity across the trial groups. Pairwise comparisons revealed significant differences between T1/T3 (p-val = 0.0012), T2/T3 (p-val = 0.0094), and T3/T4 (p-val = 0.0104), as well as a marginally significant difference for T4/T5 (p-val = 0.0119) between Fz-Pz channels (refer to Table 8.1). These findings indicate a clear habituation effect for the non-food hammer image, with significant reductions in connectivity as trial groups progressed between frontal and parietal brain regions.

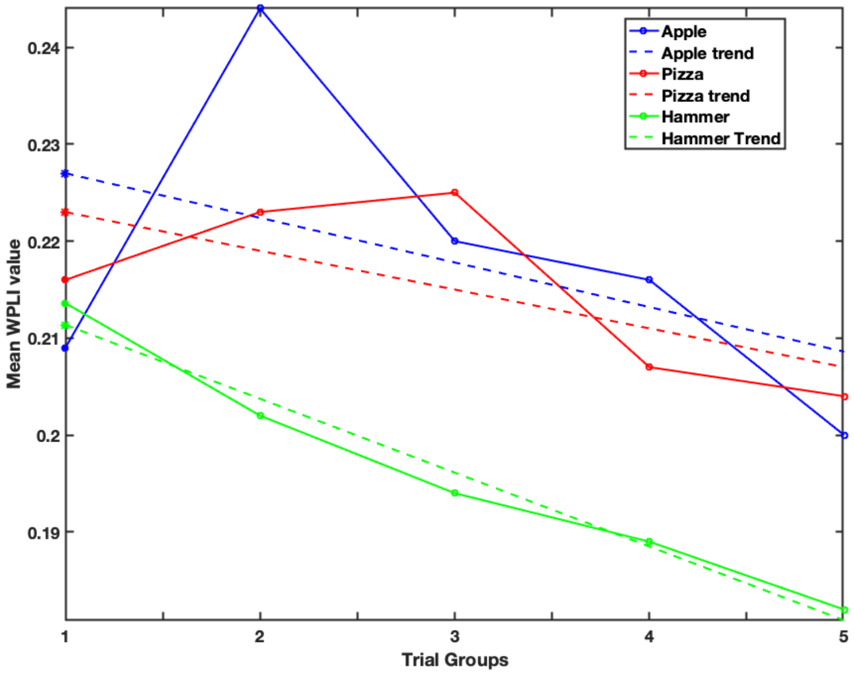


Figure 8.5: Connectitivy value (wPLI) and its linear trend for various images and trial groups for Fz-Pz channel combination in theta band

Figure 8.5 illustrates the mean WPLI connectivity values between the frontal channel (Fz) and the parietal channel (Pz) across five trial groups, along with their respective linear trends. The results indicate a clear linear decrease in WPLI values for the hammer image, signifying a significant reduction in connectivity strength over successive trial groups. In contrast, no linear decrease was observed for the apple or pizza images, suggesting limited or no habituation for these stimuli.

Moreover, the findings reveal that the rate of habituation, as reflected by the slope of the linear trend, was faster for the hammer image compared to the food images. When comparing the food images, the low-calorie apple exhibited a slower rate of habituation than the high-calorie pizza. These differences underline how calorie content and stimulus type influence neural habituation. The slope and intercept

Table 8.2: Functional Connectivity - Habituation rate details for different images in theta band.

Image	Slope	Intercept
Apple	-0.0046	0.232
Pizza	-0.0040	0.227
Hammer	-0.0076	0.219

values for the linear trends of all three image categories are detailed in Table 8.2, providing further insight into the dynamics of habituation across different stimuli.

8.5 Discussion

The study provides key insights into the neural mechanisms underlying food habituation, particularly in relation to functional connectivity measured through WPLI values in the theta band. The results indicated significant differences in functional connectivity across trial groups for low-calorie (apple) and non-food (hammer) images but not for high-calorie (pizza) images. This suggests that habituation is more pronounced for non-food stimuli and low-calorie foods, whereas high-calorie food images sustain prolonged attentional engagement. These findings align with prior research showing that high-calorie foods activate reward-related brain regions, which may contribute to persistent neural engagement and difficulty in habituation (Loeber et al. 2012).

Prior EEG research suggests that oscillatory activity, particularly in the theta (4–8 Hz) band, is closely linked to attentional modulation and sensory processing during habituation tasks (Klimesch 1999; Makeig et al. 2002). Our results reveal a significant habituation effect in the theta band for non-food stimuli (hammer images), with a reduction in phase-locking connectivity (measured by WPLI) between frontal

(Fz) and parietal (Pz) regions. This aligns with existing research showing that theta-band synchrony in frontoparietal networks is involved in attentional disengagement from repetitive stimuli (Cavanagh and Frank 2014).

The connectivity matrix analysis further supports these findings, illustrating how neural connectivity evolves across five trial groups (T1–T5). The connectivity matrices for non-food and low-calorie food images demonstrated a noticeable decline in WPLI values over time, particularly between the frontal (Fz) and parietal (Pz) regions. This suggests that synchronised neural activity decreases with repeated exposure, a key marker of habituation. However, for high-calorie food images (pizza), connectivity remained stable across trial groups, reinforcing prior studies that show energy-dense foods elicit sustained attention due to their rewarding nature (Gearhardt et al. 2011).

The habituation rate analysis sheds further light on the speed and extent of neural adaptation to repeated food stimuli. The WPLI values between Fz and Pz channels exhibited a steep linear decline for the hammer image, indicating rapid neural habituation to non-food stimuli. The low-calorie apple image showed a slower habituation rate, whereas the high-calorie pizza image demonstrated the least decline, suggesting that high-calorie foods sustain attention the longest. These findings align with EEG-based studies on food cues, which indicate that high-calorie food images trigger prolonged engagement of frontal brain regions, reducing the likelihood of attentional disengagement (Imperatori et al. 2015b). The slower habituation rate for low-calorie foods suggests that they still capture attention, albeit to a lesser extent than high-calorie foods, likely due to differences in motivational salience (Kringelbach and Rolls 2004)

The pairwise comparison of trial groups highlights specific transitions in functional connectivity. Significant differences were observed between T1/T3, T2/T3, and T3/T4 for the hammer image, whereas no significant transitions occurred for the pizza image. This suggests that the brain rapidly adapts to non-food stimuli, while high-calorie food cues maintain their salience even with repeated exposures. These results have important implications for dietary interventions, as they highlight the challenge of reducing attention to high-calorie foods, particularly among individuals with food addiction or overeating tendencies (Kösling et al. 2022).

