The Neural Mechanisms of Dietary Decision-Making

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Abstract

Every day, people make numerous decisions about what to eat. Despite the frequency and personal significance of these choices, the neural and computational mechanisms that underlie dietary decision-making are not fully understood. This thesis aimed to characterise the mechanisms underlying two core stages of dietary decisions: the valuation phase, during which food attributes are appraised and represented in the brain, and the choice phase, during which these representations are converted into a decision outcome.

Chapter 1 provides the theoretical background for the thesis. I review traditional approaches in food cognition research and identify gaps that motivated the work in the empirical chapters. I outline key theoretical frameworks, including economic and mathematical theories of choice and neural models of decision-making, with a focus on the valuation and choice processes underlying dietary decisions. The chapter closes with the motivations for curating a large-scale, open-access neural and behavioural dataset.

Chapter 2 describes the experimental paradigms and analytical approaches used in the empirical chapters. I explain the rationale for the study design and stimuli curation, and introduce multivariate and event-related potential (ERP) analyses used throughout the thesis. Lastly, I describe the data preparation steps undertaken to create the open-access repository of neural and behavioural data.

Chapter 3 introduces the FOODEEG dataset, an open-access resource comprising electroencephalographic (EEG) responses from 117 participants to a

diverse set of food images, accompanied by survey measures of food-related motivation and dietary styles and normative ratings on the food stimuli across 22 food attributes. The analyses in subsequent chapters of the thesis are performed on this dataset. This dataset descriptor constitutes a methodological contribution to the field, addressing the limited availability of publicly accessible and large-scale neural datasets in food cognition research. Released with standardised formatting, experimental code, and thorough documentation, the FOODEEG dataset is intended to support a wide range of future investigations into the neurocognitive processes underlying food-related behaviour, while adhering to open science principles of transparency and reproducibility. This chapter also provides a detailed account of the experimental design and dataset that form the basis of the empirical work in the subsequent chapters, and includes technical validation analyses of the EEG data.

In Chapter 4, we performed representational similarity analysis (RSA) on EEG data to characterise the neural time-courses of food attribute representations during valuation. Moving beyond the narrow focus on the trade-off between healthiness and tastiness that has dominated prior work, we examined a broad range of attributes spanning nutritive properties, hedonic properties, and familiarity. The majority of attributes were represented rapidly and in parallel, overlapping time windows. Contrary to longstanding assumptions in the field, healthiness was represented as early as, or earlier than, tastiness. Applying principal component analysis to address substantial covariation among attributes, we identified two broad underlying dimensions (how appetising and how

processed a food is) represented in the neural signals with distinct time-courses, revealing a multilevel representational architecture. A subset of individual attributes contributed unique variance to the neural signals beyond this shared structure. Together, these findings reveal that food appraisal is a rapid, automatic process in which a diverse array of choice-relevant attributes is encoded simultaneously within the first second of viewing.

In Chapter 5, we investigated how these endogenous value representations are converted into an action outcome. Using a task designed to temporally separate attribute appraisal from choice and action execution, we examined whether the centroparietal positivity (CPP), an established neural marker of evidence accumulation in perceptual decision-making, exhibits similar dynamics during dietary decisions. We applied careful signal deconvolution to address methodological concerns regarding overlapping stimulus- and response-locked activity. We found that the CPP displayed hallmark signatures of evidence accumulation across three types of dietary decisions, including steeper pre-response slopes for trials with faster response times (RTs) and stronger representational strength, alongside a relatively fixed pre-response amplitude. Our findings support the idea that the CPP is a domain-general neural correlate of evidence accumulation, extending to dietary decisions. We reveal that evidence accumulation may underlie the choice process during different types of dietary decisions, including single-item willingness-to-eat decisions and dimension-specific attribute judgements of foods.

Chapter 6 provides a summary of the key findings across the empirical

chapters and their implications. This thesis posits that a rapid, multilevel, and parallel food attribute appraisal process takes place during valuation and that noisy evidence accumulation underlies the conversion of these value representations into choice. These findings challenge traditional models of food choice that focus on the competition between automatic responses to palatability and effortful consideration of healthiness. I describe potential limitations across the studies and discuss how the contributions from this thesis can inform and advance research in clinical eating disorders and individual differences in dietary decision-making.

Together, these findings contribute to a mechanistically grounded, neurocognitive account of how people choose what to eat. A wide range of food attributes are appraised rapidly and at multiple levels during valuation, and these value representations are converted via a domain-general evidence accumulation process into choice outcomes. The open-access FOODEEG dataset supports future investigations into how these mechanisms are influenced by individual differences and contextual factors, and in clinical conditions. Taken together, this thesis brings us closer to building a process model of dietary decision-making.

Declaration

i) The thesis comprises only my original work towards the Doctor of Philosophy, except where indicated in the preface.

ii) Due acknowledgement has been made in the text to all other material used.

iii) The thesis is fewer than the maximum word limit (100,000 words) in length, exclusive of tables, bibliographies, and appendices.

Preface

For each study reported in this thesis, all EEG and behavioural data acquisition, data processing and analysis were carried out by the candidate at the University of Melbourne. Three chapters of this thesis are presented in article format. Chapter 3 presents an article published in *Scientific Data* on 20/07/26. Chapter 4 presents an article published in *Appetite* on 01/02/26. Chapter 5 presents a manuscript currently under review at *Open Mind*, which is accessible as a preprint on *bioRxiv*. The initial draft for each manuscript was written by the candidate. Daniel Feuerriegel and Tijl Grootswagers provided feedback for all manuscripts. All co-authors have agreed to the use of these manuscripts in this thesis, and have signed the co-author authorisation forms, which have been submitted alongside this thesis. The work detailed in this thesis has not been submitted for other qualifications nor commenced prior to enrolling in this degree. No third-party editorial assistance was used in the writing of the thesis. The work in this thesis was supported by an Australian Government Research Training Program Scholarship awarded to Violet Chae.

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List of Abbreviations

BF	Bayes factor
BIDS	Brain Imaging Data Structure
BOLD	Blood oxygenation level dependent
CPP	Centroparietal positivity
CSD	Current source density
DDM	Diffusion decision model
EEG	Electroencephalography
ERP	Event-related potential
fMRI	Functional magnetic resonance imaging
ICA	Independent component analysis
LMM	Linear mixed-effects model
MVPA	Multivariate pattern analysis
PCA	Principal component analysis
RDM	Representational dissimilarity matrix
RIDE	Residue iteration decomposition
RSA	Representational similarity analysis
RT	Response time
SVM	Support vector machine
SVR	Support vector regression

Chapter 1: Introduction

We make dozens of food choices every day, such as selecting the ripest banana at breakfast, deciding between the salad or the burger at lunch, or choosing whether to have dessert after dinner. Despite their mundanity, food choices are remarkably complex decisions that involve multiple considerations such as taste, nutritional content, emotional properties, and even memories of past eating experiences. Recent studies have identified food-selective regions in ventral visual cortex (Jain et al., 2023; Khosla et al., 2022; Pennock et al., 2023), as for other ecologically relevant categories such as faces (Kanwisher et al., 1997). However, it is yet unknown how the brain flexibly extracts information relevant to the decision at hand and uses it to reach a choice during dietary decisions. This thesis aims to advance our knowledge of the computational and neurocognitive processes underlying dietary decisions.

In the following sections of this chapter, I first outline the historical and philosophical foundations of food cognition research, followed by a review of some of the traditional approaches in the field. I provide an overview of three key frameworks, focusing on breadth rather than depth, and delineate the gaps that motivated the empirical work in this thesis. Next, I elaborate on the theoretical frameworks that are relevant to the empirical work in the thesis, including key distinctions between different types of decisions, theories of choice in economics and mathematical psychology, and neural models of decision-making. I focus on delineating the valuation and choice processes proposed to underlie dietary decisions and point out gaps in the research. Finally, I introduce the open science

principles that motivated the curation of the open dataset presented in this thesis.

1.1 Traditional Approaches in Food Cognition Research

Feeding is fundamental to survival, and so it is unsurprising that we have been preoccupied with how we eat for much of human history. Much of the existing research on food choice has the baked-in assumption that there is a 'right' way to choose what to eat. This notion is not a recent one, but one that we should acknowledge is a specific lens through which to view food choices that has meaningful influences on every level of scholarship in the field: from the kinds of research questions that are asked to the interpretations of the findings to build theory. Here, I will lay out the historical and philosophical foundations from which modern ideas about food choice stem and point out the ways these ideas have influenced the existing branches of research.

1.1.1 Historical and Philosophical Foundations

Choosing what to eat has historically generated anxiety and moral concern in Western culture (Coveney, 2006). The ancient Greeks regarded moderation of pleasure arising from satisfying natural appetites (e.g., for food or sex) as being of great importance to live an ethical, rational life. Going beyond one's natural needs and overindulging was viewed as improper conduct that reflected poorly on one's self-mastery. But for early Christians, indulging in bodily pleasures was more than just an excess; it was considered sinful, requiring punishment (Shaw, 1998). This is exemplified in the cardinal sins of gluttony and lust in the Christian theological tradition. In line with the dichotomy between the corrupt body and the pure soul, food pleasure was viewed as a temptation of the flesh that distracted from

spiritual pursuits. Abstaining from food pleasure through fasting remains a standard practice (Coveney, 2006). While ancient Greeks advocated for moderation in the realm of personal ethics and early Christians elevated asceticism as a virtue, both traditions established a moral framing to the act of controlling our food intake that persists in our contemporary feelings of guilt, remorse, and penance around eating.

Today, modern nutrition science has become the latest framework through which we make moral judgements about eating. We describe ourselves as “good” or “bad” based on our food choices, and the notion of “good food” has come to incorporate foods that fit with nutritional guidelines as well as those that are delicious and satisfying (Crotty, 1995). The medical model of nutrition focuses on the translation of scientific knowledge about disease processes into appropriate behaviours for individuals to improve their health (Coveney, 2006; Crotty, 1995). According to this model, individuals are expected to make informed choices about their eating after considering the food- and health-related information provided by experts, primarily scientists and healthcare practitioners. This approach assumes that individuals have the motivation, ability, and even responsibility to weigh up expert nutritional knowledge and manage their own diet. On the flip side, these assumptions give rise to the idea that an unhealthy state primarily results from individual choice, which can lead to stigma (Tesh, 1988). The medical model has been criticised for its emphasis on individual responsibility and neglect of the structural and social contexts in which people make food decisions (Coveney, 2006; Crotty, 1995). Alternative approaches place a greater emphasis on

community participation, collective action, education, and legislative changes, and position scientists and healthcare practitioners as facilitators, rather than authoritative experts, who work alongside communities (Crotty, 1995; Sobal et al., 1998).

Over the past few decades, large body size has been transformed from a physiological state into a moral and political crisis, creating new forms of self-surveillance and anxiety around food. While concern about fatness is not new, what has changed is the way body size is governed at the population level through public health institutions and at the individual level through self-monitoring of food intake, physical activity, and body measurements (Coveney, 2006). The reframing of fatness as an epidemic in the mid-1990s turned large body size from a risk factor into a disease state itself (Boero, 2003). This epidemiological framing gained traction globally, with countries like Australia reporting rising obesity rates on a population level (Coveney, 2006). The popularisation of the body mass index as a standard measure of health created new categories of normality, paradoxically making it normal to be abnormal when the majority of the population exceeded "healthy" weight thresholds (Nuttall, 2015). The concept of obesogenic environments, or settings that promote increased eating and discourage physical activity (Lake & Townshend, 2006; Swinburn & Egger, 2002), further intensified anxieties by suggesting that ordinary life itself had become detrimental for health. Increasing body sizes in children, along with fears around childhood onset of traditionally adult diseases like diabetes, heightened the sense of crisis (Deckelbaum & Williams, 2001; Dehghan et al., 2005). All this served to intensify

moral anxieties around food, and a large focus was placed on body size and weight as a proxy for health.

To summarise, our current conceptualisation of nutrition and food choice is imbued with the moral traditions from ancient Greece and early Christianity. Consequently, the dominant approach to nutrition today is one that emphasises personal responsibility and top-down flow of nutritional knowledge from experts to individuals. More recently, the construction of the "obesity epidemic" has propelled the conflation of body size with health and has fuelled our growing anxieties around food choice and body surveillance. These historical and philosophical contexts have shaped much of the existing research on food-related cognition, as will be elaborated on below. Much of the research in the field aims to change the dietary habits of the population and reduce fatness, focusing on self-control or restraint around eating. Difficulty with eating regulation is pathologised as a form of substance addiction in the popular food addiction framework, and much effort has been put into uncovering its neural basis. By making these background assumptions explicit, we can critically evaluate how they constrain our understanding of normative food decision-making.

1.1.2 Dietary Self-Control

A large body of work has focused on dietary self-control (Han et al., 2018; Hare et al., 2009; Mann & Ward, 2025). Eating presents a unique self-control challenge in that, unlike alcohol consumption, smoking, or gambling, it cannot be avoided altogether. One aspect of dietary self-control focuses on controlling the amount of food eaten (Mann & Ward, 2025). Successful dietary self-control under

this definition may be considered as abstaining from eating a food or eating a smaller portion of it. Another aspect involves choosing a more suitable food out of multiple options. To this end, studies have operationalised dietary self-control as an individual's tendency to choose healthy but less tasty food options over less healthy but tasty alternatives (Hare et al., 2009; Harris et al., 2013; N. Sullivan et al., 2015).

The dual-process model of dietary self-control suggests that food choices reflect a competition between the automatic responses to food palatability and the more effortful, controlled evaluation of health consequences (Kotabe & Hofmann, 2015). Hare et al. (2009) proposed that the ventromedial prefrontal cortex computes an integrated value signal that combines tastiness and healthiness information, while the dorsolateral prefrontal cortex modulates this value signal during self-control. In this study, self-identified dieters first rated food images on tastiness and healthiness and subsequently decided whether to eat each food relative to a neutral reference food while undergoing functional magnetic resonance imaging (fMRI). Participants were split into "self-controllers", who managed to resist choosing tasty but unhealthy foods, and "non-self-controllers", who did not, based on their choice patterns. When participants chose healthy foods over tasty foods, greater dorsolateral prefrontal cortex activity was associated with changes in the ventromedial prefrontal cortex signalling, suggesting that cognitive control can shift how food values are represented. Activity in the ventromedial prefrontal cortex was associated with both tastiness and healthiness in self-controllers but only reflected the former in non-self-

controllers. Self-control during food choices is thought to be difficult in part due to the different processing speeds of decision-relevant food attributes. Behavioural evidence indicates that tastiness may be evaluated more rapidly than healthiness (Lim et al., 2018; N. Sullivan et al., 2015). According to the dual-process model, these findings can be explained by differences in processing demands: basic attributes with immediate relevance (e.g., tastiness) are more readily represented, whereas abstract attributes concerning long-term consequences (e.g., healthiness) require greater cognitive effort to process (Liberman & Trope, 2008; N. Sullivan et al., 2015). Within the food choice literature, tastiness and healthiness have received the most attention for their relevance to this framework, and relatively few studies have examined other potentially relevant attributes, such as familiarity, level of food processing, or edibility.

Much of the existing research focuses on improving dietary self-control in the population by shedding light on the underlying mechanisms and developing related interventions. Successful dietary self-control is viewed as depending largely on individual differences in inhibitory control capacity, with those possessing stronger inhibitory control better able to resist food desires and achieve long-term weight management (Hofmann et al., 2014). Attention-based interventions have shown some promise, with studies demonstrating that directing attention toward healthiness or away from tastiness can shift food preferences (Krajbich et al., 2010; Mormann & Russo, 2021). Other approaches have attempted to enhance prefrontal control through cognitive training or transcranial magnetic stimulation of the dorsolateral prefrontal cortex, though results have been mixed

(Hall, 2016; Lowe et al., 2018). Mindfulness-based interventions aim to increase awareness of eating behaviour and reduce automatic responses to food cues, with some evidence of effectiveness in reducing food consumption (Kristeller & Wolever, 2014). Despite these efforts, the long-term efficacy of self-control interventions remains limited, with many participants returning to baseline eating patterns after intervention periods end (Mann & Ward, 2025).

There are several limitations of the dietary self-control literature. Firstly, it assumes a normative framing of food choice that some attributes of foods (e.g., healthiness) should be prioritised over other attributes (e.g., tastiness) by everyone. By defining successful decision-making as choosing foods based on healthiness rather than tastiness, this framework positions eating based on taste or pleasure as a failure of self-control. This framing overlooks the wide range of food motivations and other attributes people may consider when choosing what to eat (Renner et al., 2012; Steptoe et al., 1995). Cultural values, social contexts, hedonic goals, economic constraints, time limitations, and personal food philosophies all shape what constitutes a “good” food choice for the individual in a particular context. For example, choosing a culturally significant but less nutritious food at a family gathering, selecting an affordable option when resources are limited, or prioritising pleasure and satisfaction in eating are all reasonable decision-making strategies that the dietary self-control framework implicitly devalues.

This framing also neglects meaningful individual differences in food preferences and motivations. Research on food choice motives demonstrates

substantial heterogeneity in what people prioritise. While some individuals choose foods for health and weight control, others prefer to place greater importance on other eating motives (Renner et al., 2012; Steptoe et al., 1995). Furthermore, the dietary self-control literature frames health-focused choices as requiring effortful cognitive control, but this assumption does not hold universally. Some individuals may genuinely prefer the taste of healthier foods, find healthiness intrinsically rewarding, or have internalised preferences for healthiness so that selecting nutritious options requires little effortful control. For these individuals, choosing a healthy but less tasty food may not represent successful self-control but rather an authentic expression of their preferences. By categorising all health-oriented choices as products of effortful restraint, this framing may lead to the mischaracterisation of motivated, value-aligned eating as controlled inhibition of natural impulses.

1.1.3 Food Addiction

The food addiction framework exemplifies how moral anxieties about appetite and the pathologisation of body size have influenced food cognition research. This framework draws parallels between difficulties controlling eating behaviour and substance use disorders. Proponents of the framework argue that certain foods, particularly those that are high in sugar, fat, and refined carbohydrates, possess properties that can trigger addiction-like responses in susceptible individuals. The Yale Food Addiction Scale was developed to measure this construct, assessing addiction-like eating behaviours using criteria adapted from diagnostic criteria of substance use disorders (e.g., loss of control over

consumption, continued use despite negative consequences, and tolerance; Gearhardt et al., 2009). The scale has been widely adopted in research, with prevalence estimates suggesting that approximately 15-20% of adults in community samples meet criteria for food addiction, though rates vary substantially across populations (Pursey, Stanwell, Gearhardt, et al., 2014). The food addiction model has generated considerable interest as a potential explanation for the difficulty many individuals experience in regulating their food intake, particularly in environments where so-called hyperpalatable foods are readily available.