The role of frontal-parietal connectivity in food processing is crucial in understanding obesity-related behaviours. Theta-band activity in the frontal brain region is associated with cognitive control and inhibitory processing (Cavanagh and Frank 2014). In this study, the absence of habituation for high-calorie images suggests that individuals may struggle to regulate their attentional responses to energy-dense foods, potentially contributing to overeating and impulsive food choices. Furthermore, prior research has demonstrated that WPLI is a robust measure of phase synchronisation, making it useful for detecting neural connectivity patterns associated with food-related decision-making (Vinck et al. 2011).

From a broader perspective, these findings suggest that functional connectivity measures like WPLI can serve as objective markers of food-related attentional biases. Understanding how different food stimuli elicit distinct neural connectivity patterns can guide the development of targeted interventions, such as cognitive training programs aimed at reducing attentional bias toward high-calorie foods. Prior research indicates that modifying exposure to food images using attentional retraining techniques may help individuals better regulate their food intake (Boswell and Kober 2016)

These results also align with neurophysiological research on obesity and eating behaviours. Studies have shown that individuals with higher BMI exhibit stronger neural responses to high-calorie foods, potentially leading to habitual overeating and reduced self-regulation (Imperatori et al. 2015b). The findings of this study suggest that high-calorie food images sustain neural engagement longer, which may contribute to increased cravings and overconsumption in individuals prone to obesity.

8.6 Conclusion

Overall, this study highlights the importance of functional connectivity analysis in identifying neural markers of food habituation. The findings underscore the persistent attentional engagement elicited by high-calorie foods, reinforcing their role in eating behaviours and obesity risk. In the next chapter, further investigation will be done by exploring ERP differences with BMI in response to repeated food and non-food visual stimuli in the time domain. This analysis will examine how neural responses to repeated stimuli vary across individuals with different BMI levels, assessing whether attentional and motivational processing differ based on weight status. By investigating ERP components associated with food-related attention and habituation, this chapter aims to provide deeper insights into the relationship between neural processing, eating behaviours, and BMI-related differences.

Chapter 9

ERP Differences With BMI in Response to Repeated Food and Non-food Visual Stimuli

9.1 Chapter Outline

This chapter explores the neurophysiological dynamics of Body Mass Index (BMI) influence and habituation responses to repetitive visual stimuli, providing an in-depth analysis of both food and non-food paradigms using ERP analysis. By examining how individuals with different BMI levels respond to repeated exposure to specific visual stimuli, this chapter aims to uncover the underlying neural mechanisms contributing to differences in attentional and motivational processes. The chapter delves into how these responses vary between high-calorie and neutral, non-food images, shedding light on the cognitive and emotional factors driving eating behaviours. Through a detailed ERP analysis, this chapter explains the temporal patterns of brain activity associated with habituation, offering insights into how the brain's electrical activity reflects changes in stimulus processing over time. The findings presented in this chapter are crucial for understanding the complex interplay between BMI, neural responses, and behavioural outcomes in the context of visual food cues and broader environmental stimuli.

9.2 Introduction

The prevalence of overweight and obesity has significantly increased worldwide in recent decades, affecting both adults and children. In 2016, 1.9 billion adults were overweight, and 650 million of them were obese. Furthermore, the prevalence of obesity among children and adolescents aged 5-19 has also risen dramatically, from 4% in 1975 to 18% in 2016. Both boys and girls have been affected, with 8% of boys and 6% of girls being obese in 2016 (WHO 2024). Despite reported stagnation in obesity prevalence in Western Europe and North America, there are indications that rates are still rising in Eastern Europe Ahluwalia et al. (2015). The ubiquity of highly palatable food poses a health risk. It has been repeatedly shown in experimental paradigms that food consumption can be modulated by factors besides energy density, including the presence of food, presumptions about its calorie density and nutritional value, portion size, food appearance and smell (Wansink et al. 2004; Caputo and Mattes 1993; Miller et al. 1998; Rolls, Morris and Roe 2002). While childhood obesity might be increasing, not all children are at equal risk of a putatively 'obesogenic' environment, and growing evidence suggests that personality and cognitive traits can play a substantial role in hedonic intake control (Nederkoorn et al. 2006; Fay et al. 2015). Thus, we need to understand the complex and dynamic interplay between environmental, behavioural and biological factors influencing energy intake and expenditure in order to target interventions for the prevention and treatment of overeating successfully.

Research using functional magnetic resonance imaging (fMRI) has supported the incentive-sensitisation hypothesis, which explains how food's hedonic (pleasure-related) and motivational value affects behaviour. These studies have shown that obese individuals experience heightened brain activation in response to high-calorie food cues, aligning with the hypothesis's predictions Rothemund et al. (2007); Stoeckel et al. (2008). However, it remains unclear whether these brain activity differences contribute to obesity or result from it. One study suggests that this heightened response is linked to less successful weight loss efforts (Murdaugh et al. 2012). Additionally, food cravings have been connected to increased brain activity related to reward, both during rest and when exposed to high-calorie foods, making it more challenging to control these cravings as weight increases (Dietrich et al. 2016; Contreras-Rodríguez et al. 2017). This difficulty in managing desires grows with weight gain (Scharmüller et al. 2012).

BMI, a standard measure used to assess body composition by calculating the ratio of height to weight, is an essential tool for evaluating obesity risk and grouping participants in studies. In past research, ERPs have been crucial in revealing the timing of neural processing, particularly in how the brain responds emotionally and cognitively to food cues (Nijs et al. 2010b). Studies have shown that the human salivary response tends to decrease or habituate when repeatedly exposed to food cues, whether visual, olfactory, or gustatory, in both adults and children (Epstein et al. 1992, 2003). However, research indicates that slower habituation of salivation responses can lead to overeating, which in turn may contribute to obesity. This suggests that obesity could be linked to a delayed habituation process, resulting in increased food intake. Previous studies have also found that both obese children and adults tend to habituate more slowly to food cues compared to their leaner peers (Epstein et al. 2008; Temple et al. 2007a; Epstein, Paluch and Coleman 1996a).

Studies using ERPs have shown that our brains respond strongly to food-related stimuli, with food cues generating more significant neural reactions than non-food stimuli (Carbine et al. 2017). Specifically, differences in ERP components like N200, P200, and P300 have been associated with varying levels of food cravings and attentional processing in individuals with different BMI levels (Carbine et al. 2017; Thomas, Johnstone and Gonsalvez 2007). For instance, people with higher BMIs tend to show a greater P200 amplitude in response to food cues compared to those with lower BMIs, indicating that BMI may influence early sensory or visual attention to food (Nijs, Franken and Muris 2010; Hume et al. 2015). Although many studies haven't found a strong link between BMI and later ERP components related to deeper food-related attention processes (like P300, early posterior negativity (EPN), and late positive potential (LPP)), there is evidence that obese individuals have heightened initial attention responses, as shown by an increased P200 amplitude, compared to those of normal weight (Hanlon et al. 2012; Nijs, Franken and Muris 2010; Hume et al. 2015). Interestingly, the relationship between ERP components and factors like food intake, eating habits, arousal, and emotional response is mainly observed in normal-weight individuals rather than in those who are obese (Babiloni et al. 2009; Nijs et al. 2010b).

The incentive-sensitisation theory, which explains how repeated exposure to food cues can increase their motivational salience, has been further supported by methods with higher temporal accuracy (Berridge 2009; Robinson and Berridge 1993). According to this view, individual variations in mesolimbic dopaminergic functioning affect how rewarding food feels and how much hedonic value we attribute to it. As a result of recurrent experiences of reward from food consumption, individuals become more sensitive to food-related stimuli, which raises the motivational salience of food cues. This enhanced sensitivity to food cues leads to biases in attention and food cravings, ultimately leading to an increase in food consumption. For example, eye-tracking studies reveal that overweight and obese individuals display a stronger initial focus and more significant attentional bias towards high-calorie foods compared to those of normal weight (Castellanos et al. 2009; Werthmann et al. 2011).

ERP studies using EEG have mainly focused on two components: the P300 and Late Positive Potential (LPP). The P300, a positive wave occurring about 300 milliseconds after a stimulus, tends to be stronger when more attention is paid to specific stimuli, especially those considered motivationally important (Picton 1992; Polich 2007). The LPP, a slower positive wave beginning around 400 milliseconds after a stimulus, is typically heightened by emotionally significant stimuli and is linked to intentional processing and strategic attention (Schupp et al. 2003, 2000; Cuthbert et al. 2000).

Research shows that food stimuli generally elicit higher P300 and LPP amplitudes in adults compared to non-food images (Nijs, Franken and Muris 2008). In existing research, these amplitudes are even more significant in individuals who are hungry versus those who are not and when high-calorie foods are available (Nijs, Franken and Muris 2008; Nijs et al. 2010b; Blechert et al. 2010). Those who are more likely to eat in response to food cues or due to negative emotions (often called external or emotional eaters) also show higher amplitudes of these ERP components (Nijs, Franken and Muris 2009; Blechert et al. 2014a). Moreover, P300 amplitudes, but not LPP amplitudes, have been positively linked to self-reported cravings and hunger levels when viewing images of high-calorie foods, as well as to actual food consumption afterward (Svaldi et al. 2015; Nijs et al. 2010b).

However, the evidence for the incentive salience theory in children and adolescents isn't as clear-cut as it is in adults. For instance, fMRI studies have shown that satisfied obese children have higher activation in brain regions associated with inhibition compared to their normal-weight peers, but this activation decreases when they are asked to control their appetite (Bruce et al. 2010; Davids et al. 2010; Silvers et al. 2014). Similar to adults, adolescents also show higher P300 and LPP amplitudes in response to high-calorie food cues, especially emotional eaters (Wu et al. 2018). However, both obese and normal-weight adolescents show similar P300 amplitudes when responding to a mix of low- and high-calorie food cues (Hofmann et al. 2015).

One key finding in food habituation research is that habituation, where repeated exposure to food cues diminishes their impact, plays a role in understanding eating behaviours that are not driven by hunger. Understanding this process is crucial for developing interventions aimed at modifying eating patterns unrelated to energy needs. Therefore, investigating how food habituation varies across different types of foods can help design better strategies for reducing overeating. This study aims to explore the effects of food habituation, obesity, and BMI, focusing on the neurophysiological dynamics among these factors. It's the first to examine how habituation differs between high and low BMI groups when repeatedly exposed to the same food and non-food images over various time intervals within a session. Since food variety can significantly influence habituation, this study uses the same images (an apple for low-calorie food, a pizza for high-calorie food, and a hammer as a non-food item) across different brain regions for analysis.

The primary goal is to compare the brain responses of different groups when they view the same images repeatedly, focusing on how these responses vary between high and low-BMI groups. The secondary goal is to assess the consistency of habituation rates for high-calorie, low-calorie, and non-food images across different BMI groups.

9.3 Data Extraction and Analysis Method

This chapter examines how neural responses to repeated exposure to food and non-food stimuli differ between individuals with high and low BMI. Using ERPs derived from EEG data, the goal is to understand whether body weight status influences habituation patterns. The analysis builds upon the experimental design described in Chapter 3, focusing here on a stratified comparison based on BMI.

Participants were grouped into two categories: high BMI (overweight/obese) and low BMI (normal/underweight). Each group comprised 12 participants, with an equal gender split (6 male, 6 female), as shown in Table 9.1. The age and BMI distributions for each group are provided in Tables 9.2 and 9.3, respectively. This grouping allowed for the investigation of whether habitual neural processing of visual stimuli differs by body composition.

Table 9.1: Participant Information by BMI Group

BMI Group	**Participants count**
High BMI (overweight/obese)	12 (6 male, 6 female)
Low BMI (normal/underweight)	12 (6 male, 6 female)

Table 9.2: Participant Age Information by BMI Group

BMI Groups	**Age**		
	Range	**Mean**	**Standard deviation**
High BMI (overweight/obese)	24 to 48	34.81	7.92
Low BMI (normal/underweight)	19 to 40	27.72	6.43

To explore temporal patterns in neural activity, ERP waveforms were computed by averaging trials within each condition, thus enhancing stimulus-specific signals

Table 9.3: Participant BMI Information by BMI Group

BMI Groups	**BMI (kg/m^2)**		
	Range	**Mean**	**Standard deviation**
High BMI (overweight/obese)	25.66 to 39.15	29.64	4.58
Low BMI (normal/underweight)	19.72 to 23.55	22.52	2.32

while reducing noise. Each session consisted of 30 trials per image category. For analysis, these were grouped into five consecutive bins of six trials each (refer Chapter 3, Section 3.2 for more details on trial groups), allowing investigation of neural adaptation over repeated exposures.

ERP analyses were conducted separately for high and low BMI groups to assess habituation trends for each image type. The statistical evaluation used a cluster-based permutation method via the `ft_timelockstatistics` function in FieldTrip, ensuring non-parametric robustness without assuming data normality. This approach identified key time windows and scalp regions sensitive to habituation effects.