The food addiction model has been heavily criticised on conceptual, empirical, and clinical grounds (Hebebrand et al., 2014; Rogers, 2017; Ziauddeen & Fletcher, 2013). Firstly, food is necessary for survival, which is fundamentally different to the case with substance abuse (Ziauddeen & Fletcher, 2013). Unlike drugs, complete abstinence from food is impossible, making the treatment approach used for substance addictions inapplicable. In contrast to psychoactive drugs, which have identifiable addictive agents with specific potencies, it is difficult to ascertain what constitutes the addictive substance in foods beyond more vague categories (e.g., “highly processed”, “hyperpalatable”) that are widely consumed by most people without developing dependence. Evidence for key addiction hallmarks, such as withdrawal, tolerance, and escalating intake, is weak or absent for food (Hebebrand et al., 2014; Rogers & Smit, 2000). While individuals may report craving specific foods when attempting to avoid them, these experiences differ qualitatively from drug withdrawal syndromes, lacking the

severe physical and psychological symptoms seen with substances like alcohol or opioids. The model may also shift focus away from the environmental, social, and economic factors that shape eating behaviour, placing undue emphasis on individual pathology.

Furthermore, the neurobiological evidence supporting the food addiction model in humans remains inconsistent (Ziauddeen et al., 2012; Ziauddeen & Fletcher, 2013). The strongest evidence for food addiction comes from animal models in which rodents given intermittent access to sugar or palatable foods develop addiction-like behaviours, however this paradigm fundamentally differs from the human food environment (Avena, 2010; Ziauddeen & Fletcher, 2013). In humans, while early work reported reduced striatal dopamine D2 receptor density in individuals with severe obesity (a key pattern also observed in substance dependence; Wang et al., 2001), these findings have been contradicted by multiple subsequent investigations (Dang et al., 2016; Eisenstein et al., 2015; Karlsson et al., 2015). More broadly, neuroimaging studies have failed to produce consistent or replicable patterns of neural alterations that would validate food addiction as a distinct neurobiological syndrome (Ziauddeen et al., 2012; Ziauddeen & Fletcher, 2013). Critically, the neural similarities observed between food and drug cue responses may simply reflect domain-general reward processing mechanisms rather than addiction-specific pathophysiology. In summary, attempts to identify the neurobiology of food addiction in humans have not yet yielded findings that convincingly resemble the neural markers of substance dependence, and in several areas appear to contradict the addiction model (Benton & Young, 2016;

Fletcher & Kenny, 2018).

1.1.4 Food Cue Reactivity

Research on food cue reactivity provides another example of how concerns about body size and eating regulation have been operationalised in neuroscience, through a framework that interprets brain responses to appetising foods as potential markers of dysfunction. Food cue reactivity refers to the conditioned responses elicited by palatable food cues that trigger anticipatory responses and facilitate eating behaviour (Boswell & Kober, 2016; van der Laan et al., 2011). Exposure to such cues initiates a cascade of psychological (e.g., food craving), physiological (e.g., salivation, endocrine responses), and neural responses in preparation for eating (Belfort-DeAguiar & Seo, 2018; Jansen et al., 2011). Studies using fMRI have consistently demonstrated that viewing foods, particularly high-calorie foods, activates reward-related brain regions, including the striatum, orbitofrontal cortex, amygdala, and insula (for a meta-analysis, see van der Laan et al., 2011). Heightened neural responses to food cues are thought to reflect enhanced reward sensitivity and engagement of the appetitive motivational systems, leading to an increased drive to seek and consume food (Yokum et al., 2011). According to this account, individuals with higher food cue reactivity may be more likely to overeat in environments where appetising food cues are ubiquitous (Belfort-DeAguiar & Seo, 2018).

A meta-analysis reported that food cue reactivity, encompassing physiological (e.g., heart rate and salivation), subjective (craving), and neural measures, predicts increased food intake and weight gain over time (Boswell &

Kober, 2016). However, when examining the neural measures of food cue reactivity in isolation, the evidence for its association with eating behaviour and weight is more mixed. Longitudinal studies have found that baseline food cue reactivity predicts future weight gain, suggesting that heightened neural responses to food cues may be a factor in weight increase (Demos et al., 2012; Yokum et al., 2011). In line with this, neural reactivity to food cues was found to be positively associated with the body mass index (Demos et al., 2012; Pursey, Stanwell, Callister, et al., 2014); however, other work report little evidence for this effect (Doornweerd et al., 2018; Murdaugh et al., 2012). A meta-analysis found little evidence for obesity-related differences in neural responses to visual food cues and noted the importance of including measures of potential confounds such as dietary restraint, hunger, food craving, or impulsivity (Morys et al., 2020). Furthermore, it is unclear whether heightened neural reactivity represents a pre-existing factor that predisposes individuals to increased eating and weight gain, or whether it develops as a consequence of weight gain and repeated exposure to palatable foods. The inconsistent pattern of findings may also reflect substantial individual variation in how neural cue reactivity translates into real-life eating behaviour, potentially moderated by factors such as habitual eating patterns, physiological state, and the broader food environment.

1.1.5 Summary

Dietary self-control, food addiction, and food cue reactivity literatures share conceptual roots in the historical and philosophical traditions that have shaped our cultural relationship with food and eating. These approaches reflect

the medical model's emphasis on individual responsibility, positioning certain eating behaviours as problems requiring intervention and correction. The dietary self-control literature echoes ancient concerns about moderating bodily appetites and anxieties about the moral dangers of indulgence, framing the choice of tasty foods over healthy ones as a failure of willpower that requires effortful cognitive control to overcome. The food addiction model extends this moralisation further, medicalising difficulties with eating regulation by likening them to substance dependence. This approach positions certain foods and eating patterns as pathological rather than normative responses to an abundant food environment. Food cue reactivity research similarly problematises neural responses to appetising foods, equating heightened reward system activation with a vulnerability or dysfunction rather than a natural response to salient stimuli. Critically, all three frameworks are deeply entangled with concerns about obesity and body size, viewing higher body mass index as both an outcome to be prevented and an indicator of pathological eating behaviour. This reflects our contemporary conflation of body size with health, wherein research questions, theoretical frameworks, and intervention targets are organised around the goal of reducing fatness at the population level. The moral dimension that has characterised Western attitudes toward food and eating for centuries thus persists in modern neuroscience and psychology, now dressed in the ostensibly objective language of brain function, cognition, and reward sensitivity.

However, these frameworks have been insufficient in adequately explaining how some individuals in the population have a larger body size. Body size is

influenced by a myriad of complex factors, including genetic predisposition, metabolic factors, food environment, socioeconomic conditions, and cultural contexts (Loos & Yeo, 2022). Twin studies estimate the heritability of the body mass index at 40-75%, with contributions from over 100 genetic loci (Loos & Yeo, 2022; Silventoinen et al., 2016). Solely examining higher body weight as evidence of failed self-control, addiction-like processes, or dysfunctional reward sensitivity misses the larger factors at play, and runs the risk of perpetuating weight stigma (Tomiyama et al., 2018). Yet food addiction research in particular gained substantial popularity and policy attention despite inconsistent empirical support (Hebebrand et al., 2014; Ziauddeen & Fletcher, 2013), revealing how deeply entrenched the moral ideas surrounding food and body size remain within both scientific communities and public discourse.

In contrast, the present thesis adopts a descriptive, rather than a prescriptive, approach to dietary decision-making. Without assuming that particular food choices are “good” or that certain attributes should be prioritised over others, we sought to characterise the shared computational and neural mechanisms underlying dietary decisions regardless of personal goals, motivations, and contexts that shape these choices. By setting aside moral framings of food choice and adopting a cognitivist approach, we aimed to delineate the basic neurocognitive processes involved in dietary decision-making without assuming these processes are dysfunctional or require regulation. Establishing this mechanistic foundation will enable future investigation into how structural, social, and contextual factors largely absent from existing neuroscience

research influence eating behaviour at the neural level.

1.2 Theoretical Frameworks for Dietary Decisions

In this section, I introduce the theoretical frameworks relevant for the empirical work in the current thesis. Firstly, I review the traditional distinction between value-based and perceptual decisions, point out key distinguishing features of dietary decisions, and posit that domain-general mechanisms may underlie different decision types. Next, I review foundational theories of choice from economics and mathematical psychology. Finally, I describe the neurobiological evidence for the processes of valuation and choice as they are implemented in the brain and point out outstanding questions in relation to dietary decisions.

1.2.1 Distinguishing Between Types of Decisions

Traditionally, researchers have distinguished between perceptual and value-based (or preference-based) decisions (Hanks & Summerfield, 2017). Perceptual decisions are thought to primarily involve sensory processing of external stimuli in order to determine objective world properties (e.g., discerning whether the traffic light is green or red), while value-based decisions typically involve subjective considerations (e.g., choosing which snack to buy). Dietary decisions tend to be categorised as a type of value-based decision. Perceptual and value-based decisions have been investigated in distinct lines of research with little overlap, but recently efforts have been made to bridge the gap between the two fields (Krajbich & Rangel, 2011; Pisauro et al., 2017; Polanía et al., 2014; Smith & Krajbich, 2021). In this section, I will point out the key issues in the classical

distinction between perceptual and value-based decisions and review converging findings in the two fields that suggest that shared mechanisms underlie multiple types of decisions.

The distinction between perceptual and value-based decisions has been criticised as being ill-defined. Smith and Krajbich (2021) posit that, though often conflated, the *subjectivity* of a decision (whether the decision has an objectively correct answer) is dissociable from the *information source* (whether the information is drawn from external stimuli or endogenous representations). Perceptual decisions typically combine objective criteria with exogenous information sources (e.g., judging which of two lines is longer based on visual input), whilst value-based decisions typically combine subjective criteria with endogenous information sources (e.g., choosing a favourite artist based on internal preferences). However, these dimensions are dissociable, such as in memory-based decisions that draw on endogenous information and have objective criteria (e.g., recognising whether a face was previously seen).

Dietary decisions combine elements traditionally associated with both perceptual and value-based decisions. Regarding *subjectivity*, food choices involve subjective preferences that are informed by objective attributes (e.g., sweetness, calorie content, price). Regarding *information sources*, dietary decisions draw from both exogenous sensory information (e.g., colour, shape, size) and endogenous representations (e.g., memories of eating experiences, nutritional knowledge, interoceptive hunger cues). Carefully characterising dietary decisions along these two dimensions, rather than simply categorising all food choices as

value-based, may enable more specific inferences about the cognitive and neural processes engaged.

Recent work has highlighted key commonalities between perceptual and value-based decisions, such as similarity in the relationships between speed, choice proportions (e.g., accuracy), and difficulty (Folke et al., 2016; Krajbich et al., 2010; Polanía et al., 2014; Smith & Krajbich, 2021; Tavares et al., 2017). For example, choosing from more similar options (e.g., actions or objects that are similarly appealing, or perceptually difficult to discriminate) is associated with increased difficulty, errors, and time taken in both domains. There are also similarities in the relationship between gaze behaviour and choice (Konovalov & Krajbich, 2016; Newell & Le Pelley, 2018; Pärnamets et al., 2015; Smith & Krajbich, 2021; Tavares et al., 2017). For example, options that are looked at for longer are more likely to be chosen. Taken together, these findings suggest that shared mechanisms may underlie different types of decisions. Applying theoretical frameworks and computational models developed in other decision-making domains may shed light on the mechanisms underlying dietary decisions.

1.2.2 Theoretical Models of Choice

Before introducing neural models of decision-making, I will first outline relevant theories from economics and mathematical psychology from which the neural models were derived. Traditional economic models characterise the observable patterns of choice behaviour without making claims about the underlying cognitive or neural mechanisms. These models may be used to describe decision-makers as behaving *as if* they compute certain functions, but

are explicitly agnostic regarding whether such computations are neurally instantiated (Kable & Glimcher, 2009). Multiattribute utility theory, for instance, posits that the overall utility of an option can be decomposed into weighted utility functions across multiple attributes, providing a normative framework for how decisions should be made when alternatives differ along more than one dimension (Keeney et al., 1976). This provides a useful model to describe how we choose when there are multiple aspects of the decision options to weigh up, as is the case with food choice. Beyond static utility representations, dynamic process models have been developed in mathematical psychology to describe the moment-by-moment unfolding of choice through sequential sampling of noisy evidence.

1.2.2.1 Economic Models of Utility and Subjective Value. How do we compare and select between options that differ along multiple, qualitatively distinct dimensions? The concept of an integrated subjective value signal is implicit in several foundational economic theories of choice. Expected utility theory (von Neumann & Morgenstern, 1944) formalised the idea that decision-makers evaluate probabilistic outcomes by computing a single expected utility value as the probability-weighted sum of utilities across possible states, enabling comparison between risky prospects that differ in both magnitude and likelihood of outcomes. In the domain of intertemporal choice, discounted utility models (Loewenstein & Prelec, 1992; Samuelson, 1937) propose that outcomes at different time points are converted to present values through temporal discounting, allowing for a common currency of subjective value across time. Even theories that challenge normative rationality assumptions, such as prospect

theory (Kahneman & Tversky, 1979), retain the core notion that subjective value is computed for each option, though these value computations may be relative to a reference point rather than absolute.

Of particular relevance to food choices, multiattribute utility theory provides a formal framework for understanding how people make decisions when options vary along multiple dimensions or attributes (Keeney et al., 1976). According to this framework, decision-makers evaluate each attribute of a choice option separately, assigning subjective values to these attributes, then integrating them into an overall value for the option. The subjective value of an option is computed as a weighted sum of its attribute values, where the weights reflect the relative importance of each attribute to the decision-maker (Payne et al., 1993). For example, when choosing between two food items, an individual may evaluate each item on relevant dimensions (such as tastiness, healthiness, cost, and convenience) and compare the overall values of the two items. This additive model assumes that attributes are evaluated independently and combined linearly, though extensions of the theory allow for nonlinear integration and interactions between attributes (Tversky & Kahneman, 1986). The theory has been influential in economics and decision sciences as it provides testable predictions about choice behaviour and offers a rational framework for how decisions should be made when facing trade-offs between competing attributes (von Winterfeldt & Edwards, 1986).

1.2.2.2 Sequential Sampling Models. In mathematical psychology, sequential sampling models provide a mechanistic account of how decisions unfold over time by conceptualising decision-making as a process of evidence

accumulation (Ratcliff & McKoon, 2008). These models posit that when faced with a decision, noisy evidence favouring each alternative is continuously sampled, accumulating over time until sufficient evidence has been gathered to trigger a choice. This accumulated evidence is represented as a decision variable that evolves dynamically, approaching one of several decision boundaries, each corresponding to a different response option. When the decision variable reaches a boundary, the associated choice is executed. This framework elegantly captures the speed-accuracy trade-off in decision-making (Forstmann et al., 2016; Ratcliff & Smith, 2004): accumulating more evidence increases accuracy but takes more time, while committing to a choice quickly risks errors due to insufficient information.

The diffusion decision model (DDM) is one of the most widely studied sequential sampling models, particularly for binary (two-alternative) choices (Ratcliff, 1978; Ratcliff & McKoon, 2008). The DDM posits that evidence accumulation proceeds as a noisy random walk between two response boundaries. The model includes several key parameters that capture distinct cognitive processes (Figure 1). The *drift rate* represents the average rate of evidence accumulation toward one option or the other. Higher drift rates indicate stronger evidence or clearer discrimination between alternatives. The rate of accumulation may also vary across trials, as represented by *drift rate variability*. The *boundary separation* reflects the amount of evidence required before a decision is made, embodying the decision threshold or response caution; wider boundaries lead to slower but more accurate choices. The *starting point* indicates

any initial bias toward one response over the other before evidence accumulation begins, allowing the model to capture pre-existing preferences. Finally, *non-decision time* accounts for processes outside the core decision mechanism, including perceptual encoding of stimuli and motor execution of responses.

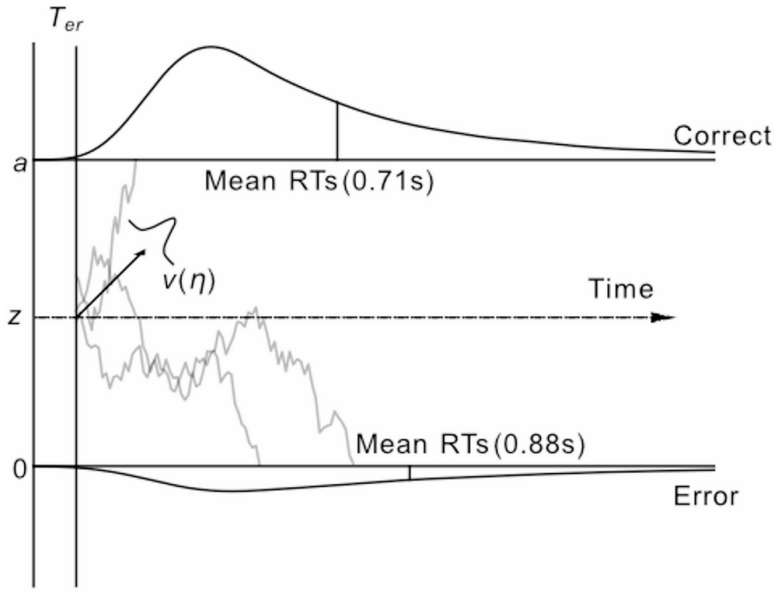

Figure 1. The diffusion decision model for binary choice. Adapted from Sun et al. (2026). Evidence accumulates noisily between two response boundaries. Key parameters include drift rate *v* (average rate of evidence accumulation), drift rate variability *η* (across-trial variability in the rate of evidence accumulation), boundary separation *a* (decision threshold reflecting response caution), starting point *z* (initial bias towards one option), and non-decision time T_{er} (encoding and motor execution processes). Higher drift rates produce faster accumulation and shorter response times (RTs).

The DDM has demonstrated remarkable success in accounting for choice behaviour across diverse cognitive domains. In perceptual discrimination tasks, the model simultaneously captures accuracy rates and the shapes of response

time (RT) distributions for both correct and error trials (Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998). Critically, the model's parameters exhibit meaningful sensitivity to experimental manipulations. Degrading stimulus quality reduces drift rate without affecting boundary separation, while instructions emphasising speed over accuracy decrease boundary separation without changing drift rate (Ratcliff & Rouder, 1998; Voss et al., 2004). These dissociations suggest that the parameters reflect genuine psychological processes. More recently, sequential sampling frameworks have been applied to value-based choice, where drift rate is proposed to reflect the difference in subjective value between options that drives the decision (Krajbich et al., 2010, 2012; Krajbich & Rangel, 2011; Milosavljevic et al., 2010; Philiastides & Ratcliff, 2013). These models have successfully been able to capture patterns of choice proportion and RT distribution data.

1.2.3 Neurobiological Models of Decision-Making

Theories of choice outlined above have spurred investigations into whether and how such value signal computation and evidence accumulation may be implemented in the brain. The goal of neural models of decision-making is to shed light on the computational and neural mechanisms used by the brain to generate choice behaviour. These models aim to address both the choice outcomes and the neural implementations that give rise to those choices (Kable & Glimcher, 2009).