Overall, this structured and stratified methodology enabled detailed exploration of how neural responses to repeated food and non-food stimuli differ as a function of BMI, laying the foundation for interpreting the role of habitual attentional engagement in dietary behaviour.

Statistical Analysis

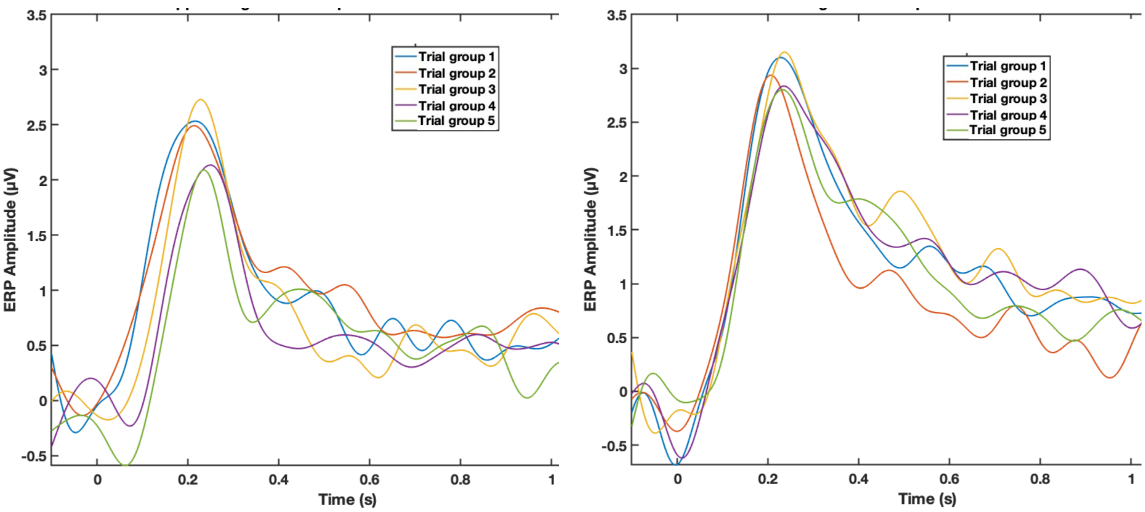
The study aimed to investigate the main effects and interactions of ERP responses to three different images within the first 1000 milliseconds after the cue appeared. Specifically, it explored habituation effects within each session by comparing five trial groups across different BMI groups for each image. A mass-univariate analysis using a cluster-based statistical approach was employed for this purpose. The study was carried out using EEGLAB and FieldTrip plugins (Oostenveld et al. 2011), in line with the FieldTrip documentation and relevant academic studies (Rodriguez-Larios et al. 2020; Quiroga-Martinez et al. 2020). A non-parametric cluster-based permutation test with Monte Carlo randomization (Maris and Oostenveld 2007) was used to avoid making assumptions about the normal distribution of the data.

This non-parametric approach operates on the assumption that true neural activity results in signal changes over consecutive time points. To create a reference distribution for the mean cluster magnitude, random permutation testing was performed 1,000 times for each trial group and condition on a subject-specific basis. Following this, a test statistic (t-value) was calculated to evaluate the hypothesised linear decrease in amplitude, which would indicate habituation (i.e., trial group 1 > trial group 2 > trial group 3 > trial group 4 > trial group 5). This was done using the *ft_statfun_depsamplesregrT* function in FieldTrip.

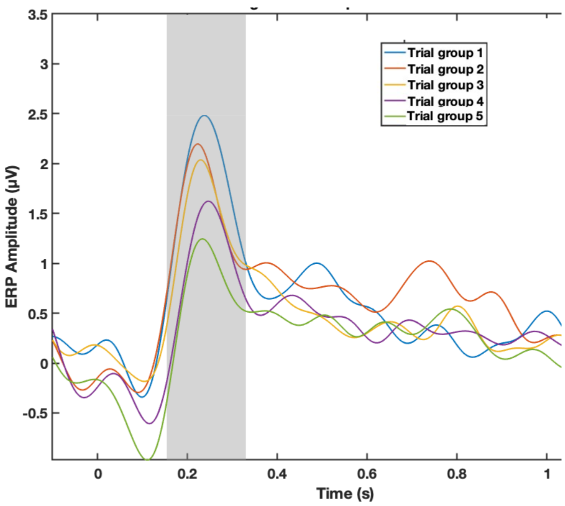
Clusters in the observed data were considered significant if their magnitude exceeded the 2.5th and 97.5th percentiles, corresponding to a 5% significance level for a two-tailed test. This thorough statistical analysis allowed for the examination of habituation effects and their significance in ERP responses to food and non-food stimuli across different trial groups and BMI categories.

9.4 Results

The study investigated significant main effects and interactions in ERPs across different time windows and brain regions, specifically targeting the parietal (P7, P3, Pz, P4, P8), frontal (Fp1, Fp2, F7, F3, Fz, F4, F8), central (C3, Cz, C4), temporal (T7, T8), and occipital (O1, Oz, O2) areas. The cluster-based permutation test revealed significant differences in hammer for both the low BMI and the high BMI groups,