In neuroscience, converging lines of evidence suggest that decision-making involves two separable but interacting processes of valuation and choice (Hare, Schultz, et al., 2011; Hutcherson et al., 2012; Kable & Glimcher, 2009; Rangel et al., 2008). During valuation, the subjective values of the options under

consideration are computed. In the choice process, these value representations feed into a dynamic decision signal that reflects the relative evidence accumulated for each action outcome until a threshold is reached, triggering choice (Krajbich et al., 2010; Milosavljevic et al., 2010; Ratcliff & McKoon, 2008). We apply this framework to dietary decision-making in the current thesis. During dietary decisions, it is assumed that we firstly appraise each food option on attributes that are relevant for choice (e.g., healthiness, tastiness, cost, and convenience) and assign values to each attribute. These individual attribute values are integrated into an overall value that drives a choice process. Evidence supporting each possible action (e.g., to eat or to not eat) is accumulated over time until a threshold is crossed, initiating an action (e.g., eat the cake). In this section, I will delve into the processes of valuation and choice in dietary decision-making and identify gaps in our current understanding.

1.2.3.1 Valuation. Neuroimaging research using fMRI has identified specific brain regions that appear to encode subjective value during decision-making (Figure 2). Converging evidence points to the ventromedial prefrontal cortex and the striatum as key nodes in a valuation network that computes integrated value signals across diverse choice contexts (Bartra et al., 2013; Clithero & Rangel, 2014; Levy & Glimcher, 2012). In the context of dietary decisions, this network appears to integrate multiple attributes of a food into an overall value signal that guides choice. Plassmann et al. (2007) found that blood-oxygenation-level-dependent (BOLD) signals in prefrontal and orbitofrontal regions tracked participants' willingness to pay for snack foods, with neural responses in those regions scaling

with subjective valuation. Hare et al. (2009) showed that BOLD signals in the ventromedial prefrontal cortex reflected the combined value for the food item that integrated both tastiness and healthiness considerations. When dieters successfully exercised self-control by choosing healthier options, the dorsolateral prefrontal cortex modulated this value signal, suggesting a mechanism by which cognitive control influences the weighting of different attributes. Hare et al. (2011) further demonstrated that directing attention toward the healthiness of foods enhanced their representation in the ventromedial prefrontal cortex and shifted choices toward healthier options. Together, these regions comprise an interconnected network through which the subjective value of available options is computed to guide decision-making.

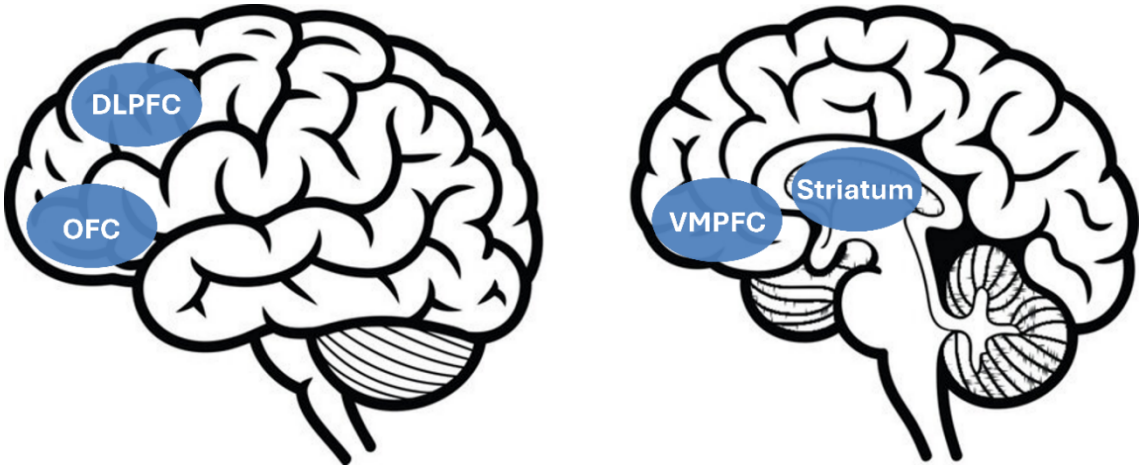

Figure 2. Key brain regions implicated in valuation. The ventromedial prefrontal cortex (VMPFC) serves as a central hub for computing integrated subjective value signals that combine multiple attributes (e.g., tastiness and healthiness) to guide choice. The orbitofrontal cortex (OFC) and striatum also encode stimulus value during value-based choice. The dorsolateral prefrontal cortex (DLPFC) exerts top-down modulatory influence over VMPFC during self-control, shifting the relative

weighting of stimulus attribute values. Together, these regions form an interconnected network that calculates the subjective value of options to guide decision-making.

However, questions remain about the temporal dynamics of how different food attributes are initially represented before being integrated into this final common value signal (Figure 3). The ventromedial prefrontal cortex receives inputs from sensory cortices, medial temporal lobe structures involved in memory, and regions processing affective and visceral states (Haber & Knutson, 2010). Food attributes, such as sensory features, remembered eating experiences, and nutritional knowledge, must be represented and conveyed to the valuation regions during dietary decisions. Understanding this earlier stage of attribute representation is critical for a complete account of the valuation process. Electroencephalography (EEG) provides a valuable complementary approach to fMRI for examining attribute representation. While fMRI is suited for localising brain regions involved in computing integrated value, its temporal resolution (on the order of seconds) is insufficient for distinguishing the rapid processing of different food attributes. EEG, with millisecond-level temporal precision, enables investigation of *when* different attributes are extracted and represented during valuation. Using EEG, studies have demonstrated that high-level object properties (e.g., animacy, naturalness, and category membership) emerge in neural signals within approximately 100–200 ms of stimulus onset (Carlson et al., 2013; Cichy et al., 2014; Grootswagers, Robinson, & Carlson, 2019). Recent work applying similar approaches to food images has begun to reveal that food-relevant attributes are

likewise represented rapidly in early neural signals (Moerel et al., 2024, 2026; Schubert, Rosenblatt, et al., 2021).

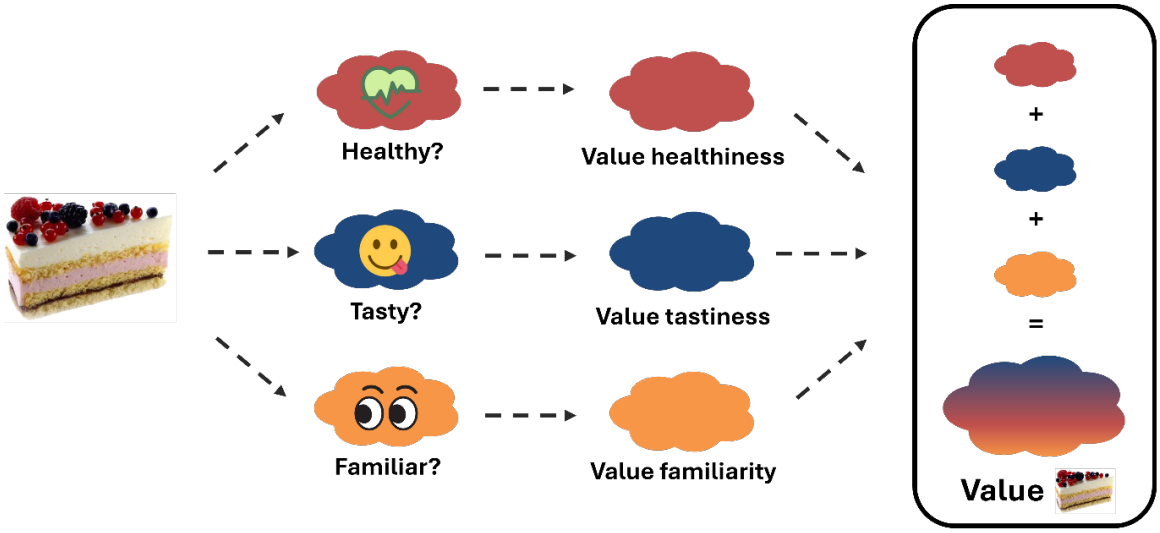

Figure 3. Valuation in dietary decisions. During valuation, the food item is appraised on a set of choice-relevant attributes (e.g., healthiness, tastiness, familiarity) and values are assigned for each attribute based on the current context (e.g., physiological state) and past consumption experiences. The individual attribute values are integrated to compute an overall subjective value for the food item under consideration.

1.2.3.1.1 Outstanding Questions. There are several outstanding questions in food choice research regarding the valuation phase of decision-making. When computing an overall value signal for each food option during dietary decisions, there are numerous and often conflicting attributes of foods that we may take into account (Chen & Antonelli, 2020; Glanz et al., 1998). Some of these gaps pertain to which of the numerous potentially choice-relevant attributes are considered. Do we sometimes appraise foods on a wide range of attributes, or do we tend to be more frugal? Neuroimaging work have largely focused on tastiness and healthiness

as key drivers of choice, and relatively little attention has been given to other choice-relevant attributes. Another gap is related to the timing at which these attributes are processed. For example, it is unclear whether there are systematic differences in the speed at which attributes are processed.

According to classical theories of multiattribute choice, a rational decision-maker should appraise each food option on all choice-relevant attributes then weight each attribute according to its importance in the overall value calculation (Keeney et al., 1976; Payne et al., 1993). However, it is contested whether this is reflective of how people make decisions in real life. Given the limitations on time, motivation, and computational resources, people may opt to use simpler strategies during valuation that do not take all the relevant attributes into account (Cohen & Babey, 2012; Gigerenzer & Gaissmaier, 2011). Behavioural work has found that simple heuristics (e.g., comparing foods on one most important attribute) can predict participants' food choices as accurately as the classic weighted additive model (Scheibehenne et al., 2007) or even outperform it (Schulte-Mecklenbeck et al., 2013). These behavioural findings challenge the view that people consider a wide range of choice-relevant attributes when choosing foods. However, we lack the means to parse whether people are genuinely implementing one strategy or another, especially if multiple strategies perform similarly in their prediction of choice behaviour (e.g., Scheibehenne et al., 2007). Analysing neural data may offer a more direct window into the brain processes that underlie food attribute appraisal and allow comparisons between competing accounts. For example, if the neural signals during food valuation contain

information about multiple food attributes, it provides support for the idea that those attributes are represented by the brain and potentially relevant for valuation. Furthermore, by establishing methods to assess food appraisal processes on a neural level, we can study the mechanisms through which different contexts (e.g., varying urgency, attention, knowledge, or motivation) impact dietary choice.

The timing at which different attributes are evaluated during valuation also has an important influence on subsequent choice. Informed by construal level theory (Liberman & Trope, 2008; Trope & Liberman, 2010), it is a longstanding view in food cognition literature that basic attributes (e.g., tastiness) are represented more easily and quickly compared to more abstract attributes (e.g., healthiness), which are thought to be more effortful to represent (Rangel, 2013; N. Sullivan et al., 2015). An attribute that is represented earlier is thought to be integrated more quickly into the overall value computation and subsequently weighted more heavily in the decision (Figure 4). This difference in processing speed is thought to contribute to why resisting tasty but unhealthy foods is difficult.

By analysing the mouse cursor trajectory towards one of the two food options, mouse tracking work revealed that tastiness may indeed be reflected in the decision trajectory earlier than healthiness (Lim et al., 2018; N. Sullivan et al., 2015). Specifically, N. Sullivan et al. (2015) had participants rate foods on tastiness and healthiness before choosing between food pairs while their cursor movements were tracked continuously. By modelling how strongly each attribute predicted the trajectory's angle at each time point, they estimated that tastiness became a significant predictor of movement roughly 195 ms before healthiness, and that this

latency difference accounted for 13–39% of individual variation in dietary self-control. Lim et al. (2018) used a similar paradigm and found that in overweight individuals, integration of healthiness lagged tastiness by about 230 ms when no calorie information was shown, and that adding calorie labels sped up the processing of healthiness and promoted healthier choices.

Evidence from neuroimaging studies is also mixed, with studies reporting that healthiness of foods is reflected in the differences in amplitude of event-related potential (ERP) components as early as ~100-200 ms after food cue onset (Harris et al., 2013; Rosenblatt et al., 2018). Other work has demonstrated that information about healthiness can be represented earlier compared to tastiness in the EEG signals (Harris et al., 2018; Schubert, Rosenblatt, et al., 2021). Schubert, Rosenblatt, et al. (2021) directly compared explicit and implicit attribute processing across two experiments using multivariate decoding of EEG activity: in an explicit rating task (Experiment 1), taste information was decodable earlier than health information, but in a second, reanalysed dataset in which participants simply indicated their desire to consume a food without explicit instruction to consider either attribute (Experiment 2), health representations became decodable earlier than taste. The difference in the speed at which attributes are appraised is important to consider, as it has an influence on the weighting of attribute information in the subsequent decision. There is a need to carefully characterise the fine-grained neural time-courses of food attribute representations.

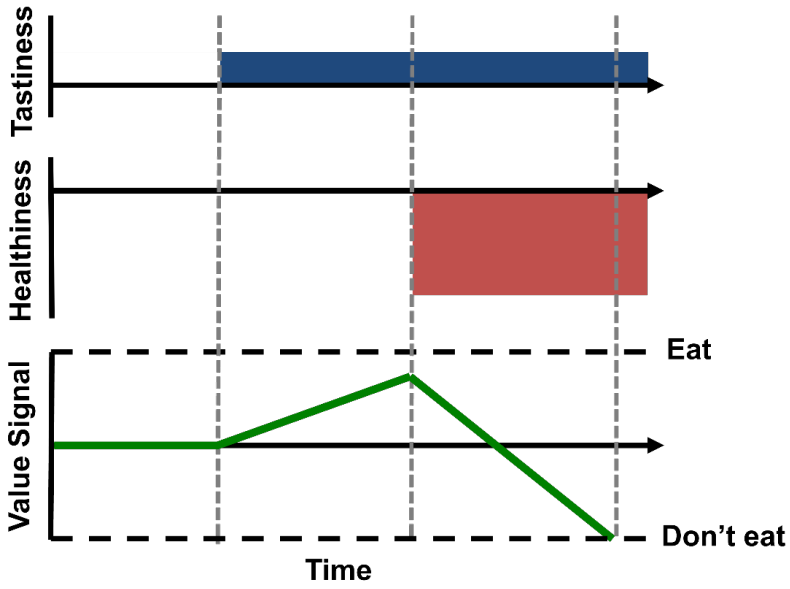

Figure 4. The influence of attribute processing speed on decision outcomes. Adapted from N. Sullivan et al. (2015). Tastiness (blue) and healthiness (red) information are integrated into an overall value signal. In this scenario, the food item is a little tasty and very unhealthy. If taste information becomes available earlier and health information only emerges later, this difference in processing speed influences the overall value signal and can impact choice outcomes. In sequential sampling models, a dynamic value signal begins at zero and accumulates evidence by integrating a weighted sum of currently available attribute values plus noise, with weights reflecting the individual's true preferences. A decision is triggered when this accumulated signal reaches either the "Eat" or "Don't eat" boundary. As only taste information influences the value signal for a portion of time before healthiness information is processed, this increases the probability of choosing the food option despite the health costs outweighing its taste benefits when both attributes are fully represented.

Existing neuroimaging work has focused on the appraisal of tastiness and

healthiness as the most influential drivers of food choices (Hare et al., 2009; Hare, Malmaud, et al., 2011; Harris et al., 2013, 2018; Rosenblatt et al., 2018; Schubert, Rosenblatt, et al., 2021). The neural processing of calorie content has also been extensively studied (Duraisingam et al., 2021; Meule et al., 2013; Toepel et al., 2009). However, research on individual food attitudes and motivations have shown that people consider many other aspects important for food decisions (Renner et al., 2012; Steptoe et al., 1995), and are therefore likely represented in the neural signals. Recent work has shown that the degree of processing of foods, reflecting the work and ingredients involved in their preparation, is encoded in neural responses during food perception (Coricelli et al., 2019; Moerel et al., 2024). Although familiarity is thought to be a major factor in food choices (Blechert, Meule, et al., 2014; Foroni et al., 2013; Steptoe et al., 1995), its neural processing in healthy populations outside of the context of food neophobia has not been investigated in-depth. Moreover, familiarity encompasses multiple dimensions (e.g., previous experiences with the food, recognisability, and how typical it is of its category) that may be represented distinctly during valuation. Affective properties of foods, particularly emotional valence and arousal, also vary across food items and likely contribute to choice (Blechert, Meule, et al., 2014; Foroni et al., 2013; Gutjar et al., 2015). The focus on the processing of tastiness, healthiness, and calorie content of foods in neuroimaging studies is in line with the medical model that emphasises health and weight concerns. There is a need to examine the neural processing of other food attributes that are influential in people's dietary decisions, to gain a fuller understanding of food valuation.

There are some critical methodological challenges in examining the neural representations of food attributes. Firstly, there is substantial covariation among key food attributes. For example, healthiness judgements are correlated with valence, calorie content, and familiarity (Foroni et al., 2022). This presents an interpretational challenge, as it is unclear whether the observed brain activity reflects processing of a specific attribute. Stimuli can be carefully curated to decorrelate key attributes. For example, Rosenblatt et al. (2018) used the participants' individual healthiness and tastiness ratings on the stimuli to categorise the food stimuli as healthy and tasty, healthy and not tasty, not healthy and tasty, and not healthy and not tasty, to ensure that there was an even balance of items across these categories. However, this approach becomes less feasible when investigating a larger number of attributes. Furthermore, foods are naturalistic stimuli with inherent patterns in low-level perceptual features that correlate with attribute judgements. For example, foods that are more beige in colour may be more highly processed. Low-level visual properties, such as colour, luminance, silhouette, and contrast, are reflected in the neural signals across multiple post-stimulus latencies and may confound the associations between the neural activity and food attributes (Grootswagers et al., 2024).

1.2.3.2 Choice.

In the choice phase, the value signals computed during the valuation phase are used to guide decisions and associated motor commands. Sequential sampling models characterise this process as noisy evidence accumulation towards a decision boundary, and a growing body of evidence supports the notion

that evidence accumulation may be feasibly implemented on a neural level. In non-human primates, individual neurons in decision-related brain regions exhibit activity that gradually increases during deliberation and reaches a stable peak at the moment of choice during perceptual decisions (Hanes & Schall, 1996; Shadlen & Newsome, 2001). Shadlen and colleagues recorded from neurons in the lateral intraparietal area while monkeys performed a random dot motion discrimination task (Roitman & Shadlen, 2002; Shadlen & Newsome, 1996, 2001). They observed that neurons in this area that are selective for a particular saccade direction showed firing rates that increased gradually when evidence favoured that direction, with the rate of increase (analogous to drift rate) dependent on motion coherence. Critically, firing rates reached approximately the same threshold level just before saccade initiation regardless of task difficulty or decision speed, consistent with a fixed decision boundary. Similar ramping-to-threshold dynamics have been observed in frontal eye fields (Gold & Shadlen, 2000; Hanes & Schall, 1996), superior colliculus (Horwitz & Newsome, 1999; Ratcliff et al., 2007), and dorsolateral prefrontal cortex (Kim & Shadlen, 1999), suggesting a distributed network implementing evidence accumulation for perceptual choice.

In humans, the centroparietal positivity (CPP) component of the ERP has been posited as a neural correlate of evidence accumulation. A growing body of literature suggests that a positive-going signal over centroparietal electrodes builds gradually during perceptual decision-making and reaches an approximately fixed amplitude just before the response (Kelly & O'Connell, 2013; O'Connell et al., 2012; Twomey et al., 2015). Critically, the CPP exhibits several key properties

predicted by sequential sampling models. First, its build-up rate is sensitive to evidence strength: stronger sensory evidence produces steeper CPP slopes (Feuerriegel et al., 2021; O'Connell et al., 2012; Steinemann et al., 2018). For example, in random dot motion tasks, higher motion coherence yields faster CPP build-up rates, directly paralleling the drift rate parameter in the DDM (Kelly & O'Connell, 2013). This slope-evidence relationship holds at the single-trial level, with steeper slopes predicting faster RTs within individual participants. Second, the signal reaches a consistent peak amplitude at the decision point regardless of task difficulty or speed pressure, consistent with a fixed decision threshold (Kelly & O'Connell, 2013; O'Connell et al., 2012). These converging properties establish the CPP as a promising candidate neural marker for the evidence accumulation process posited by sequential sampling models.

1.2.3.2.1 Outstanding Questions. The exact mechanism by which the choice process is implemented in the brain for dietary decisions is not yet fully known. While a growing body of research supports the idea that the CPP traces evidence accumulation in perceptual decisions, fundamental questions persist about whether these mechanisms also underlie dietary choices and other types of non-perceptual decisions. Dietary decisions differ from perceptual tasks in critical ways, combining endogenous representations (memory, preferences, interoceptive states) with exogenous sensory information (sensory and perceptual properties of food) and involving subjective preferences informed by objective attributes. Furthermore, theoretical debates continue as to whether food choices arise from competing dual systems (autonomic, rapid responses to immediately

relevant attributes versus controlled consideration of long-term consequences; Cosme et al., 2019) or from an evidence accumulation process that takes multiple attributes into account. Finally, while existing research on dietary decisions has illuminated processes involved in choosing between two or more food options (e.g., Krajbich et al., 2010; Krajbich & Rangel, 2011; Pisauro et al., 2017), many real-world dietary decisions involve evaluating a single food item, raising questions about whether evidence accumulation principles extend to these single-option decision structures.

Models of evidence accumulation are increasingly applied to other kinds of decisions beyond perceptual choices. Several studies have identified ramping neural signals during traditionally value-based decisions that resemble evidence accumulation dynamics observed in perceptual tasks. Fong et al. (2026) investigated voluntary, self-paced decisions in which participants viewed and chose between coloured balloons without time pressure. These decisions have a subjective decision criterion (there being no objectively correct answer) and draw from exogenous sensory evidence as well as endogenous colour preferences. They identified neural signatures that resembled evidence accumulation, with steeper slopes for faster RTs. Pisauro et al. (2017) used simultaneous EEG-fMRI to demonstrate that dietary choices involving choosing between two food items elicit centroparietal signals resembling the evidence accumulation dynamics. However, this interpretation has been challenged by researchers questioning whether these effects may be driven by confounds such as overlapping stimulus-evoked signals (Frömer et al., 2024). It is worth noting that Fong et al. (2026) addressed these

concerns by using deconvolution methods to isolate decision-related signals from stimulus-locked signals, and subsequent work has argued that the analytical approach used by Frömer et al. may be inappropriate for detecting genuine ramping signals in decision tasks (O'Connell et al., 2025). It remains to be seen whether similar evidence accumulation processes underlie dietary decisions, which combine endogenous representations (memory, interoception, affective states) with exogenous sensory information, involve subjective preferences informed by objective attributes, and often occur in naturalistic self-paced contexts.

A persistent theoretical tension exists between dual-process models of dietary self-control and evidence accumulation accounts of food choice. The dietary self-control framework proposes that food choice involves competition between the rapid, automatic responses to palatability and the deliberate, controlled evaluation of health consequences (Cosme et al., 2019; Hare et al., 2009; Hutcherson et al., 2012). In contrast, evidence accumulation models conceptualise food choice as a unified process where value signals (potentially integrating both tastiness and healthiness) drive a decision variable towards a decision boundary (Krajbich & Rangel, 2011). From this perspective, self-control "failures" reflect noisy accumulation processes in which differences in processing speed, evidence strength, attention, or stochastic variability regarding tastiness versus healthiness influence which decision outcome threshold is reached, rather than a failure of one system in inhibiting another. Identifying neural correlates of evidence accumulation during dietary decisions could help adjudicate between

these competing accounts by revealing whether an integrated accumulation process may explain food choices.

There is evidence that the CPP may trace evidence accumulation processes in food decisions when deciding between two food item alternatives (Pisauro et al., 2017, but see Frömer et al., 2024). However, many real-world dietary decisions involve different choice structures. Consider standing in front of a refrigerator while deciding whether to eat yesterday's leftovers (i.e., a binary decision about a single food item). These single-option decisions differ fundamentally from choosing between two food items: there is no explicit comparison between alternatives, yet a decision threshold must still be reached. However, whether the same computational principles govern these varied decision types remains unclear. Given that dietary decisions in naturalistic contexts often involve evaluating single foods ("Should I eat this cookie?") or categorising foods along dimensions like healthiness ("Is this stew healthy?"), understanding how evidence accumulation models apply to these single-option decision structures is essential for a comprehensive account of food choice.

1.2.4 Summary

This section reviewed key theoretical frameworks for understanding dietary decision-making, drawing on insights from economics, mathematical psychology, and cognitive neuroscience. While food choices are traditionally considered value- or preference-based rather than perceptual decisions, there are limitations to these distinctions, and the field can benefit from insights from perceptual decision-making literature. Economic theories propose that decision-makers

integrate multiple food attributes (tastiness, healthiness, familiarity, cost) into a common subjective value signal, formalised through the multiattribute utility theory (Keeney et al., 1976). Sequential sampling models, such as the DDM, conceptualise decision-making as noisy evidence accumulation toward a threshold (Ratcliff, 1978; Ratcliff & Smith, 2004). Neurobiological evidence supports the view that this two-stage process is implemented in the brain: valuation, involving appraisal of relevant attributes and computation of integrated value signals, and choice, in which the value signals feed into an evidence accumulation process toward decision boundaries.

Critical gaps remain in our understanding of dietary decisions. During valuation, it is unclear which food attributes are appraised (e.g., a comprehensive evaluation or frugal heuristics), when different attributes are processed (e.g., whether attributes differ in processing speed), and whether attributes beyond the extensively studied few are also represented in the neural signals. Methodological challenges, including high covariation among food attributes and low-level visual feature confounds, need to be addressed to fill these gaps in our understanding of attribute appraisal processes. During choice, fundamental questions persist about whether evidence accumulation mechanisms generalise from perceptual to dietary decisions (challenging the dual-process model of food choices), and whether these mechanisms can be extended to single-option decisions beyond explicit comparisons between alternatives. The empirical studies in subsequent chapters aim to address these outstanding questions by examining food attribute representation during valuation (Chapter 4) and neural signatures of evidence

accumulation during dietary choice (Chapter 5).

1.3 Open Dataset and Code Sharing

Despite the substantial theoretical and empirical progress in food cognition research, a critical barrier to advancing the field has been the absence of large-scale, publicly available neural datasets. The acquisition of neuroimaging data of a sufficient sample size can be costly and time consuming. To address this gap, we created the FOODEEG dataset, a large-scale, open-access resource containing EEG responses from 117 participants to a diverse set of food images, alongside behavioural measures of food cognition and comprehensive normative ratings for 22 food attributes. This dataset, presented in Chapter 3, was designed to enable future hypothesis- and data-driven investigations into the neural substrates of visual food cue processing, dietary decisions, and individual differences.

The value of large-scale, openly available neural datasets has been compellingly demonstrated in other areas of cognitive neuroscience. The THINGS-EEG dataset, containing EEG responses from 50 participants to over 22,000 images, has enabled researchers to build encoding models of visual object recognition, test the generalisability of findings across stimulus sets, and train deep neural networks to predict brain responses to arbitrary images (Grootswagers et al., 2022). Similarly, a large-scale EEG dataset for visual object recognition comprising 10 participants with over 82,000 trials each has facilitated the development of computational models that synthesise neural responses to novel images and has advanced understanding of the temporal dynamics of object processing (Gifford et al., 2022). The Natural Scenes Dataset, which includes high-

resolution fMRI data from 8 participants viewing 73,000 natural scene images, has become a foundational resource for investigating the neural basis of visual perception and has enabled discoveries about the organisation of visual cortex (E. J. Allen et al., 2022). Recently, EEG datasets have been released to facilitate research in visual processing in infants (Grootswagers et al., 2025) and visual touch perception (Smit et al., 2026). These examples illustrate how publicly available neural datasets can stimulate scientific progress by enabling data-intensive computational modelling approaches, supporting replication and robustness checks, and allowing researchers to test new hypotheses on existing data.

To ensure that the open datasets are genuinely useful for future researchers, it is crucial that they are accompanied by transparent sharing of code and extensive documentation. Consistent with open science principles (Munafò et al., 2017), making raw data and analysis code publicly available enables independent verification of reported analyses, facilitates meta-analyses and mega-analyses that aggregate evidence across studies, and supports the development of computational models that require large datasets for training and validation. It also allows the broader scientific community to test new hypotheses and build upon existing work without the cost and time investment of new data collection. The FOODEEG dataset was developed with these principles in mind, and is released alongside fully documented analysis code to maximise its utility and reproducibility.

1.4 The Present Thesis

This thesis aims to advance our understanding of dietary decision-making through both empirical and methodological contributions. Empirically, we characterised the computational and neural mechanisms underlying food choices by examining the valuation and choice processes posited by neurobiological models of decision-making. Using frameworks from decision science and cognitive psychology, we focused on the shared mechanisms that underlie dietary decisions regardless of individual dietary goals or structural or social contexts. Methodologically, we contribute a large-scale, high-quality neural and behavioural dataset to stimulate future research in food cognition. Using EEG, we address critical gaps in understanding food attribute appraisal during valuation and the neural dynamics of evidence accumulation during food choices.

Chapter 2 presents the methodological foundations for investigating neural dynamics of dietary decision-making. This chapter includes an outline of the study design and stimulus characteristics, situating our approach within the broader landscape of food cognition research methodologies. Next, multivariate pattern analysis (MVPA) and ERP techniques employed throughout the thesis are described, discussing how their respective strengths and limitations align with our research questions. The chapter concludes with an overview of the data preparation pipeline for the FOODEEG dataset, an open-access resource for food cognition research.

Chapter 3 presents the FOODEEG dataset, a comprehensive open-access dataset containing EEG responses from 117 participants to diverse food images, alongside comprehensive normative ratings for 22 food attributes and individual

difference measures of food cognition. This dataset descriptor paper constitutes a methodological contribution to the field, addressing the critical barrier of limited publicly available neural datasets in food cognition research. Large-scale neuroimaging data acquisition is resource-intensive and time-consuming, restricting many research groups' ability to conduct adequately powered studies or develop data-intensive computational models. By releasing the FOODEEG dataset with standardised data formatting, reproducible analysis pipelines, and comprehensive documentation, we hope to stimulate future investigations into food cognition while promoting open science practices through transparent, reproducible, and verifiable analyses. This chapter also includes a comprehensive description of the experiment and dataset used in the subsequent chapters.

Chapter 4 investigates the valuation phase of dietary decision-making, addressing outstanding questions about which food attributes are appraised and the neural time-courses of these attribute representations. While existing neuroimaging research has focused predominantly on the processing of tastiness and healthiness, people consider numerous other attributes when making dietary decisions. We examine neural representations of three broad categories of food attributes. Beyond healthiness, other *nutritive attributes* are considered, including calorie content, how processed the food is, and how edible the food is (Foroni et al., 2013). *Hedonic attributes* are features of foods that are related to preferences, such as tastiness, willingness to eat, and emotional properties including valence and arousal (Gutjar et al., 2015). *Familiarity attributes* encompass aspects such as previous experiences with the food, recognisability, and how typical the food is of

its category (Foroni et al., 2013). While this is by no means an exhaustive list of choice-relevant food attributes, we aimed to be more comprehensive than other work in our investigation of food attribute appraisal and move beyond the narrow focus on healthiness and tastiness. Leveraging the high temporal resolution of EEG, we characterised the fine-grained time-courses at which different attributes are represented in neural signals, testing whether basic, more immediately relevant attributes (e.g., tastiness) are processed more rapidly than abstract attributes with long-term impacts (e.g., healthiness). To address the methodological challenge of high covariation among food attributes, we employ a two-pronged analytical approach: examining broad underlying dimensions that capture shared variance across covarying attributes as well as investigating unique attribute contributions in the neural signals. Furthermore, we carefully control for the influence of low-level image properties that may confound the relationship between key attributes and the neural activity. This work characterises the structure and time-courses of a wide range of choice-relevant food attributes on a neural level, advancing our understanding of the appraisal processes involved in dietary decisions.

Chapter 5 examines the choice phase of dietary decisions, investigating whether neural signatures of evidence accumulation observed during perceptual decisions extend to food choices. Sequential sampling models conceptualise choice as noisy evidence accumulation toward a decision boundary, with the rate of accumulation (drift rate) determined by evidence strength. The CPP has been identified as a neural correlate of this accumulation in perceptual decisions, with

its build-up rate scaling with evidence strength and a consistent amplitude just prior to the response. However, it remains unclear whether these mechanisms generalise to dietary decisions. We examine whether the CPP traces evidence accumulation during food decisions by testing key predictions: that single-trial CPP build-up rate should be positively associated with evidence strength and negatively associated with RT, consistent with more rapid evidence accumulation. Identifying shared neural signatures of evidence accumulation across perceptual and dietary decisions would provide support for domain-general mechanisms underlying diverse types of decisions and help adjudicate between dual-process accounts that posit distinct systems for automatic versus controlled mechanisms for food choices and single-process accumulation models. We focus specifically on single-option decisions that characterise many real-world dietary choices (e.g., "Would I like to eat this cookie?"), examining whether evidence accumulation principles extend beyond explicit comparisons between food options to evaluative judgements about individual food items. This work bridges the gap between perceptual and value-based decision-making literatures, revealing the extent to which domain-general evidence accumulation mechanisms underlie dietary choices.

Chapter 6 synthesises the empirical findings from Chapters 4 and 5, considering what they reveal in combination about the broader architecture of dietary decision-making. The implications of these findings are considered in relation to existing theoretical accounts, including dual-process models and multiattribute choice frameworks. I advocate for building a process model of

dietary decision-making that moves away from the normative and moralistic framings that have long pervaded the field. I argue that this cognitivist approach is not merely philosophical but fruitful: by not assuming that healthiness and tastiness are the primary axes of food evaluation, we revealed a richer and more complex appraisal process than existing frameworks have captured, and by not framing food choices as successes or failures of willpower, we revealed a domain-general evidence accumulation process shared across many decision types. Limitations of the current work are considered, including questions of ecological validity and the inferential gap between neural representations and the information meaningfully used by the brain to produce behaviour. The chapter concludes by outlining future directions, including applications of the process model to clinical populations such as individuals with eating disorders, and the role of the FOODEEG dataset as a reference resource against which targeted populations can be compared.

Chapter 2: Methods

This chapter outlines the experimental paradigms and analytical methods used to investigate the neural dynamics of dietary decision-making in the current thesis. The data for Chapters 3, 4, and 5 were collected over two in-person testing sessions and through online data collection. Precise procedural details for data collection are provided in Chapter 3. In this section, I firstly describe stimuli characteristics, review common methodological approaches in food cognition research, and outline the motivations regarding the current study design. I also give an overview of the multivariate analyses and event-related potential (ERP) analyses used in the thesis and explain the motivations for the analytical choices in relation to the research questions. Finally, I give an overview of the data preparation steps involved in the creation of the FOODEEG dataset, an openly available resource of neural and behavioural data for food cognition research.

2.1 Study Design

2.1.1 Food Image Stimuli

Visual information plays a large part in dietary decision-making (van der Laan et al., 2011), often signalling information about relevant food attributes such as portion size, edibility, and taste (McCrickerd & Forde, 2016). While other sensory features of foods (e.g., smell and taste) are also used to inform food choices (Rolls, 2015), visual information can convey choice-relevant information from a distance and without requiring real food to be present. In modern food choice environments, we often make food choices while heavily relying on visual food cues (e.g., ordering a meal through a food delivery app, buying groceries online,

and exposure to advertisements in the form of videos and images). Thus, we chose to use food images as the stimuli.

Multiple lines of evidence support the validity of using food images as stimuli in food cognition research. Viewing food images elicit physiological responses such as salivation (Wooley & Wooley, 1981) and neural activity in reward-related regions (Goldstone et al., 2009; LaBar et al., 2001; Siep et al., 2009; Uher et al., 2006). Neural responses while viewing food images compared to control images reveal an increased attentional bias when hungry (Nijs et al., 2010; Stockburger et al., 2009). Furthermore, neural processing of visual food cues has been linked to individual differences in eating styles (Blechert et al., 2010; Blechert, Goltsche, et al., 2014; Hachl et al., 2003; Kong et al., 2015; Nijs et al., 2009) and differs in individuals with eating disorders (for a systematic review, see Chami et al., 2019). Lastly, interventions that use food images to train food-related inhibitory control have been shown to translate to real-life eating behaviour (Kakoschke et al., 2014; van Koningsbruggen et al., 2014). Taken together, neurophysiological responses elicited by food images are influenced by state (e.g., hunger) as well as trait variables (e.g., dietary style), and the effects of behavioural interventions that use food images appear to carry over to real food choices.

Using food images as experimental stimuli also has several advantages. Compared to using real food, using food images allows for a precise measurement of stimulus properties (e.g., colour, silhouette, and luminance) so that these features can be kept within a set range or accounted for in later analyses (Moerel et al., 2024). This is particularly important in neuroimaging studies, as neural

responses are highly sensitive to visual properties such as luminance, contrast, spatial frequency, and colour composition (Blechert, Meule, et al., 2014). Another important facet of experimental paradigms in cognitive neuroscience is stimulus timing. Image-based stimuli enable precise control over the timing and repetition of stimulus presentation. Finally, using food images takes less time to prepare and is cheaper compared to using real food.

For the current thesis, the food image stimuli included 91 images from the Food-pics database (Blechert, Meule, et al., 2014) and 29 images from online image hosting platforms. Together, the stimuli consisted of 120 colour images of food items against a white background. Food-pics is a database of food images containing images of a wide variety of food and non-food items, designed to facilitate research on eating behaviour. We selected images from Food-pics to include a wide range of food types (e.g., vegetables, fruits, savoury dishes, sweet dishes, meats). Food images that portrayed multiple portions of a food, cutlery, or colourful plates or bowls were not included. We additionally included 29 food images from online image hosting platforms (e.g., Flickr, Adobe Stock) with the aim of increasing variance in key food attributes among the stimuli. Most people tend to find most foods appealing, which can lead to low variance in some key food attributes (e.g., tastiness, valence). To address this issue, studies and food image databases have included rotten or mouldy foods as stimuli to include stimuli that people will not find appetising (Foroni et al., 2013; Piqueras-Fiszman et al., 2014). However, such foods are inedible and may be perceived as distinct from regular foods. To increase variance in attributes such as tastiness and valence, we

selected foods thought to be generally less appetising or less familiar, but are nevertheless edible. Example food images include overcooked meats, fermented fish, and offal.