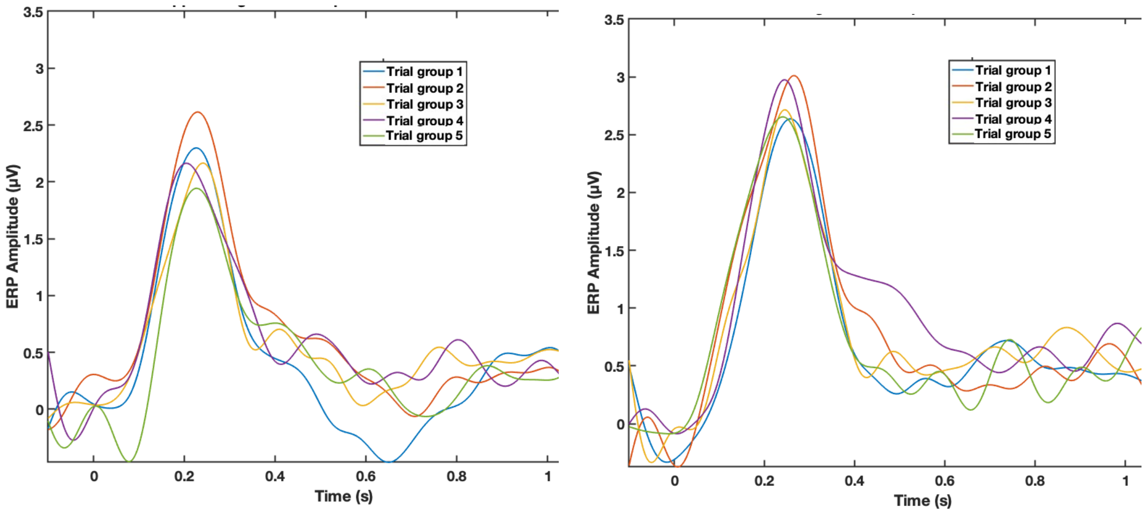


(a) Apple (b) Pizza

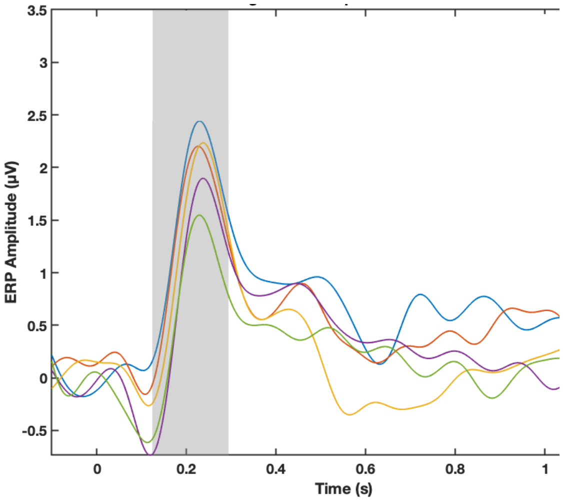


(c) Hammer

Figure 9.1: The figures show the mean ERP amplitudes for different images in the high BMI group. Figure (a) depicts the ERP amplitude for the low-calorie image (apple) over the parietal region, with no habituation effect observed. Figure (b) shows the ERP amplitude for the high-calorie image (pizza), where habituation was also absent. However, Figure (c) reveals a significant habituation effect for the non-food image (hammer) in the same parietal region.



(a) Apple (b) Pizza



(c) Hammer

Figure 9.2: The figures show the mean ERP amplitudes for different images in the low BMI group. Figure (a) depicts the ERP amplitude for the low-calorie image (apple) over the parietal region, with a significant habituation effect observed. Figure (b) shows the ERP amplitude for the high-calorie image (pizza), where habituation was also absent. Figure (c) depicts the ERP amplitude for the non-food image (hammer) over the parietal region, with no habituation effect observed.

with the difference most pronounced over the parietal area of the brain. The ERPs for both high BMI and low BMI groups in response to different images are shown in Figures 9.1 and 9.2, respectively.

Although all brain regions were analysed, the parietal region showed the most statistically significant and consistent effects related to habituation, particularly for non-food stimuli (hammer). Therefore, results in the main text focus on this region. However, to ensure transparency and completeness, Tables 9.4 and 9.5 presents p-values for all regions of interest (ROIs) across the three image categories and both BMI groups.

Table 9.4: P-values of habituation effects across different ROIs and image categories for the Low BMI group. Bold values indicate statistical significance ($p < 0.05$).

ROI	**Apple**	**Pizza**	**Hammer**
Frontal	0.421	0.453	0.178
Central	0.325	0.298	0.094
Parietal	0.660	0.292	**0.005**
Occipital	0.147	0.265	0.119
Temporal	0.234	0.401	0.133

Table 9.5: P-values of habituation effects across different ROIs and image categories for the High BMI group. Bold values indicate statistical significance ($p < 0.05$).

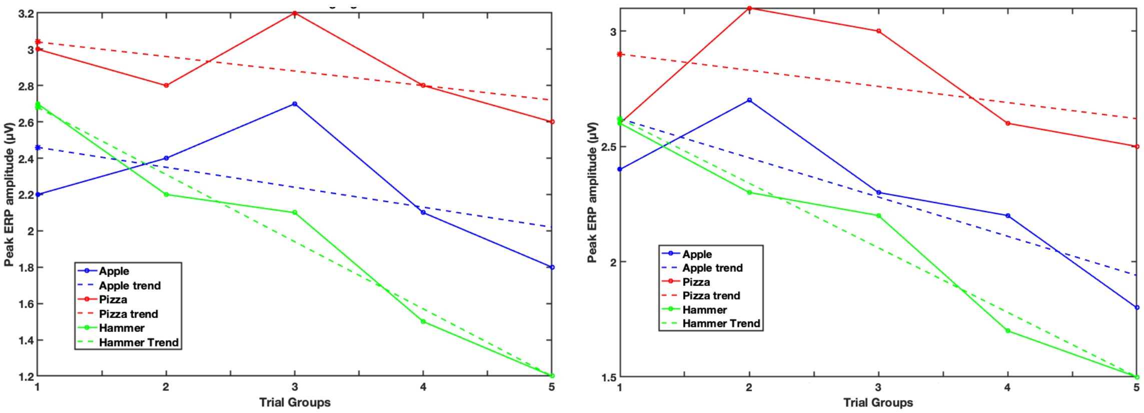
ROI	**Apple**	**Pizza**	**Hammer**
Frontal	0.390	0.501	0.143
Central	0.312	0.344	0.087
Parietal	0.134	0.371	**0.009**
Occipital	0.189	0.310	0.103
Temporal	0.220	0.387	0.127

Figures 9.1 and 9.2 provide a visual summary of mean ERP amplitudes across trial groups for each stimulus type in the high and low BMI groups.

Looking at the response to low-calorie stimuli (apple), Figures 9.1a and 9.2a show the ERP amplitudes measured over the parietal region. No statistically significant habituation effect was observed in either group, as indicated by p-values of 0.134 for the high BMI group and 0.660 for the low BMI group.

A similar pattern emerged for high-calorie images (pizza), shown in Figures 9.1b and 9.2b. Here too, neither group exhibited significant habituation effects, with p-values of 0.371 for the high BMI group and 0.292 for the low BMI group, suggesting persistent attentional engagement with high-calorie food stimuli.

In contrast, the ERP responses to non-food images (hammer), illustrated in Figures 9.1c and 9.2c, revealed significant habituation in both BMI groups. The linear regression analysis identified statistically significant declines in ERP amplitudes over time in the parietal region, with p-values of 0.009 for the high BMI group and 0.005 for the low BMI group, within the respective time windows of 170–300 ms and 180–320 ms.