2.1.2 Food Cognition Tasks

In this section, I review commonly used tasks in food cognition research, outlining their typical structure and the specific cognitive processes they are intended to assess. Additionally, I discuss key methodological considerations and limitations associated with each task. The purpose of this section is to provide the reasoning and context for the task choices made in the present thesis.

2.1.2.1 Passive Viewing Tasks. A passive viewing task involves the participants simply viewing stimuli without performing any specific cognitive task while their brain activity is recorded (Figure 1A). Passive viewing tasks are commonly used to study early attentional processes towards foods by comparing neural activity elicited by food cues that differ on key attributes (e.g., high- vs low-calorie foods; Blechert et al., 2010; Killgore et al., 2003) or comparing neural responses to food cues and non-food cues (e.g., foods vs office items; Nijs et al., 2008; foods vs flowers; Stockburger et al., 2009). Foods, compared to non-foods, have been found to elicit larger amplitudes of the P3 and late positive potential ERP components, and this has been interpreted to reflect attentional biases towards food cues and the greater motivational value of foods (Carbine, Larson, et al., 2017; Nijs et al., 2008). These tasks have also been used to assess group differences in early neural responses to foods (e.g., restrained eaters vs controls; Blechert et al., 2010). Passive viewing tasks have the advantage of being easy to

perform as they do not require training, but it may be difficult to keep participants engaged over a long period of time. Therefore, it is common to include an orthogonal task to maintain participant engagement and serve as an attentional check.

2.1.2.2 Food Choice Tasks. Another popular paradigm is a food choice task that involves choosing between two or more food options (Figure 1B). In a typical binary food choice task, participants are presented with a pair of food items and indicate the item they would prefer to eat. This simple forced-choice format lends itself to quantitative modelling of decision processes that has a long history of application in perceptual decision-making. For example, Krajbich, Rangel, and colleagues have used binary food choice tasks together with subjective ratings of food items to demonstrate that preferential decisions can be captured by sequential sampling models, such as the diffusion decision model (DDM), in which evidence for each option is continuously accumulated until a decision threshold is reached (Krajbich et al., 2010; Krajbich & Rangel, 2011). Another study combined neuroimaging and computational modelling to identify a neural correlate of this evidence accumulation process during binary food choice decisions (Pisauro et al., 2017).

Binary food choice tasks capture choices between competing options and are useful for investigating processes involved in assessing food options relative to one another. Furthermore, these tasks have high ecological relevance to real food choices that involve deciding between a limited set of options (e.g., choosing between a muffin and a pastry at a cafe). These choices differ from decisions

about a single food item in isolation, which involves an absolute evaluation against an internal decision criterion (e.g., “Is this food healthy?” or “Do I want to eat this food?”). In food choice tasks involving multiple options, participants may base their decisions on factors not explicitly considered by the researcher, such as novelty preferences, portion size comparisons, or considerations about which combination of foods would constitute a balanced meal. These additional decision dimensions can introduce variance that is orthogonal to the specific food attributes of interest, potentially obscuring the neural signatures of the cognitive processes under investigation.

2.1.2.3 Inhibitory Control Tasks. Classic inhibitory control tasks, such as the go/no-go task or the stop-signal task, have been adapted to measure food-related inhibitory control and impulsive responses to food cues (Jones et al., 2016). In a food go/no-go task, participants are presented with a series of food stimuli and are instructed to respond as quickly as possible to “go” foods and withhold any responses to “no-go” foods (Figure 1C). Typically, participants are presented with more “go” foods than “no-go” foods in order to create a prepotent response, so that withholding the response for a “no-go” food requires exercising inhibitory control. When comparing neural responses to high- and low-calorie foods in a go/no-go paradigm, inhibiting responses to high-calorie foods elicited a greater N2 amplitude compared to inhibiting responses to low-calorie foods (Carbine, Christensen, et al., 2017). Similarly, greater N2 and P3 amplitudes were observed while inhibiting responses to foods compared to non-foods (Watson & Garvey, 2013). These findings suggest that increased cognitive resources are

required to suppress responses to appetitive foods, indicating that foods may be motivationally salient. These types of tasks can provide a useful behavioural and neural measure of food-related inhibitory control.

2.1.2.4 Evaluation Tasks. In these tasks, participants evaluate food stimuli on attributes of interest (Figure 1D). Participants may respond on a Likert scale or a continuous rating scale, or give binary responses. For example, participants may evaluate foods according to personal opinion, preferences, or prior knowledge (e.g., healthiness, tastiness, calorie content, familiarity, or willingness to eat). Evaluation tasks have been used to obtain group- or individual-level judgements on food attributes, which can subsequently be used to compare neural responses between foods that differ on key attributes. In contrast to food choice tasks, evaluation tasks usually involve making decisions about one food at a time.

Two main approaches exist for combining evaluation tasks with neuroimaging. In the first approach, participants view a food stimulus and evaluate it on attributes of interest while neural activity is simultaneously recorded (HajiHosseini & Hutcherson, 2021; Hare et al., 2009; Hare, Malmaud, et al., 2011; Rosenblatt et al., 2018; Schubert, Rosenblatt, et al., 2021; Tusche & Hutcherson, 2018). This design allows for a close temporal relationship between the evaluation and neural activity, with minimal delay between the cognitive process and its measurement. However, concurrent evaluation may lead to contamination of signals from response-related anticipatory motor preparation, making it difficult to isolate neural activity reflecting pure attribute appraisal from activity related to response selection and execution. Furthermore, scale-based responses are less

compatible with speeded response paradigms. Participants require sufficient time to consider their position on the scale and execute their response, which introduces substantial trial-to-trial variability in response timing. This variability makes it difficult to temporally separate distinct processing stages such as food appraisal from response selection.

In the second approach, the neuroimaging task and the evaluation task are separated. Participants perform an orthogonal task (e.g., passive viewing or preference judgement) while neural activity is recorded. The foods are then evaluated on the attributes of interest either in a separate session by the same participants, or by a different group of participants entirely. This separation reduces priming effects (i.e., participants are not explicitly considering the attributes of interest during neural recording) and allows for a more naturalistic processing of food cues. A potential drawback, however, is that the correlation between neural and evaluation measures may be weaker, due to variability in food evaluations across time or samples. Nevertheless, normative food attribute ratings obtained from a separate sample have been shown to correlate with electroencephalographic (EEG) activity recorded during food viewing (Moerel et al., 2024, 2026).

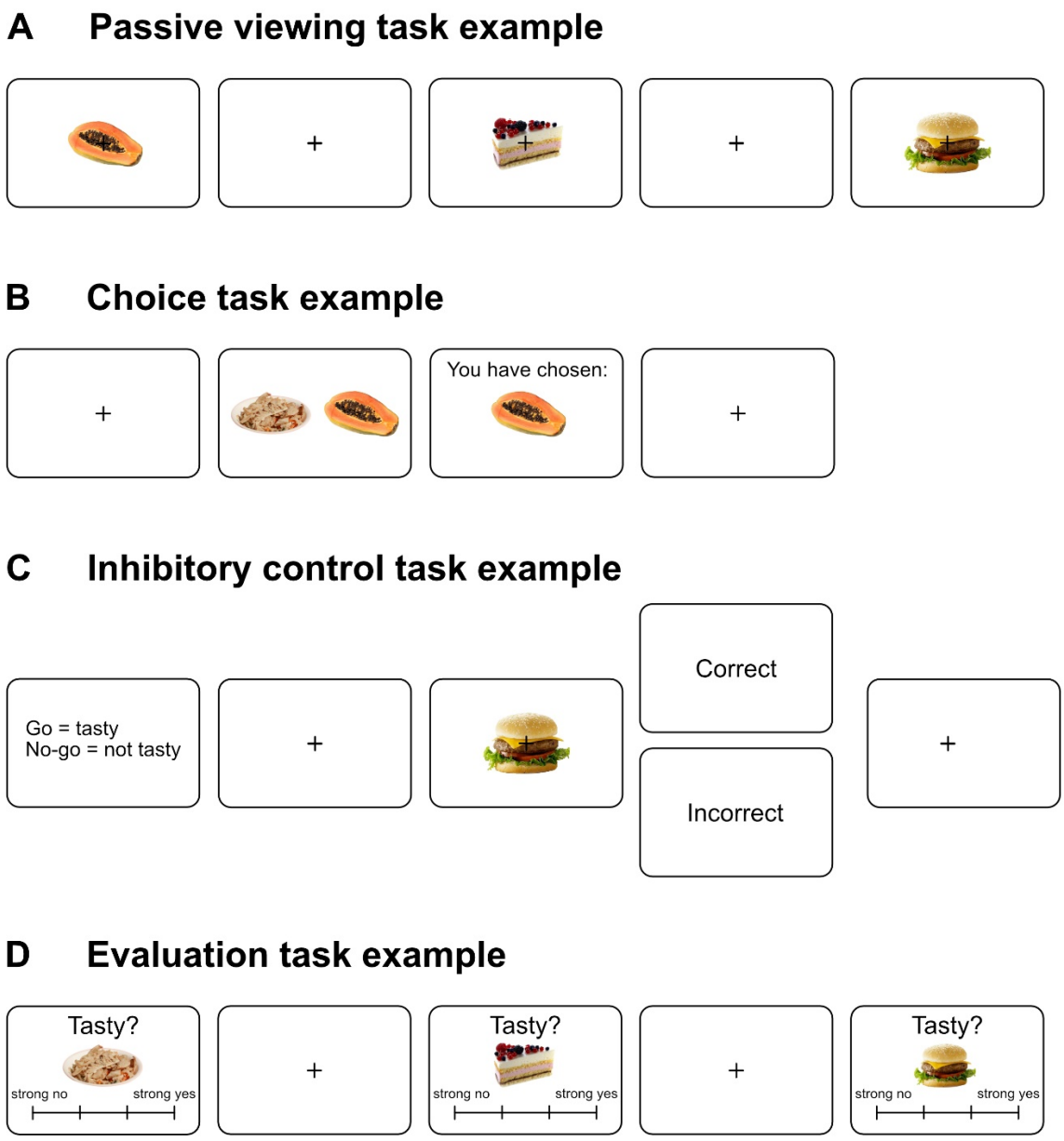

Figure 1. Overview of common food cognition tasks. A) Passive viewing task example. Participants view food stimuli without performing any explicit cognitive task while neural activity is recorded, allowing early attentional responses to food cues to be examined. B) Choice task example. Participants are presented with multiple food items and indicate which they would prefer to eat, capturing the cognitive processes involved in evaluating competing food options. C) Inhibitory control task example. Participants respond as quickly as possible to designated

"go" food stimuli and withhold responses to "no-go" food stimuli, with a higher proportion of "go" trials creating a prepotent response tendency that requires active inhibition to overcome. D) Evaluation task example. Participants rate individual food stimuli on attributes of interest (e.g., tastiness) on a Likert scale or a continuous rating scale.

2.1.3 Paradigms Used in the Thesis

Building on the strengths and limitations of existing paradigms outlined above, we developed a battery of experimental tasks designed to capture different aspects of food cognition. The details of each task are outlined below.

2.1.3.1 Food Categorisation Task With EEG Recording. We used a food categorisation task adapted from similar paradigms that have been used to probe participants' appraisal of food images (Rosenblatt et al., 2018; Schubert, Rosenblatt, et al., 2021), with key modifications. In this task, participants were presented with a food image before they were asked to evaluate the foods on one of three attributes (healthiness, tastiness, and willingness to eat) as quickly as possible. Each of the 120 foods was evaluated on all three attributes, in six blocks of 60 trials. To evaluate the food, participants responded either "Yes" or "No" with a left or a right key press. This task was designed to address some of the limitations of previous work, as well as make the task as suitable for an EEG experiment as possible. These design considerations are outlined below.

We sought to minimise priming effects that may have an impact on our outcome measures of interest, such as the time-courses of neural representations of food attributes. Previous studies have used blocked designs in which each block

contained one type of trial and participants were notified of the attribute they would be asked to evaluate the food on at the start of the block (e.g., healthiness block; Rosenblatt et al., 2018; Schubert et al., 2021). In such designs, participants may be primed on the attribute of interest before each trial, which may have an influence on the subsequent appraisal processes. Given that we were interested in investigating the precise time-courses of neural processes (e.g., time-courses of neural attribute representations, or neural correlates of evidence accumulation processes), we wanted to reduce priming effects as much as possible. Consequently, we did not use a blocked design in our paradigm with respect to the food attributes. Instead, each food item was presented three times during the experiment (once for healthiness, tastiness, and willingness to eat trials). The trial order with respect to each attribute judgement as well as the order of the food item shown was randomised for each participant, while ensuring that the same food image was not shown across two consecutive trials.

Furthermore, we designed the response option mapping to reduce anticipatory preparation and to ensure that the paradigm is compatible with decoding analyses. Response option mapping was randomly assigned in each trial so that there was a 50% chance of the key press with the left index finger indicating "Yes" and the key press with the right index finger indicating "No", and 50% chance of the reverse mapping. This further ensured that participants could not prepare a response during the passive viewing phase of the food image, in combination with the randomised order of healthiness, tastiness, and willingness to eat trials. Multivariate analyses such as neural decoding take all patterns of activity into

account to decode patterns of responses, and the randomisation of response option mapping ensured that we were not simply decoding left and right keypress-related motor activity or preparation instead of evaluations on the attributes of interest.

Additionally, we sought to separate the appraisal and choice stages of the food categorisation task in our paradigm design. In previous work, participants were often presented with a food stimulus and were asked to evaluate it in some way at the same time, allowing participants to appraise and then make a choice at their own leisure (Rosenblatt et al., 2018; Schubert, Rosenblatt, et al., 2021). Alternatively, participants were asked to view the food stimuli passively without explicit instructions to evaluate the food (e.g., Blechert et al., 2010; Carbine, Larson, et al., 2017; Nijs et al., 2008). In our paradigm, each trial included a viewing phase, during which the food image was presented in isolation for 2 s and participants were not able to make a response. This was followed by a choice phase, in which the attribute prompt ("Healthy?", "Tasty?", or "Like to eat?") and two response options ("Yes" and "No") were displayed alongside the food image and participants were able to make a response. During food image viewing, participants were not made aware of which of the three attributes they would be asked to evaluate the food on, allowing for a separation of the appraisal processes from the integration of the features towards a decision threshold. It must be noted that there were only three attributes that the participants were asked to evaluate the foods on, so it is possible that the participants were able to prepare a response for the three attributes during the passive viewing phase. However, this is effortful

to do so for each trial and so is unlikely to have occurred. Although we may not have completely isolated the appraisal and choice stages of the food categorisation task, this paradigm has clear advantages of reducing priming effects compared to previous studies.

EEG recordings are susceptible to artifacts, which are the parts of the recording that arise from sources external to the brain such as eye blinks, lateral eye movements (saccades), and muscle activity. To minimise these artifacts as much as possible, a fixation cross was displayed on the centre of the screen throughout the experimental blocks and participants were instructed to fixate their eyes throughout the trials. The food image, attribute prompt, and response options were displayed small and close to the centre so that it was possible to see everything while keeping the eyes fixated on the fixation cross. Participants were asked to use a chin rest to minimise head movement and the associated muscle activity. The experiment took around 45 minutes to complete, and participants were given breaks every 60 trials to ensure that they could rest and relax before continuing.

2.1.3.2 Food Rating Task. After the food categorisation task, participants were asked to evaluate each food image once more on the same three food attributes (healthiness, tastiness, and willingness to eat), this time on a continuous rating scale spanning from “Not at all” to “Very much”. EEG was not recorded and participants were not asked to respond as quickly as possible. Through this, we were able to measure participants’ fine-grained evaluation on the three food attributes, in addition to their speeded categorisation responses

recorded during the categorisation task. To reduce the delay between the EEG recording and rating task, participants completed the rating task after only a short break to take off the EEG cap and briefly stretch. We also used these continuous ratings to screen for any participants who may have been responding randomly during the food categorisation task, by examining whether there were any participants who were highly incongruent between their categorisation responses and their continuous ratings. The fine-grained rating data also provided a proxy measure of the representational strength underlying participants' categorisation responses, which is explored in depth in Chapter 5.

Additionally, a separate sample of online participants provided ratings for the food image stimuli on a wide range of food attributes, spanning nutritive, hedonic, and taste properties, familiarity, and elicited emotions. It has been shown that normative food attribute ratings are reflected in the neural data collected from a different sample (Moerel et al., 2024). Participants rated each food image on a continuous rating scale spanning from "Not at all" to "Very much". These normative evaluations of the food stimuli on key attributes were found to be associated with patterns of food image-evoked EEG activity (Chapter 4), and are included for future researchers to utilise (Chapter 3).

2.1.3.3 Food Go/No-Go Task. We additionally included a measure of food-related inhibition with a food go/no-go task to enable future investigations into food-specific inhibitory control. As participants' evaluation of the food images on healthiness and tastiness differed, we used their own continuous ratings collected after the EEG task for stimuli selection. 15 Most-Healthy, 15 Least-Healthy, 15

Most-Tasty, and 15 Least-Tasty food images were selected. For careful counterbalancing, each of the categories served as both “go” and “no-go” stimuli. For instance, Most-Healthy foods served as the “go” foods in one block with Least-Healthy foods serving as the “no-go” foods, and this was reversed for another block. This was to control for any other features that differed between the categories that may influence response inhibition. “Go” food images were presented in 75% of the trials in a block to ensure a prepotent response. Responses on this task were included in the FOODEEG dataset for future researchers interested in linking food-related inhibitory control to other measures in the dataset, such as neural data or attribute ratings (Chapter 3).

2.1.3.4 Paired Food Choice Task. We included a food choice task that involved choosing between two food options. As was the case with the food go/no-go task, this task was originally intended to be used for investigations into individual differences in food-related cognition. The data related to this task are provided in the open dataset for future studies on food preferences. This task is differentiated from the food categorisation task in that it involves comparative evaluation of the food options, rather than judging a single food option on an internal decision criterion. A subset of the full food image stimuli was selected as the 25 foods that participants had indicated they would be willing to eat. Out of all food images the participants had rated as over 50 on willingness to eat, 25 images were randomly selected. If fewer than 25 food images had been rated as over 50, the next highest rated food images were included to bring the total number of stimuli to 25. Participants were presented with every possible pairs of food images

once (300 trials) and were instructed to choose the food they would prefer to eat more of the two. Behavioural data collected during this task was included in the FOODEEG dataset for future work examining food preferences or multi-option decision-making (Chapter 3).