(a) High BMI

(b) Low BMI

Figure 9.3: Figure (a) shows peak ERP amplitude and its linear trend of different images and trial groups of the High BMI group. Figure (b) peak ERP amplitude and its linear trend of different images and trial groups of the Low BMI group.

Table 9.6: BMI Analysis - Habituation rate details for different images.

Image	Low BMI		High BMI	
	Slope	Intercept	Slope	Intercept
Apple	-0.11	2.57	-0.17	2.70
Pizza	-0.08	3.12	-0.07	2.97
Hammer	-0.37	3.05	-0.28	2.9

To further characterize the rate of habituation, Figures 9.3a and 9.3b show the peak ERP amplitude trends across all trial groups, separated by BMI group and stimulus category. The corresponding slope and intercept values are reported in Table 9.6. These results show that non-food stimuli elicited the steepest decline in ERP amplitude, indicating the fastest rate of habituation (Low BMI slope = -0.37; High BMI slope = -0.28). In comparison, habituation to food-related images was slower and less pronounced. High-calorie images, in particular, showed minimal change over time (Low BMI slope = -0.08; High BMI slope = -0.07), suggesting a more sustained attentional or emotional response.

Overall, these findings reveal distinct neural patterns associated with repeated exposure to food versus non-food stimuli, with BMI status influencing both the strength and speed of habituation. While non-food cues were processed more efficiently with repeated presentation, food-related images—especially high-calorie ones—appeared to maintain their salience over time, particularly in individuals with higher BMI.

9.5 Discussion

This study is the first to examine how habituation affects responses across various time intervals within a single session, explicitly focusing on repeated exposure to food and non-food images among individuals with different BMI levels. The main goal was to compare the ERP responses from different trial groups exposed to the same food and non-food images, depending on their calorie value, among participants with both high and low BMIs.

In the initial analysis, ERP responses were evaluated to understand cognitive and motivational reactions to repeated image presentations for both high and low BMI groups. To achieve this, 30 trials of each image were organised into five groups, each consisting of six trials. This setup allowed for a comparison of motivation and attention across trial groups, supporting the idea that habituation might be evident in how repeated image presentations affect individuals with different BMI statuses.

The findings suggest that both low and high BMI groups exhibit changes in neural responses to repeated food presentations, supporting the hypothesis that these changes may reflect the habituation process. Notably, significant habituation effects were observed in both BMI groups, primarily localised within the parietal region of the brain. Specifically, significant reductions in neural responses were identified for non-food stimuli, with high BMI individuals showing habituation within the 180 ms–320 ms time window, while low BMI participants exhibited a similar effect between 170 ms–310 ms. However, no significant habituation effects were found for high-calorie or low-calorie food images in either BMI group, indicating that food-related stimuli may sustain attention regardless of BMI.

Figures 9.3a and 9.3b illustrate the trends over time, showing a decreasing linear trend for low-calorie stimuli in low BMI participants and non-food stimuli in high BMI individuals. In contrast, no clear habituation effect was observed for pizza, as both BMI groups did not exhibit a decreasing linear trend for this stimulus. These ERP findings are consistent with prior research on food habituation, including studies on salivation responses in children and adults (Epstein et al. 1992, 2003), facial muscle responses in adults (Epstein and Paluch 1997), and motivational behaviours related to food (Epstein et al. 2009a; Temple et al. 2006). The absence of significant ERP differences for high-calorie food images between BMI groups may be due to the strong, universal appeal of such foods. Prior research has shown that high-energy foods are associated with increased reward value and emotional engagement, making them more resistant to habituation even with repeated exposure (DelParigi et al. 2007; Lowe and Butryn 2007). In contrast, non-food images lack this reward value, allowing differences in attentional disengagement to emerge. This may explain why low-BMI participants showed clearer habituation to non-food stimuli, while high-BMI individuals remained more engaged.

Previous physiological studies have shown that obese individuals exhibit a heightened automatic attentional response to food-related stimuli. For instance, research has identified a P200 bias toward food-related words in obese participants, a bias that was absent in individuals with normal weight. This suggests that, early in the information processing stage, obese individuals allocate greater automatic attention to food-related stimuli compared to neutral stimuli. The findings of this study align with these observations, as participants with a high BMI demonstrated a bias and sustained attention toward food images more than non-food images. This supports prior research on automatic food-related attentional biases in obesity. For example, Castellanos et al. Castellanos et al. (2009) reported that obese individuals exhibited a preferential initial orientation towards food pictures compared to normal-weight individuals. Similarly, Nijs et al. Nijs, Franken and Muris (2010) found that overweight and obese females showed an enhanced attentional shift toward food images relative to control pictures when compared to normal-weight females. These findings collectively suggest that heightened attention toward food-related stimuli may contribute to overeating behaviours in individuals with higher BMI.

This study found that individuals with a low BMI exhibited habituation effects in response to non-food images but not to food images. This suggests that, even among those with lower BMI, there is a cognitive bias or sustained attention towards food images compared to non-food images. Consistent with prior research, visual evoked potentials have shown that neural activity decreases more significantly during food viewing than non-food viewing in females with lower BMI, particularly in brain regions associated with food reward valuation Toepel et al. (2012). This finding indicates that individuals with a lower BMI may have heightened sensitivity or valuation of food-related cues, which persists over repeated exposures rather than diminishing as seen with non-food stimuli.

Additionally, previous studies have demonstrated that food images evoke longer latency ERP responses compared to non-food images, suggesting a link between prolonged ERP latencies and motivation to eat Nijs, Franken and Muris (2008); Stoeckel et al. (2009). The present study supports this, showing that food images elicited longer ERP latencies than non-food images in both BMI groups. High-energy foods, in particular, are associated with increased reward and motivational salience, making them more resistant to habituation even with repeated visual exposure Rosburg et al. (2006); Frömer, Maier and Abdel Rahman (2018). Several external factors, such as dietary variety, attentional allocation, and television watching, have also been identified as potential disruptors of habituation, contributing to increased energy intake and potentially influencing the development of obesity.

The rate at which habituation to food occurs may play a significant role in obesity development. Various factors, such as dietary variety McCrory et al. (1999), attentional allocation Temple et al. (2008b), and television watching Temple et al. (2007a), have been linked to differences in habituation rates for both food-related and non-food-related stimuli. These factors have also been associated with obesity, likely due to their influence on energy intake Epstein and Paluch (1997). This study provides insight into how calorie differences affect habituation rates in adults by investigating the rate of habituation to food stimuli within sessions using motivational ERP responses over time. The analysis examined changes in habituation trends between different trial groups and across high and low BMI groups. As shown in Figures 9.3a and 9.3b, a decreasing linear trend in ERP responses suggests the occurrence of habituation, with the rates of decline detailed in Table 5.2. Although both high and low BMI groups exhibited habituation to food and non-food images, the rate of decline in attention and motivation varied between trial groups.