2.1.4 Study Design Summary

The present thesis employed a multimodal data collection approach designed to capture complementary aspects of food cognition. Food images were chosen as stimuli for their ecological validity, controllability in experimental settings, and established use in neurocognitive studies. The food categorisation task was designed with several key modifications to existing paradigms in order to minimise priming effects and optimise compatibility with multivariate EEG analyses. Continuous food attribute ratings collected immediately after the EEG task provided fine-grained individual-level measures of food appraisal that complemented the speeded categorisation responses. Normative ratings on a broad range of food attributes, collected from a large independent online sample, enabled examination of how normative food attribute judgements are reflected in the neural data. Finally, the food go/no-go and paired food choice tasks were included to broaden the scope of the dataset for future researchers, providing measures of food-related inhibitory control and comparative food preferences respectively.

2.2 Analyses

A wide range of analytical techniques are available for the analysis of EEG data, each offering distinct strengths and limitations depending on the aims and

experimental design. In this section, I outline the primary analysis approaches used in Chapters 3, 4, and 5 and explain how specific analysis strategies were selected to address the research questions of the thesis.

2.2.1 Multivariate Analyses

It is theorised that the brain encodes neural representations (e.g., perceived healthiness and tastiness of a food item) as patterns of activity across a distributed set of neurons (Averbeck et al., 2006). Neural representations are particularly relevant in the field of food cognition, as there is a large focus on how different food attributes are represented in the brain when evaluating a food cue (e.g., healthiness, tastiness, calorie content). Studies have attempted to delineate differences in neural responses to foods that differ on key attributes (e.g., healthy vs unhealthy foods, tasty vs not tasty foods), but most previous work has relied on univariate methods, such as comparing averaged ERPs, that were limited in their ability to assess fine-grained patterns of neural activity. Unlike univariate methods, which typically average activity across multiple channels or voxels, multivariate methods enable the simultaneous analysis of multiple variables (Figure 2). In the case of EEG, multivariate analyses involve examining patterns of activity across multiple channels. Hence, multivariate methods are well-suited for revealing subtle spatiotemporal neural activity patterns and may be functionally useful for uncovering neural representations (Ritchie et al., 2019). In object recognition research, multivariate methods of analysis have become popular as a way to delineate the temporal dynamics of category information representation (Carlson et al., 2013; Cichy et al., 2014; Grootswagers, Robinson, & Carlson, 2019). Two

examples of popular multivariate analysis methods, multivariate pattern analysis (MVPA) and representational similarity analysis (RSA), are elaborated on below.

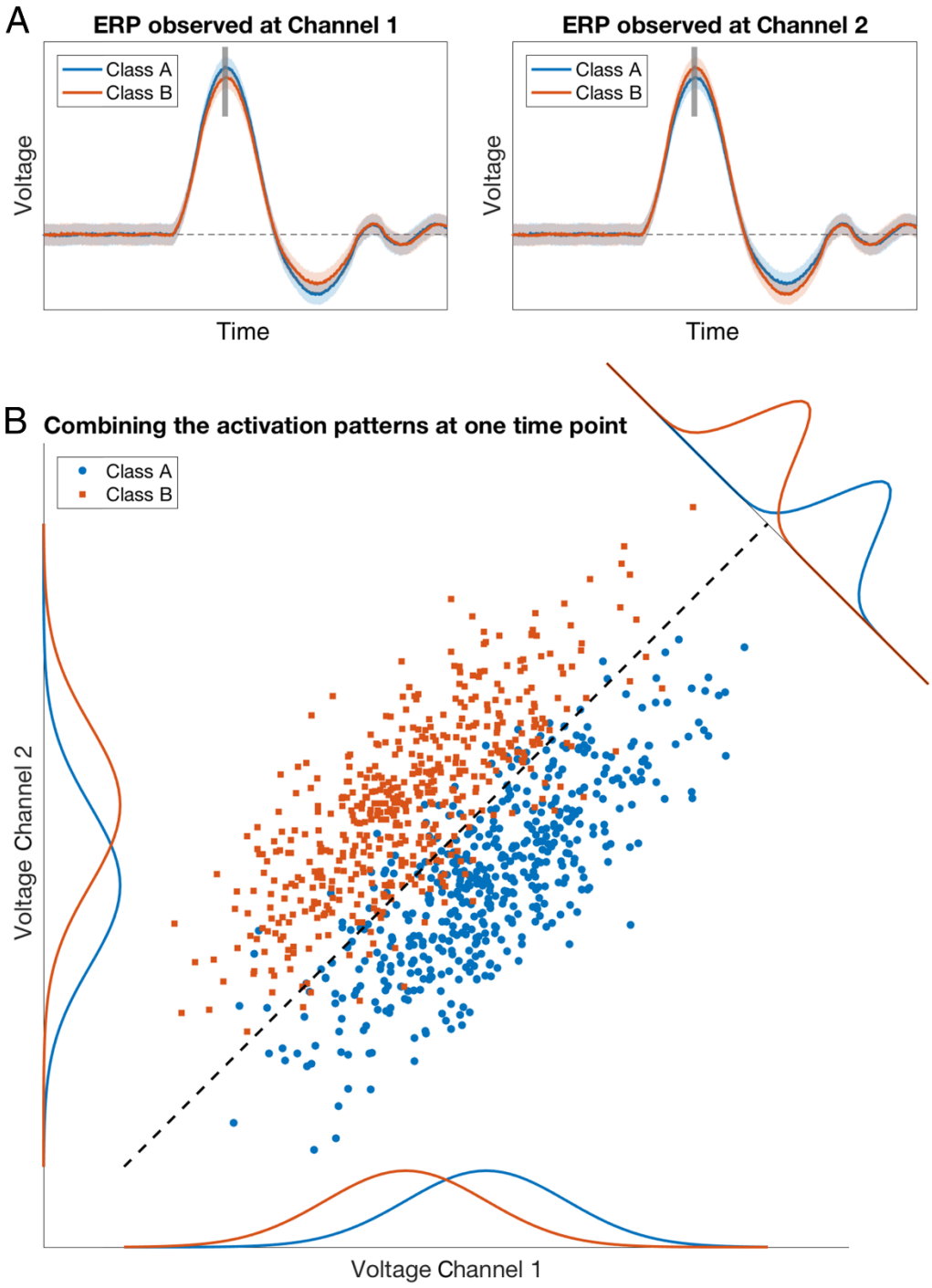

Figure 2. Sensitivity advantage of multivariate analysis over univariate analysis. Adapted from Grootswagers et al. (2017). A) Average ERPs elicited by two stimulus classes (Class A and Class B) are shown separately for two channels (left

and right). In each individual channel, the responses to the two classes overlap considerably and may not reach statistical significance in a univariate framework. B) The same data are replotted as points in two-dimensional space in which each axis represents the amplitude in one channel at a single time point (indicated by the vertical grey bar in panel A). By leveraging information from both channels, a decision boundary (dashed line) can be drawn that reliably separates the two classes.

2.2.1.1 Multivariate Pattern Analysis. MVPA involves two broad steps: data collection and pattern classification. Firstly, neural data is collected under multiple distinct experimental conditions. For each trial, the multivariate pattern of activity across all electrodes (or a selected subset) at a given time point or time window constitutes a feature vector that serves as input to the classifier. The data is split into training and test datasets for each experimental condition, typically using cross-validation procedures to ensure generalisability of the results. In k-fold cross-validation, the data is divided into k subsets, with k-1 subsets used for training and the remaining subset used for testing, rotating through all possible combinations. This procedure is repeated multiple times to obtain a robust estimate of classification performance while ensuring that the classifier is always tested on novel data that was not used for training, to prevent overfitting. A machine learning classifier is trained to distinguish between patterns of activity associated with different experimental conditions using the training dataset. Common classifiers include linear discriminant analysis and support vector machines/regressions (SVM/SVR). Although both linear discriminant analysis and

SVM/SVR are widely used in EEG decoding and have been shown to yield comparable classification performance (Grootswagers et al., 2017), SVR was adopted in the present study (Chapter 3) as it is the more commonly employed approach in the food cognition literature, facilitating direct comparison with prior work (e.g., Schubert et al., 2021). These algorithms learn a decision boundary in the high-dimensional feature space that optimally separates the different experimental conditions based on the patterns in the neural activity. Using the test dataset, the classifier's performance is tested to determine whether the experimental conditions can be predicted by the classifier at a level above chance. For categorical experimental conditions, classification performance is typically assessed as the percentage of correctly classified trials, with chance performance being 50% for binary classification. For decoding of continuous variables, classification performance reflects the alignment between classifier's predicted labels and the true labels (e.g., a correlation coefficient). To determine above-chance performance, the decoding procedure is repeated for each participant using the same data but with randomly shuffled trial labels to generate an empirical null distribution, and statistical tests are performed to test for significant differences between the two distributions (Bode et al., 2019; Schubert et al., 2021). For time-resolved decoding, this classification procedure is carried out independently at each time point, yielding decoding performance over time that reveals when information about the experimental conditions becomes decodable from the neural signals.

MVPA has been used to successfully decode object features (e.g., animacy;

Grootswagers, Robinson, & Carlson, 2019) as well as more abstract representations such as processing of faces (Mares et al., 2020) and semantic information (Heikel et al., 2018) from EEG data. In the field of food cognition, a study successfully decoded health and taste representations during food choices from patterns of whole-brain EEG activity (Schubert, Rosenblatt, et al., 2021). In this study, participants rated pictures of food items on health, taste, and decision to eat on a continuous sliding scale while their EEG activity was recorded. Using MVPA, health and taste information could be decoded from early EEG activity, both when explicitly asked to consider health and taste through ratings, and implicitly when asked to consider how much they wanted to consume the food. Interestingly, the decoding of taste and health representations occurred before the decoding of the decision to consume. These findings are in line with the idea that the decoded food attribute representations are used in the subsequent food decisions.

2.2.1.2 Representational Similarity Analysis. RSA is a multivariate analysis technique that has rapidly gained popularity in its application in cognitive neuroscience since its introduction (Kriegeskorte et al., 2008; Kriegeskorte & Kievit, 2013). Comparing across different modalities in neural data is difficult as one-to-one mapping often cannot be assumed. RSA circumvents this issue by operating at the level of representational geometry rather than individual response patterns. The method allows us to evaluate the similarity of internal representations by constructing representational dissimilarity matrices (RDMs), which capture the pairwise dissimilarity structure between all stimuli in a set.

For a given set of n stimuli, an RDM is an $n \times n$ symmetric matrix where each

entry (*i, j*) represents the dissimilarity between stimulus *i* and stimulus *j*. For neural data, dissimilarity can be computed between the multivariate activity patterns evoked by each stimulus pair, using 1 minus the correlation coefficient, classification performance metrics, or distance metrics such as Euclidean distance. For EEG data, the activity pattern for each stimulus typically comprises the voltage values across all electrodes at a given time point or within a time window, yielding a feature vector that characterises the spatial distribution of neural activity. The dissimilarity between two stimuli reflects how differently the brain responds to them: highly similar neural responses yield low dissimilarity values, while distinct neural responses yield high dissimilarity values.

Multiple RDMs can be constructed from different data modalities or models to encode the similarity structure between the same set of stimuli. For example, we could create RDMs that capture dissimilarity in EEG activity, behavioural data such as ratings or response times (RTs), and stimulus properties (e.g., colour, silhouette, and luminance). Behavioural RDMs can be constructed by computing dissimilarity between the stimuli based on participants' ratings or judgements, while stimulus property RDMs can be derived from objective measurements of the visual features of the stimuli, such as pixelwise luminance profiles. The core insight of RSA is that if two RDMs share similar structure (i.e., if the patterns of dissimilarity between stimuli are similar across the modalities), this suggests that the underlying representations capture shared information about the stimuli.

The comparison between RDMs is quantified using correlation measures, such as Spearman's rank correlation, to assess the shared similarity between the

dissimilarity structures. When working with time-series data such as EEG data, we can construct time-varying neural RDMs by computing dissimilarity matrices independently at each time point, and assess when the neural representational structure correlates with model or behavioural RDMs (Grootswagers et al., 2017). This approach yields a time-course showing when information is represented in the neural signal, providing insights into the temporal dynamics of information processing.

RSA has been used to examine the encoding of low-level object features such as orientation, spatial frequency, contrast, and colour (Grootswagers et al., 2024), to abstract and high-level features such as animacy (Carlson et al., 2013), humanness (Contini et al., 2020), and agentic action (Haxby et al., 2020). In food cognition research, Moerel et al. (2024) investigated the temporal dynamics of food representations in the brain. Using time-varying RSA with EEG data, the study examined when various food attributes were represented in the neural activity. The results revealed that information about various features of foods, including naturalness, level of transformation, and perceived calorie content, is rapidly represented in the neural signals and even after controlling for low-level visual properties of the images through partial correlations.

2.2.1.3 Advantages and Disadvantages. Multivariate analyses are powerful tools for detecting subtle differences in neural activity, but they function as “black boxes” in that it is difficult to determine precisely which features drive classifier performance or RDM correlations (Gessell et al., 2021). This can be particularly problematic in the context of naturalistic stimuli like food images,

where it is not possible to control for all possible confounding features. Stimulus properties (e.g., colour, silhouette, and complexity) are inextricably bound to the food attributes we make decisions based on. For example, our perception of the healthiness of foods may correlate with the visual property of greenness, but this is not merely a confound; vegetables, which make up a large proportion of the foods perceived to be healthy, are often green. When MVPA classifiers successfully decode food attributes such as healthiness or tastiness from neural data, we must carefully consider whether these classifications are driven by neural representations of the abstract food attributes themselves, or if there are contributions from representations of correlated perceptual features. This interpretational challenge does not invalidate multivariate approaches and may in fact reflect the ecological reality that our brains use visual heuristics to rapidly infer food attributes. More broadly, it must be noted that successful decoding establishes only that attribute-relevant information is present in the neural signal, not that this information is used by the brain to inform the decision: attribute information may be decodable without playing any functional role in the choice process.

While RSA faces similar interpretational challenges, it offers specific advantages for addressing low-level visual feature confounds. Visual feature RDMs can be constructed to capture dissimilarity in low-level image properties among the stimuli, and these can be controlled for when examining the relationship between neural activity and the stimulus feature of interest. For example, a colour RDM capturing differences in colour across food images can be included alongside

EEG RDMs and a healthiness RDM. Using partial correlations, we can examine the correlation between neural activity patterns and healthiness while statistically controlling for variance explained by colour. This approach can be extended beyond individual low-level features by utilising deep convolutional neural networks designed to model human visual processing (e.g., CORnet; Kubilius et al., 2019; AlexNet; Krizhevsky et al., 2012). Activations can be extracted from specific layers of these networks, and pairwise distances between stimuli can be computed to create general visual feature RDMs. Partial correlation analyses can then control for the similarity structures captured by these deep neural network models, allowing us to assess whether neural representations of food attributes remain significant after accounting for these low- and mid-level visual features (Moerel et al., 2024). This partial correlation approach provides a way of disentangling high-level cognitive representations from the low- and mid-level image features that inevitably correlate with them in naturalistic stimuli. While this approach helps control for the effects of low- and mid-level visual features, the broader question of whether a represented attribute is used to inform the decision remains open, and care should be taken in interpretation.

2.2.1.4 Applications in the Current Thesis. In Chapter 3, MVPA is used to provide technical validation for the open FOODEEG dataset. The aim of a dataset descriptor is not to uncover new findings, but to provide sufficient description and quality check for the open dataset to motivate other researchers to use the dataset to generate new research findings. We chose MVPA alongside more traditional ERP analyses to show that information about key food attribute judgements (e.g.,

healthiness and tastiness) are decodable in the EEG signals in a sustained window from ~150 ms after food image presentation.

In Chapter 4, RSA is used to delineate the neural time-courses and structures of a wide range of choice-relevant food attributes during food image viewing. While both RSA and MVPA are sensitive to fine-grained patterns of neural activity that may correlate with attribute information, we chose RSA for its key strength of allowing for control over low- and mid-level visual features through partial correlation analyses. Furthermore, partial correlation analyses could be adapted to examine the unique contributions of individual food attributes in the neural signals while controlling for the effects of other food attributes of interest.

2.2.2 Event-Related Potential Analysis

ERPs are time-locked electrical responses of the brain to specific sensory, cognitive, or motor events (Luck, 2014). They are extracted from the continuous EEG signal, allowing researchers to isolate neural activity associated with specific cognitive processes. ERPs are characterised by distinct waveform components occurring at specific time intervals aligned to events (e.g., stimulus onset or response onset), typically described in terms of their polarity (positive or negative), latency (time of peak occurrence), and scalp topography. These components reflect different stages of information processing, such as sensory encoding, attention allocation, and decision-making. Researchers may define regions of interest and time windows based on prior literature or visual inspection of grand-averaged waveforms, though this approach risks circular analysis if the same data is used for both component identification and hypothesis testing. Alternatively,

data-driven approaches such as mass-univariate analyses can identify spatiotemporal clusters of significant effects without a priori assumptions. For a systematic review of ERP research in food cognition, see Carbine et al. (2018).

2.2.2.1 Deconvolution. Traditional ERP analysis assumes that neural responses to events are time-locked and additive, and that events are sufficiently spaced in time so that their evoked responses do not overlap. However, it is often not possible to temporally separate events of interest, which leads to an overlap in the evoked responses. The food categorisation task involves multiple sequential events within each trial (e.g., food image onset, response prompt onset, attribute appraisal, and motor response execution), each of which may elicit overlapping neural activity. If the temporal overlap of event-related responses were identical across experimental conditions, contrasts between conditions would remain unbiased. However, this assumption is rarely met in practice. Event timing variables (e.g., RTs) are systematically correlated with cognitive factors of interest such as stimulus properties, decision difficulty, and attentional demands. When RTs differ between conditions (e.g., faster responses to highly tasty foods versus mildly tasty foods), the degree of temporal overlap between successive ERPs also differs, leading to biased ERP estimates. Such condition-dependent overlap can both mask genuine neural differences and generate spurious effects.

Deconvolution methods correct for this overlap in signal by decomposing the EEG signal into separate components based on their temporal alignment to different experimental events. We used the RIDE toolbox (Residue Iteration Decomposition toolbox; Ouyang et al., 2015), which allows for decomposition of

ERPs into components that are time-locked to events in a trial (e.g., stimulus-locked and response-locked components) and reconstruction of the components into averaged ERPs with the overlap corrected for. Under the assumption that ERPs are made up of multiple subcomponents with variable delays between them, the method employs an iterative estimation procedure to extract ERP components that exhibit consistent alignment with event onset across trials. Firstly, a preliminary average waveform is computed for the stimulus-locked component, which is then removed from the stimulus-locked single-trial epochs. Subsequently, these residual epochs are realigned to the response to yield an estimate of the response-locked component. After subtracting this response-locked component from the data, a refined stimulus-locked component estimate is derived from the stimulus-locked epochs. These iterative steps repeat until the component estimates reach convergence. The decomposition yields separate stimulus-locked (S) and response-locked (R) components, and optionally a time-varying (C) component that captures activity with intermediate or variable latency characteristics. Each component represents neural processes that maintain consistent timing relative to its reference event, with contamination from other temporally jittered components removed. This allows for cleaner characterisation of processes such as early sensory responses (stimulus-locked), motor preparation and execution (response-locked), and intermediate processes that may have variable timing (e.g., evidence accumulation processes; see Chapter 5).

2.2.2.2 Current Source Density Transformation. Current source density (CSD) transformation, also known as the surface Laplacian, is a spatial filtering

technique applied to scalp-recorded EEG data to enhance the spatial resolution of the recorded signals. This technique involves estimating the second spatial derivative of the EEG potential field. The transformation addresses volume conduction, a fundamental limitation of standard EEG recordings. When neural sources generate electrical activity, the currents spread widely through the conductive tissues of the head (brain, cerebrospinal fluid, skull, and scalp), causing the scalp-recorded potentials to reflect a spatially blurred mixture of multiple underlying sources. This blurring effect leads to the activity from one focal source being detectable across distant electrode sites, complicating the interpretation of topographic patterns. CSD transformation mitigates this issue by working as a high-pass spatial filter. The result is a reference-free representation of the data that emphasises activity directly beneath each electrode while attenuating the contribution of distant sources. The transformed waveforms typically show sharper topographic peaks with reduced spatial spread, making it easier to distinguish between spatially adjacent neural sources.

2.2.2.3 Mass-Univariate Analysis. Mass-univariate analysis is a statistical approach that involves conducting separate univariate tests at each time point within an epoch, at each electrode location, or across both temporal and spatial dimensions simultaneously within the multidimensional EEG dataset. Rather than averaging or condensing the data into summary measures (such as mean amplitude within a predetermined time window), we can test for experimental effects at every discrete measurement point. For instance, when comparing ERP waveforms between two conditions, a separate statistical test (e.g., t-test) can be

carried out at each time-point across the entire epoch and at each electrode site. This approach allows for data-driven identification of when and where experimental effects emerge in the ERP data without requiring *a priori* assumptions about their timing or topography.

However, mass-univariate testing introduces a substantial multiple comparisons problem, as hundreds or thousands of statistical tests may be performed on a single dataset (e.g., 1000 time points × 64 electrodes = 64,000 tests). Employing appropriate corrections for multiple comparisons is therefore essential. In the current thesis, we used cluster-based permutation testing (Maris & Oostenveld, 2007). This method identifies spatiotemporally contiguous clusters of data points that exceed an initial threshold (e.g., $p < .01$ at each point), then sums a test statistic (e.g., t-values) within each cluster. The significance of these cluster-level statistics is assessed by comparing them against a null distribution generated through permutation. Condition labels are randomly shuffled many times (e.g., 10,000 permutations), and the analysis is repeated to generate a distribution of maximum cluster statistics under the null hypothesis. Observed clusters with statistics exceeding the 95th percentile of this null distribution can be considered statistically significant. This approach is particularly well-suited for EEG data as it accounts for the spatiotemporal correlation structure and provides good sensitivity to detect effects that are extended in time or space, though it may be less sensitive to highly focal effects.

2.2.2.4 Applications in the Current Thesis. In Chapter 3, ERP analyses, alongside MVPA, were used to provide technical validation for the open FOODEEG

dataset. Drawing on a large body of work that have shown that food-evoked EEG responses differ across foods according to key food attributes (e.g., healthiness and tastiness), we demonstrated that early (e.g., N1, P1, and P2) and later (e.g., P3 or late positive potential) ERP components in our dataset are consistent with observations in previous work.

In Chapter 5, we assessed the ERP component centroparietal positivity (CPP) as a potential neural correlate of evidence accumulation processes in dietary decision-making. We examined whether the slope and amplitude of the CPP prior to the response were modulated by RT and evidence strength, in line with evidence accumulation dynamics. We used RIDE to control for confounds related to stimulus-locked activity and applied a CSD transformation to improve spatial resolution. To complement the more traditional approach of examining the CPP effect in a fixed pre-response window (Kelly et al., 2021; Steinemann et al., 2018), we used mass-univariate analyses to test for RT and evidence strength modulations across the full response-locked epoch.

2.2.3 Analyses Summary

A combination of univariate and multivariate approaches was used in the current thesis according to the specific research questions in each study. While multivariate techniques are excellent for detecting distributed patterns of information across multiple channels, examination of ERPs provides a more direct window into the timing of specific neural processes. Multivariate analyses were used to reveal the fine-grained time-courses of food attribute information in the brain during appraisal (Chapter 4), while ERP analyses illuminated domain-specific

cognitive processes (e.g., evidence accumulation during decision-making; Chapter 5). Both approaches were used to provide complementary technical validation for the publicly available FOODEEG dataset in the dataset descriptor manuscript (Chapter 3).

2.3 Dataset Curation

The replication crisis in psychology and cognitive neuroscience has highlighted widespread concerns about the reproducibility of empirical findings, with a significant proportion of published results failing to replicate when subjected to independent verification (Open Science Collaboration, 2015). In response, the open science movement has advocated for greater transparency and data sharing as a means of improving the reliability and quality of research and scientific progress. The purpose of the FOODEEG dataset (as described in Chapter 3) is to make the collected data as usable as possible for future researchers interested in food cognition. To this end, all data, stimuli, experimental code, and preprocessing scripts are publicly available, and the dataset has been structured to conform to community standards for neuroimaging data organisation.

A central framework guiding open data practices is the FAIR principles, which specify that research data should be Findable, Accessible, Interoperable, and Reusable (Wilkinson et al., 2016). Findable data are assigned persistent identifiers and described with rich metadata so that they can be discovered by both humans and automated systems. Accessible data are retrievable through standardised protocols, ideally without requiring specialised permissions. Interoperable data adhere to community standards and use shared vocabularies,

enabling integration with other datasets and tools. Reusable data are accompanied by clear licensing information, source details, and sufficient documentation to allow others to understand and repurpose the data for new analyses. Adhering to these principles maximises the scientific return on data collection efforts, enabling future researchers to address questions beyond the scope of the original study, conduct meta-analyses, and use the data for methods development and validation.

2.3.1 Brain Imaging Data Structure

A practical barrier to data sharing in neuroimaging research is the absence of a universal standard for organising and describing data files, which has historically resulted in idiosyncratic data structures that are difficult for others to navigate and use. The Brain Imaging Data Structure (BIDS) standard was introduced to address this problem by providing a community-driven specification for organising neuroimaging and electrophysiological data in a consistent, well-documented format (Gorgolewski et al., 2016). Originally developed for magnetic resonance imaging (MRI) data, BIDS has since been extended to cover other modalities, including EEG data (Pernet et al., 2019).

In a dataset formatted according to the BIDS standard, data are organised hierarchically by participant, session, and data type, with standardised file naming conventions that encode key metadata directly in the filename in the order of subject identifier, task name, and data type (e.g., sub-006_task-categorisation_eeg). Alongside the raw data files, BIDS requires accompanying sidecar files in JSON and TSV formats that document acquisition parameters,

electrode configurations, event codes, and participant-level information. This self-describing structure means that a researcher unfamiliar with the original study can understand the dataset structure without referring to external documentation. Furthermore, BIDS compatibility enables the use of a growing ecosystem of automated analysis pipelines that expect data in this format, such as the MNE-BIDS package in Python (Appelhoff et al., 2019) and plugins in the FieldTrip (Oostenveld et al., 2011) and EEGLAB (Delorme & Makeig, 2004) toolboxes for EEG preprocessing.

2.3.2 OpenNeuro Repository

The FOODEEG dataset is hosted on OpenNeuro. The raw EEG recordings collected during the food categorisation task and the behavioural data from the food go/no-go task and the paired food choice task were prepared in BIDS format. To further increase accessibility of the neural dataset, cleaned continuous recordings are provided alongside the raw recordings.

At the root level of the dataset, several sidecar files are provided to document metadata relevant to all of the lower levels of the hierarchy. The participant-related TSV file records demographic and descriptive information such as ID, age, gender, whether they are suggested to be excluded, and any additional notes. The accompanying JSON sidecar file provides column-level metadata describing the meaning and units in the TSV file. A dataset description JSON file provides top-level information about the entire dataset, including its name, the BIDS version it conforms to, author information, and links to associated publications or data repositories. An EEG JSON file contains metadata for the EEG

recording, including task name, the number of EEG channels, the amplifier and electrode system used, the type of EEG reference and ground electrode, hardware and software filter settings, the recording institution, and the recording type. The events-related JSON files serve as data dictionaries for the accompanying TSV files containing the raw event-related data.

Within each subject folder, data are organised by modality into datatype subdirectories. EEG recordings are stored under eeg/, while the behavioural data from the food go/no-go and paired food choice tasks are stored under beh/. Each subject's EEG directory contains the raw EEG data file alongside TSV files containing details of all experimental events that occurred during the recording.

2.3.3 Open Science Framework Repository

To maximise transparency and replicability, we aimed to provide as much information on the dataset as possible. All code required to reproduce data collection, preprocessing, and analyses is provided in the Open Science Framework repository. This repository also contains the food image stimuli, normative ratings on 22 food attributes, and questionnaire data on measures of food-related motivation and dietary style.

Experimental scripts for the food categorisation task were written in Matlab R2022a using Psychtoolbox-3 (Kleiner et al., 2007), while the food go/no-go and paired food choice tasks were implemented in Python using PsychoPy. Adjustable experiment parameters are documented within the scripts, and supporting stimulus files used during instructions and practice trials are included alongside the main experimental code. EEG preprocessing was carried out in Matlab using

EEGLAB across three sequential scripted steps. The first involved data import, channel location assignment, event recoding, and initial formatting. The second covered manual rejection of noisy data segments and channels, re-referencing to an average reference, and independent component analysis (ICA) decomposition. The third involved the removal of ICA components corresponding to eye movement artifacts and interpolation of rejected channels. The specific channels, data segments, and ICA components rejected for each participant are documented within dedicated functions, ensuring that all preprocessing decisions are transparent and reproducible.

The 120 food image stimuli used across all tasks are provided in the stimuli directory, with 91 images drawn from the Food-pics database (Blechert, Meule, et al., 2014) under a CC BY-NC-SA licence and the remaining images sourced online. These images are referenced by filename in the event files accompanying the EEG data, allowing stimulus-level information to be linked to neural and behavioural measures.

Ratings on three food attributes (healthiness, tastiness, and willingness to eat) were collected from in-person participants (N = 117) after the food categorisation task. Each participant provided continuous ratings (0–100) for all 120 food images. These ratings are stored in individual participant files identifiable by participant number, and contain each participant's ratings on all three attributes as well as their RTs from the food categorisation task, allowing individual-level attribute evaluations to be linked to both neural data and speeded categorisation responses.

In addition to the in-person ratings, normative ratings on a broader set of 22 food attributes were collected from a separate online sample (total *N* = 624). These attributes encompassed nutritive properties (healthiness, calorie content, edibility, and level of transformation), hedonic properties (tastiness, willingness to eat, positive and negative valence, and arousal), taste properties (sweetness, saltiness, sourness, bitterness, and savouriness), familiarity (previous exposure, recognisability, and typicality), and elicited emotions (happiness, surprise, disgust, craving, and guilt). As each online participant rated a subset of food images (40 out of 120) and a subset of attributes (10 out of 22), individual rating files are organised by food image, with NaNs used to indicate attributes or participants for which no rating was provided. Summary statistics (means, standard deviations, and range) are provided at the level of each food image and attribute, enabling rapid integration of normative attribute data into new analyses without processing the raw files. Demographic information and self-reported hunger, satiety, and time since eating are provided for online participants alongside the survey instruments used to collect the ratings.

Questionnaire data are also provided. Dietary style was assessed using the Dutch Eating Behaviour Questionnaire (van Strien et al., 1986) and the Three Factor Eating Questionnaire Revised 21-Item (Stunkard & Messick, 1985; Tholin et al., 2005), which index restrained, emotional, and external eating styles. Food-related motivations were measured using relevant subscales of the Food Choice Questionnaire (Steptoe et al., 1995) and the Eating Motivations Survey – Brief (Renner et al., 2012). General motivational tendencies were assessed with the

Behavioural Inhibition and Behavioural Activation System Scales (Carver & White, 1994), and hedonic orientation was measured using the Hedonism subscale of the Present Time Orientation Scale (Sobol-Kwapinska, 2009). Raw item-level responses are provided alongside summary statistics at both the subscale and item level, and a copy of the survey instrument is included to allow unambiguous mapping between response columns and questionnaire items.

2.3.4 Dataset Curation Summary

In summary, the FOODEEG dataset was curated with the aim of maximising its utility for future researchers and transparency of documentation. By adhering to FAIR principles and the BIDS standard, the dataset is structured to be discoverable, accessible, and interpretable for food cognition researchers. Raw and preprocessed EEG recordings and behavioural data are hosted on OpenNeuro, while stimuli, ratings, questionnaire data, and all code needed to reproduce data collection and analyses are available on the Open Science Framework repository. We aimed to create a resource to encourage future investigations into the neural and behavioural correlates of food cognition.

Chapter 3: Open Dataset of Human Electroencephalographic and Behavioural Responses to Food Images

The following chapter presents the dataset descriptor for a large-scale, open-access resource containing neural and behavioural responses to visual food cues developed for food cognition research. This study was published in *Scientific Data* on 20/07/26 and is presented in its published format.

Open Dataset of Human Electroencephalographic and Behavioural Responses to Food Images

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3.1 Abstract

Investigating the neurocognitive mechanisms underlying food choices has the potential to advance our understanding of eating behaviour and inform health-targeted interventions and policy. Large, publicly available neural and behavioural datasets can enable new discoveries and targeted hypothesis tests, yet no such datasets are currently available. We present the FOODEEG dataset containing electroencephalographic (EEG) responses to a diverse array of food images, as well as behavioural measures of food cognition (food categorisation task, food go/no-go task, and food choice task responses), collected from 117 participants. We also provide normative ratings for the food image stimuli with respect to 22 food attributes, including nutritive, hedonic and taste properties, familiarity, and elicited emotions. Our dataset also includes questionnaire-based measures of participants' food motivations, dietary styles, and general motivational tendencies. In the validation analyses, we demonstrate that early food-evoked EEG responses in our dataset are consistent with observations in previous work. The FOODEEG dataset will be valuable for accelerating research into the neural substrates of visual food processing, dietary decisions, and individual differences.

3.2 Background & Summary

Food-related decisions are highly complex, often involving the integration of sensory and mnemonic information as well as the influence of social, cognitive, and contextual factors. Poor diet has been linked to a number of negative health consequences, including increased risks for cardiovascular and neurodegenerative diseases, and certain types of cancer[1,2]; yet, maintaining a healthy diet is a challenge for many people. While recent neuroimaging work has shed light on the mechanisms underlying food-related cognition, such as the visual processing of foods[3–8], cognitive reappraisal[9–14], working memory[15–17], and reward processing[18–20], we do not yet fully understand how people make dietary decisions. Gaining insight into these neural processes could inform future interventions aimed at improving dietary choice, and subsequent health and wellbeing.

Using visual food cues (e.g., food images) to investigate the neural mechanisms of dietary choice confers several advantages. Compared to using real foods as stimuli, using food images allows for precise characterisation of stimulus features (e.g., size, colour), increases reproducibility across and within studies, and reduces cost. There is also evidence that responses to food images are associated with eating behaviour. A meta-analysis[21] reported that cue reactivity and craving elicited by visual food cues predicted eating behaviour and weight gain with a similar effect size as those elicited by exposure to real foods, and with a greater effect size than those elicited by olfactory food cues. Researchers can also readily access food image stimulus sets for use in experimental research, such as

Food-pics[22,23], the FoodCast Research Image Database[24], the Cross-Cultural Food Image Database[25], the Open Library of Affective Foods[26,27], and the Macronutrient Picture System[28].

These image databases can be used to systematically measure neural responses to foods that vary across a wide range of choice-relevant dimensions. However, collecting a large amount of neuroimaging data using these stimulus sets can be time-consuming and expensive. Recently, large-scale neuroimaging datasets collected while viewing scenes, objects, and animals have become publicly available (e.g., Natural Scenes Dataset[29]; THINGS-EEG[30]), allowing for a rapid expansion in research on the visual processing of objects and scenes. Providing large, high-quality datasets containing neural responses to visual food cues can similarly help researchers to devise and test novel questions in food cognition research and nutrition science. Such datasets also enable replication analyses in conjunction with other neuroimaging datasets to test the generalisability of novel findings. Furthermore, large-scale behavioural and neural datasets can be used to train models of eating behaviour to predict health outcomes[31].

Food choice behaviour can also vary widely, and may reflect individual differences in eating styles[32–34]. Such differences may also be reflected in neural activity. Examination of neural responses to food images could potentially reveal mechanisms that underpin individual differences in dietary choices. Differences in food-evoked neural responses have been reported for people who differ in their levels of restrained eating (the tendency to restrict food intake to control body size

or weight)[35–37], external eating (tendency to eat in response to external food cues)[38,39], and emotional eating (tendency to eat in response to negative emotions)[40]. Individuals can also vary in their motivations when making food choices, with different levels of consideration given to factors such as health, mood, pleasure, familiarity, habits, and hunger when choosing what to eat[41,42]. However, few studies have examined the associations between food motivations and the neural processing of food cues. Another important facet of food cognition is inhibitory control. A recent meta-analysis[43] revealed that food-related inhibitory control (as measured using laboratory-based behavioural tasks) plays a role in food consumption, though the strength of the association was small. However, few studies have included measures to examine similar differences in neural responses[39]. Large datasets are particularly important when examining the links between neural processing of foods and individual differences in eating style, food motivations, and inhibitory control abilities, given the high power required for between-subject group comparisons or correlational analyses.

Here, we present a large dataset (N = 117) comprising electroencephalographic (EEG) and behavioural responses to a broad set of 120 food image stimuli. This dataset includes EEG data and behavioural responses recorded during a food categorisation task, and also behavioural data collected during a food go/no-go task and a paired food choice task. Questionnaire-based measures of participants' food motivations (Food Choice Questionnaire42, Eating Motivation Survey41), dietary styles (Dutch Eating Behaviour Questionnaire34, Three Factor Eating Questionnaire-R2133,44), general motivational tendencies

(Behavioural Inhibition and Behavioural Activation System Scales45), and hedonism (Present Time Orientation Scale46) are included. Additionally, we provide normative ratings on 22 food attributes for each of the food images, spanning nutritive properties (healthiness, calorie content, edibility, and level of transformation), hedonic properties (tastiness, willingness to eat, positive and negative valence, and arousal), familiarity (previous exposure, recognisability, and typicality), taste properties (sweetness, saltiness, sourness, bitterness, and savouriness), and emotional properties (happiness, surprise, disgust, craving, and guilt) collected from separate online samples (total N = 624).

Users may take advantage of the high temporal resolution afforded by EEG, which allows for the characterisation of rapid neural processes that underlie visual perception and decision-making. Previous work has shown that abstract information about objects beyond low-level visual features, such as animacy, naturalness, and elicited emotions, are reflected in EEG signals within the first several hundred milliseconds after image onset47–49. This dataset is well suited for uncovering the precise timing of neural processes that occur in response to food images.