Across both BMI groups, non-food images demonstrated the fastest habituation, followed by low-calorie food (apple), with high-calorie food (pizza) showing the slowest habituation. This finding indicates that high-calorie foods exert the strongest influence on attention and motivation, as measured by ERP responses, compared to low-calorie foods and non-food items. The prolonged neural engagement with high-calorie foods suggests that these images maintain a higher motivational and attentional value over repeated exposures.

The priming model proposed by Wagner Wagner (1981) explains habituation as a process that occurs when a stimulus is no longer surprising, as it matches information already stored in short-term memory. When a repeated stimulus aligns with stored memory traces, neural processing and response intensity decrease. For example, when a food item is tasted, it is temporarily held in short-term memory. If subsequent exposures to the same food match the stored information, the processing load and response magnitude decline. However, factors that interfere with this short-term memory representation can slow or prevent habituation Epstein et al. (2009a). In this context, sustained attention to food images, particularly high-calorie foods, may slow or prevent habituation, whereas non-food images do not elicit the same prolonged attention since they do not align with stored reward-related information. This highlights the role of top-down cognitive control and attentional mechanisms in regulating the maintenance of representations in visual short-term memory Kuo, Stokes and Nobre (2012), contributing to the observed differences in habituation rates across stimuli in individuals with varying BMI levels.

9.6 Conclusion

In conclusion, individuals in both high and low BMI groups demonstrate heightened automatic, preconscious attentional processing of high-calorie food-related stimuli, suggesting an initial sensitivity to food cues Nijs, Franken and Muris (2010). In today's food-rich environment, this increased responsiveness to food cues could play a significant role in overeating. Habituation, an adaptive response marked by a reduced reaction to repeated stimuli, whether food-related or not, is crucial in this context. The lack of habituation observed in low BMI individuals towards both food and non-food stimuli might indicate a potential risk for overeating and subsequent weight gain, particularly with ongoing exposure to these stimuli. Further research is needed to validate this hypothesis and investigate the underlying mechanisms.

In the next chapter, we will provide a comprehensive discussion of the conclusions drawn from this research, highlighting key findings and their broader implications. We will explore how these results contribute to the existing body of knowledge on food-related attentional biases, habituation mechanisms, and neural processing of repeated stimuli. Finally, we will acknowledge the limitations of this study, addressing methodological constraints and potential avenues for future research to further refine.

Chapter 10

Conclusion and Future Directions

Conclusion

This research explored the neurodynamic responses to repeated exposure to food and non-food visual stimuli, with a particular focus on the within-session habituation process. Using established EEG data processing and analysis techniques, this study aimed to identify neural markers of habituation and examine how the brain responds to high-calorie, low-calorie, and non-food images. In addition to that, the rate of habituation was also analysed to show how further the neural responses decrease to repeated exposure, which provides deeper insights into the dynamics of attentional engagement to the food and non-food related stimuli. Based on that, this research successfully identified key EEG markers of food habituation through a systematic methodology involving data acquisition, preprocessing, feature extraction, and statistical validation.

Using time-domain and time-frequency domain analysis, this research captured neural responses associated with food habituation. It examined differences in responses to high-calorie, low-calorie, and non-food stimuli by measuring both habituation decrease and habituation rate over repeated exposures. Additionally, functional connectivity was analysed using the WPLI to explore neural interactions during habituation. To make sure the results were not just due to mental fatigue, this study looked at both habituation and dishabituation effects. It also compared brain responses in people with different BMI levels when they viewed high-calorie, low-calorie, and non-food images. The results show how attention and motivation toward food vary between individuals, giving valuable insights into eating behaviour and obesity research.

The initial ERP study examined attentional bias toward high- and low-calorie foods by comparing repeated exposure to a single image with studies using varied image sets. Findings showed that high-calorie images, particularly pizza, elicited sustained neural responses, while low-calorie and non-food images showed habituation. Increased frontal negativity for high-calorie foods suggested stronger cognitive inhibitory control, aligning with previous research. The results confirm that neural effects of image repetition can be captured effectively using the same image rather than a mix. This study explored the overall differences between high/low calorie and non-food images, but future studies are needed to observe responses across more participant data, BMI variations, participants with eating disorders variation, etc.

The time-domain analysis provides important insights into how the brain reacts to repeated exposure to food and non-food images during a session. The findings show that non-food and low-calorie images gradually lose attention over time, while high-calorie food images, like pizza, continue to hold attention for longer. This suggests that high-calorie foods activate brain areas linked to attention and motivation. The study also highlights the role of early brain responses (P200) in maintaining attention to high-calorie foods, while low-calorie and non-food images are processed and habituated more quickly (170 ms - 330 ms time window). These findings align with the previous research showing that food habituation is linked to salivation responses and attentional and motivational neural responses. Additionally, the results show that a slower habituation rate for high-calorie foods may be linked to overeating and obesity. This study mainly focused on measuring the rate of habituation rather than the overall strength of neural responses, helping to minimise any influence from image characteristics such as colour or brightness.

Furthermore, the results of the time-frequency analysis reveal important differences in how the brain adapts to food and non-food images, particularly in the frontal theta band (4–7 Hz) in a 110 ms - 220 ms time window. Non-food images showed a strong habituation effect, with a rapid decrease in frontal theta activity, indicating that these stimuli are processed as less important and require fewer cognitive resources over time. In contrast, high-calorie food images continued to hold attention, showing the slowest habituation rate, likely due to their strong motivational and reward-related significance. This suggests that high-calorie foods demand more cognitive engagement and may lead to food cravings, potentially leading to overeating behaviours. The differences in habituation rates show that while non-food stimuli are processed more efficiently, energy-dense foods sustain prolonged cognitive engagement. These findings highlight the role of frontal theta oscillations in regulating attention and emphasise the lasting impact of food-related attentional biases, which may contribute to obesity and unhealthy eating behaviours.

This research also provides key insights into the neural mechanisms of habituation and dishabituation in response to repeated presentations of food and non-food images. While non-food images exhibited significant habituation and dishabituation effects, food images, particularly high-calorie ones, maintained prolonged attentional engagement, suggesting a stronger motivational influence rather than cognitive fatigue. The findings confirm that habituation is stimulus-specific rather than a uniform decline in neural responses. The presence of dishabituation effects across all image categories highlights the role of attentional modulation in food-related neural processing. These results align with prior research, indicating that energy-dense foods hold greater motivational salience and are more resistant to habituation. The ability of novel stimuli to reset neural responses, even for food images, suggests potential strategies for reducing excessive attentional biases toward food cues. Overall, these findings enhance our understanding of food-related attention and emphasise the need for further research on individual differences in habituation and dishabituation, particularly in relation to eating behaviours and obesity.

Another study provides important insights into how the brain adjusts to repeated exposure to food and non-food images by analysing functional connectivity in the theta band using WPLI. The findings reveal that non-food and low-calorie images gradually show reduced connectivity between the frontal and parietal brain regions, indicating that the brain gets used to them over time. In contrast, high-calorie images maintained strong connectivity, suggesting that they continue to capture attention and are harder for the brain to ignore. This prolonged engagement may make high-calorie foods more appealing and difficult to resist. Additionally, the study highlights the role of frontal-parietal connectivity in cognitive control, suggesting that high-calorie foods may interfere with the brain's natural ability to shift focus away from repeated stimuli, potentially contributing to overeating and poor dietary choices.

Beyond the neural mechanisms, another study also explored how individuals with different BMI levels respond to repeated food and non-food images. The results showed that participants with lower BMI adapted to low-calorie images over time, while those with higher BMI adapted more to non-food images. However, high-calorie food images did not show significant habituation in either group, meaning they continued to capture attention even after repeated exposure. This suggests that high-calorie foods may have a lasting impact on attention, making them more difficult to ignore. These findings support previous research showing that people with higher BMI often have a stronger automatic focus on food-related images, which may influence their eating habits and contribute to weight gain.

Implications and Potential Applications

This thesis identified several neural markers linked to habituation in response to repeated visual exposure to food and non-food stimuli. In the time domain, ERP components such as P2 (early attentional processing), N2 (cognitive evaluation), and LPP (sustained attention and emotional engagement) were found to be modulated across trials, particularly in parietal and frontal regions. Time-frequency analysis revealed increased frontal theta activity, associated with cognitive control, while functional connectivity analysis using WPLI showed reduced synchronisation over time, especially for non-food stimuli, indicating attentional disengagement. These findings contribute to a more precise understanding of food-related attentional biases, dietary behaviour, and the neural underpinnings of obesity. The observed slower habituation rate to high-calorie foods suggests that repeated exposure sustains neural engagement, potentially contributing to increased cravings and overeating. This aligns with prior research suggesting that persistent attentional focus on high-calorie food cues may impair self-regulation and decision-making in eating behaviour.

These results reinforce the idea that modifying the food environment, such as reducing exposure to high-calorie food advertisements and increasing the visibility of healthier options, can help redirect attentional biases and support better dietary habits. From an individual perspective, strategies like mindfulness practices, attentional retraining, and cognitive control training may help regulate responses to food cues and promote healthier eating. Public health interventions might incorporate these findings into digital tools or awareness campaigns to reduce impulsive eating behaviours. Furthermore, these insights open avenues for future research into how attentional patterns differ in individuals with eating disorders or disordered dietary habits. A deeper understanding of these processes could enable the development of personalised interventions aimed at minimising impulsivity and improving self-regulation in the context of food-related decision-making.

Limitations and Future Directions

While this study offers important insights, it has some limitations. One concern is the difference between the food stimuli used, apple (a snack) and pizza (a meal), which may have influenced neural responses beyond just their calorie content. Future research should use food images that are more similar in type to ensure fair comparisons. Another limitation is the sample size of 24 participants. Although this is a reasonable number for EEG studies, increasing the sample size and including a more diverse group of participants would help improve the reliability and generalizability of the findings. A larger dataset could also provide a deeper understanding of habituation processes.

Additionally, this study used WPLI to measure functional connectivity, which is useful for examining phase synchronisation but does not establish causal relationships between brain regions. Future research could apply methods like Granger causality or Transfer Entropy to better understand how brain regions communicate during food-related decision-making. Another limitation is that this study focused on attentional responses to food images but did not consider participants' experiences of food cravings or their actual eating habits. Future studies could include self-reported data on cravings and dietary intake to explore how neural responses to food images relate to real-world eating behaviours.

One more limitation of this study is that apple and pizza images, especially pizza, showed signs of sensitisation, as seen in Figure 5.4 in Chapter 5, Figure 6.4 in Chapter 6, Figure 9.3 in Chapter 9 and Figure 8.5 in Chapter 8. However, this effect was not observed for the hammer image. Sensitisation is a process where repeated exposure to a stimulus leads to a stronger response, particularly if the stimulus is new or emotionally significant. In contrast, habituation happens when repeated exposure causes a reduced response as the stimulus becomes familiar or less important (Rankin et al. 2009). While both processes help shape how we react to our environment, habituation allows us to filter out unimportant stimuli, while sensitisation increases attention to meaningful ones (Groves and Thompson 1970). Although this finding is relevant, a detailed discussion of sensitisation is beyond the focus of this study, which mainly looks at habituation and dishabituation. Future research could explore sensitisation further to better understand how it influences attention and motivation, particularly in response to food-related stimuli.

Also, while this study did not include an analysis of eating behaviour traits, participants also completed the DEBQ, which looks at patterns like emotional, external, and restrained eating. Since these behaviours can shape how people respond to food cues, especially at the neural level, exploring this data in the future could offer valuable insights. It may help explain why some individuals react more strongly to certain food images and could deepen our understanding of the cognitive and emotional factors behind eating habits.

By acknowledging these limitations and pursuing new research directions, we can refine our understanding of how the brain processes food-related stimuli and how these processes influence eating behaviours. Future studies should explore the long-term impact of repeated exposure to food cues and determine whether patterns of neural habituation can predict real-world dietary choices. Integrating neural, behavioural, and psychological factors would allow researchers to develop more effective strategies for managing food-related attentional biases, reducing overeating, and promoting healthier dietary habits.

Expanding on these research areas will further clarify how the brain responds to food stimuli and the ways in which these responses affect eating behaviours. This knowledge can contribute to the development of more precise strategies for regulating food intake, preventing obesity, and encouraging healthier eating patterns. With a refined approach, researchers can create targeted interventions that support long-term improvements in food-related decision-making and self-regulation.

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Appendices

Appendix A

Supplementary Materials

(a) Low caloric - Apple

(b) High caloric - Pizza

(c) Non-food - Hammer

Figure A.1: Images used in experiment