The EEG task was carefully designed to separately measure the appraisal and decision stages of food evaluation (Figure 1A). In this task, participants were presented with a food image and were asked to evaluate the food on one of three attributes: healthiness, tastiness, and willingness to eat. Each food image was presented three times (once for each attribute). We sought to separate the appraisal and decision stages of food evaluation by including a viewing phase, in

which participants viewed the food image in isolation for 2 s, before the response phase, in which participants were presented with the prompt indicating the attribute they were to evaluate the food on. The mapping of the response options onto response keys was randomised across trials to prevent anticipatory motor preparation. We reduced priming effects by presenting healthiness, tastiness, and willingness to eat trials in a randomised order within blocks, rather than presenting each trial type in separate blocks. This ensured that the participants were not able to anticipate which of the three attributes would be judged during food image viewing. This task design allows for investigations into the neural mechanisms underlying food appraisal and the visual processing of foods while minimising the influences of neural signals related to decision or motor preparation. Users interested in the neural correlates of food-related decision-making processes can instead examine relationships between choice behaviour (e.g., response times) and neural activity in the response phase. We recommend conducting analyses on the attribute (e.g., healthiness, tastiness) or category (e.g., meals, snack foods) level, rather than at the level of individual food images, due to the low number of trials per image (3 trials).

The food image stimuli were carefully curated to ensure that there was substantial variance in key food attributes. This is often difficult to achieve because people tend to view most foods as appetising and positively valenced. Ninety-one images were selected from an established food image database (Food-pics23) and consisted of mostly palatable and familiar foods. Twenty-nine images of foods that are less palatable or familiar, but still edible, were sourced from

online searches and included in the stimulus set. Some existing work has compared behavioural responses towards edible versus inedible foods (e.g., rotten or decayed foods50,51), but few studies have included foods that are unappetising but not harmful to eat in their stimuli.

Rating data on a wide range of food attributes indicate that our stimuli sufficiently varied on key attributes that are relevant for dietary choice. This indicates that our dataset is suitable for analyses that are sensitive to fine-grained differences in the variables of interest, such as multivariate pattern analysis (MVPA) or representational similarity analysis (RSA). For example, MVPA can be applied to investigate how fine-grained rating information about a food attribute of interest covaries with patterns of EEG data, to delineate the precise neural time-courses of these representations during food viewing (see Technical Validation for an example). Alternatively, fine-grained rating information can be used to construct models of similarity for a given food attribute and compare them to models of similarity for neural or behavioural data. Recent work has demonstrated how RSA can be applied to this dataset[3].

Beyond what we provide here, additional ratings can be easily collected from new online participant samples to assess an even wider range of food attributes and how they covary with neural responses in our dataset. Users may also use these normative ratings in combination with the food images to inform stimuli selection, to ensure a particular distribution of attributes to suit their research goals.

In sum, the FOODEEG dataset comprises a rich array of neural and behavioural measures during food cognition tasks collected from a large sample (N = 117). Given the multifaceted nature of eating behaviour, we have included measures of eating styles, food motivation, and relevant personality traits which may be useful in controlling for, or investigating, individual differences. We also provide a comprehensive set of ratings on 22 food attributes that encompass nutritive, hedonic, familiarity, taste, and emotional properties of foods. The FOODEEG dataset has the potential to advance food cognition research by supporting a wide range of research projects, including investigations linking neurocognitive mechanisms to individual differences, food attribute processing, and the dynamics of choice behaviour.

3.3 Methods

Neural and behavioural data were collected in-person over two testing sessions. In Session 1, participants performed a food categorisation task (Figure 1B) in a testing booth while EEG was recorded. Participants then rated the same food images on healthiness, tastiness, and willingness to eat. In Session 2, participants completed a food go/no-go task (Figure 1C) and a paired food choice task (Figure 1D). They also completed questionnaires relating to their eating styles, food-specific motivations, and general motivational tendencies. A separate sample of participants completed an online food rating task, in which participants were asked to rate the food image stimuli on multiple food attributes. Figure 1A shows the overview of the data collection procedure. This study was approved by

the Human Research Ethics Committee of the University of Melbourne (HREC ID 24850).

3.3.1 Participants

For the in-person sessions, participants (*N* = 117) were recruited through online study advertisements on the University of Melbourne student portal and via posters placed around the University of Melbourne Parkville campus. The advertisements contained a link to an online survey regarding the eligibility criteria and those that met the requirements were contacted through email. Participants were eligible to participate if they were at least 18 years old, were fluent in written and spoken English, did not have a history of any eating disorders, were not on a calorie restriction diet, and did not have any dietary restrictions (e.g., for health or religious reasons). Participants were instructed to refrain from eating any food for a minimum of three hours prior to both in-person sessions. Participants were reimbursed AUD $50 after completing both sessions. The sample had a mean age of 26.8 years (SD = 8.50, range 18-57 years). 84 participants identified as female, 32 as male, and one as other. Note that a large proportion of our in-person sample consisted of female participants. As gender and sex-related differences have been reported in some aspects of dietary behaviour (e.g., eating styles and food craving)[52], researchers who wish to examine such processes may consider taking a balanced sample from the full dataset or opt for using data from the female participants only.

Online participants (*N* = 624) were separately recruited through the University of Melbourne Research Experience Program, which offers research

participation opportunity to undergraduate students in the Melbourne School of Psychological Sciences. Participants took part in the study to earn course credit. All online participants were at least 18 years old and fluent in written and spoken English. Participants indicated that they did not have a history of any eating disorders, were not on a calorie restriction diet, did not have any dietary restrictions, and had not previously taken part in the in-person testing sessions. The online sample had a mean age of 19.55 years (SD = 2.92, range 18-53 years). 482 participants identified as female, 132 as male, 7 as non-binary/other, and 3 preferred not to disclose. Course credit was allocated to those who participated in the online experiment in full.

All participants were given a Plain Language Statement detailing the study procedure, potential risks involved, and how their data would be stored and shared. In-person participants were informed of the possibility of minor discomfort from wearing the EEG cap and fatigue during the task, while online participants were informed that there were low to negligible risks. All participants were advised that their information would be kept confidential subject to legal requirements and that the data from the study may be used in future research and may be made publicly accessible in a de-identified format. Participants signed a consent form after reading the Plain Language Statement. Prior to the deposition of the data in the repositories, all data were deidentified to protect participant anonymity. Specifically, each participant's name and contact information was removed and replaced by an arbitrary ID number.

3.3.2 Stimuli

The stimuli consisted of 120 colour images of food items against a white background. Ninety-one images were drawn from the Food-pics database[23] and 29 images were drawn from online search. Food-pics[23] is a database of food images containing images of a wide variety of food items designed for use in research on eating behaviour. The 91 food images were selected to include a wide range of food types (e.g., vegetables, fruits, savoury dishes, sweet dishes, meats). Food images that portrayed multiple types of foods or included cutlery were not included. An additional 29 images were obtained from image hosting websites (e.g., Flickr, Adobe Stock). We aimed to increase variance in key food attributes (e.g., tastiness, valence, familiarity) in our stimuli set. To this end, we included images of foods that were generally less palatable but were nevertheless edible. Examples of the food images are displayed in Figure 1E.

We note that foods naturally vary on low-level visual features (e.g., colour, contrast, and visual complexity) which may covary with other aspects of foods, such as healthiness, level of transformation, or valence. For example, vegetables make up a large proportion of foods that are green and at the same time, tend to be judged as healthy. Processed foods tend to be more visually symmetrical compared to raw foods. Such low-level image properties are known to reliably modulate early neural responses (e.g., N1, P1)[53,54]. However, fully controlling for these image properties is difficult to achieve while keeping the stimuli recognisable and ecologically valid. We encourage users to control for relevant low-level visual features in their

analyses[3]. To support this, we have included luminance and contrast values for each food image in the Stimuli directory on the Open Science Framework repository[55]. Luminance and root mean square contrast values were calculated as the mean and standard deviation of the greyscale values of the image, respectively[56]. These image properties are provided to help users with stimuli selection or for inclusion into analyses to control for neural activity evoked by these low-level visual features. Users can extract other image properties using the full set of food images provided in the Stimuli directory on the Open Science Framework repository[55].

3.3.3 Procedure

Participants attended the two in-person sessions on different days, approximately 1 week apart. In Session 1, participants carried out a food categorisation task presented using Psychtoolbox[57] interfacing Matlab R2022a. Next, participants evaluated each food image on three food attributes (healthiness, tastiness and willingness to eat) using Qualtrics. During the second session, participants completed two behavioural tasks: a food go/no-go task and a paired food choice task presented using PsychoPy[58] interfacing Python (v3.11). All experimental code are available via the Open Science Framework[55]. Participants also completed questionnaires relating to dietary styles, food motivations, and general motivational tendencies using Qualtrics.

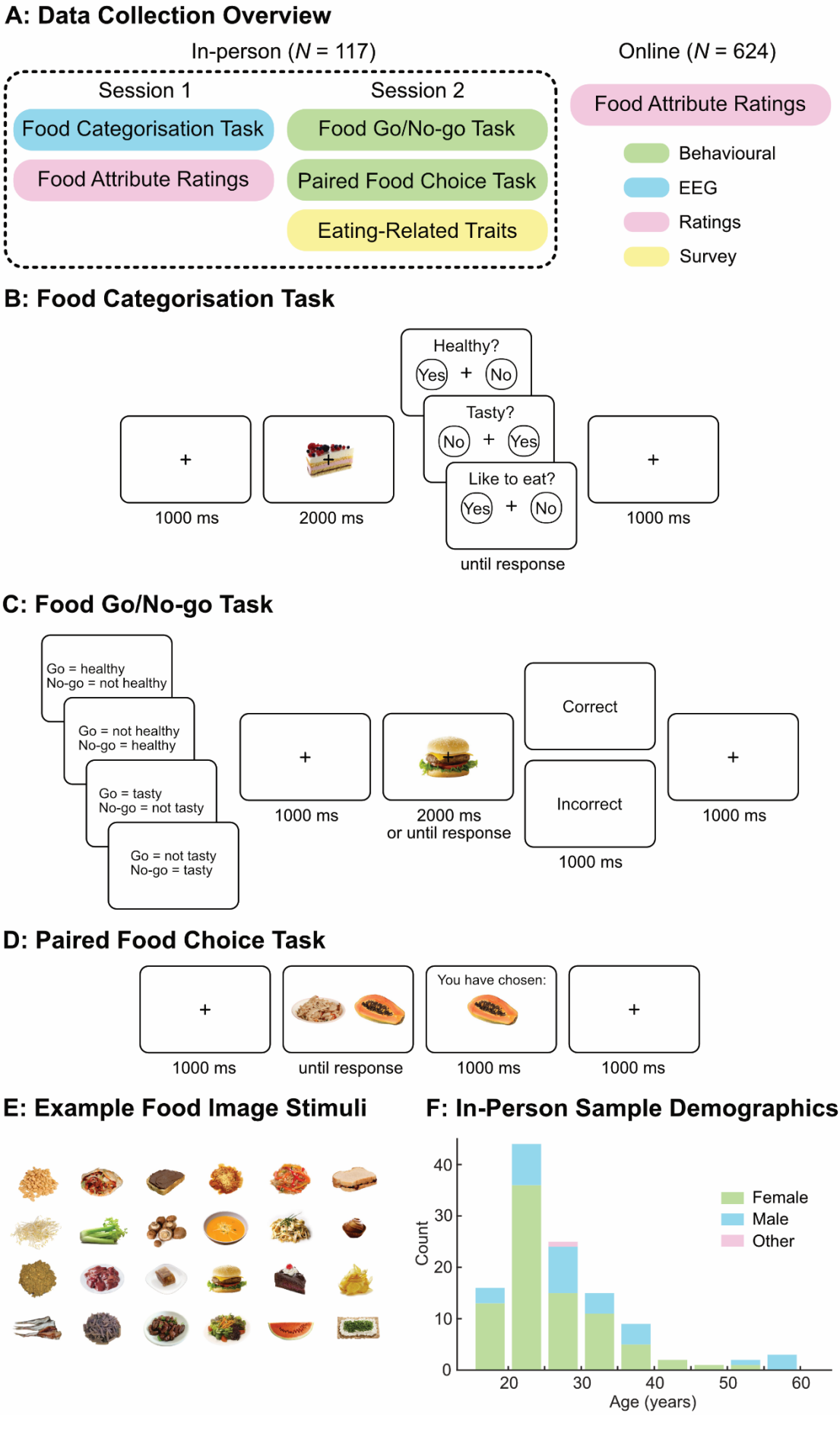
A: Data Collection Overview
In-person (N = 117)
Online (N = 624)
Session 1
Session 2
Food Categorisation Task
Food Attribute Ratings
Food Go/No-go Task
Paired Food Choice Task
Eating-Related Traits
Food Attribute Ratings
Behavioural
EEG
Ratings
Survey
B: Food Categorisation Task
Healthy?
Yes + No
Tasty?
No + Yes
Like to eat?
Yes + No
until response
1000 ms
2000 ms
1000 ms
C: Food Go/No-go Task
Go = healthy
No-go = not healthy
Go = not healthy
No-go = healthy
Go = tasty
No-go = not tasty
Go = not tasty
No-go = tasty
1000 ms
2000 ms
or until response
Correct
Incorrect
1000 ms
1000 ms
D: Paired Food Choice Task
1000 ms
until response
You have chosen:
1000 ms
1000 ms
E: Example Food Image Stimuli
F: In-Person Sample Demographics
Count
Age (years)
Female
Male
Other

Figure 1. Overview of data collection and experimental trial diagrams. A) Data collection overview. The data was collected over two in-person sessions and online. In the first in-person session, participants completed the food categorisation task (while EEG was recorded) and provided ratings on the food images for three attributes. In the second in-person session, participants completed two behavioural tasks (food go/no-go task and paired food choice task) and filled out survey measures of dietary styles, food motivations, and general motivational tendencies. In an online experiment using a separate sample, attribute ratings were collected for the food images for 22 choice-relevant food attributes. B) Food categorisation task. For each trial, participants viewed a food image (2 s), followed by a response screen with one of three prompts probing healthiness, tastiness, or willingness to eat and one of two keyboard press response mappings ('z' key for Yes and 'm' key for No, or the reverse). Participants were instructed to respond as quickly as possible. C) Food go/no-go task. In each trial, participants were presented with a food image and either responded as quickly as possible with a keyboard press for Go foods or withheld any responses (2 s) for the No-go foods. Feedback ('Correct' or 'Incorrect') was given after each trial. Participants completed four blocks with different Go and No-go foods. D) Paired food choice task. Participants were presented with two food images and were asked to choose the food that they would prefer to eat more, followed by a feedback screen showing the food image that they had selected. E) Example food image stimuli. Food images were selected to include a wide variety of food types and also included foods generally

thought to be less appetising or familiar. F) In-person sample demographics. Age distribution for the in-person sample (*N* = 117) is shown in a histogram. Green, blue, and pink denote the proportions of participants who identified as female, male, and other respectively.

3.3.3.1 Food Categorisation Task With EEG Recording. During the food categorisation task, each food item was presented to the participants three times (once per trial type: healthiness, tastiness, and willingness to eat) while EEG data was collected (Figure 1B). Food images were presented centrally on an ASUS ROG Swift PG258Q monitor (24.5 inch, 1920 x 1080 pixels, 60 Hz refresh rate), subtending 6.6 × 3.5 degrees of visual angle. To minimise head movement, participants were seated approximately 50 cm from the screen with their head stabilised using a chin and forehead rest. Each trial started with the presentation of a fixation cross for 1 s, after which the food image appeared alongside the fixation cross for 2 s. The participants were then shown a question prompt corresponding to the trial type: “Healthy?” in a healthiness trial, “Tasty?” in a tastiness trial, and “Like to eat?” in a willingness to eat trial. Response mapping was presented alongside the prompt to indicate which of the left (‘z’) and the right (‘m’) keyboard keys represented a “Yes” and a “No” response. The assignment of keys to responses was equally likely to be the left keyboard press indicating a “Yes” response and the right keyboard press indicating a “No” response, as the reverse left/right mapping, on any given trial. For each participant, the trial types (healthiness, tastiness, and willingness to eat) were intermixed and presented in a randomised order, as was the order of food images within the sequence. The

randomisation of the trial type order and response mapping prevented participants from planning a keypress motor action in advance during the image presentation period. Participants were instructed to respond as quickly and accurately as possible, and to monitor the switching of the response mapping carefully as it could change for each trial. Prior to the main experiment, participants completed five practice trials and confirmed that they had understood the task. To minimise eye movement artifacts, participants were asked to maintain fixation on the central cross, which remained on screen throughout each experimental block. Response time (the interval between the prompt and response mapping presentation and the participant's keypress) was recorded for each trial. Participants completed six blocks of 60 trials each, with self-paced breaks between each block. The task took approximately 45 minutes to complete, including breaks.

EEG was recorded using a Biosemi Active II system (Biosemi, The Netherlands) with 64 scalp electrodes at a sampling rate of 512 Hz using common mode sense and driven right leg electrodes (http://www.biosemi.com/faq/cms&drl.htm). Eight additional electrodes (two electrodes placed 1 cm from the outer canthi of each eye, four electrodes placed above and below the centre of each eye, and two electrodes placed above the left and right mastoids) were also attached. Throughout the recording, electrode offsets were maintained within the range of ±20 μV.

3.3.3.2 Healthiness, Tastiness, and Willingness to Eat Ratings. After the food categorisation task, participants rated each food image on healthiness ("How

healthy is this food?"), tastiness ("How tasty is this food?") and how willing they were to eat it ("How much would you like to eat this food?"). Participants were asked to use a computer mouse to indicate their response on a continuous rating scale ranging from "Not at all" to "Very much". We randomised image presentation order for each participant, while ensuring that the same food image was not presented across two consecutive trials.

3.3.3.3 Food Go/No-Go Task. Adapted from the standard go/no-go paradigm, the food-specific go/no-go task has been used in previous research to measure food-related inhibitory abilities[59,60]. Stimulus set selection was carried out for each individual participant, using their attribute ratings from Session 1. Healthiness and tastiness ratings from Session 1 were used to select 60 food image stimuli across four categories: 15 Most-Healthy foods, 15 Least-Healthy foods, 15 Most-Tasty foods, and 15 Least-Tasty foods. To select the Most-Tasty foods, 15 foods with the highest tastiness ratings were selected. To select Least-Tasty foods, 15 foods with the lowest tastiness ratings were selected. From the remaining foods, Most-Healthy and Least-Healthy foods were selected in the same way. If there were more than 15 foods with the highest or lowest ratings for an attribute, 15 were randomly selected from those foods. No foods were included in multiple categories. Prior to the start of the task, participants were shown all 60 food images and the category each belonged to. It was indicated to the participants that the foods were categorised according to their own ratings from the previous session, and they were asked to let the experimenter know if they disagreed with the categorisations for any of the foods. If the participant disagreed

with the categorisation of a food, the food was removed from the category and replaced with the food with the highest (for Most-Healthy and Most-Tasty categories) or the lowest (for Least-Healthy and Least-Tasty) rating on the appropriate attribute out of the unselected foods.

Participants completed four blocks of the go/no-go task. In the first block, Most-Healthy foods served as the Go stimuli and the Least-Healthy foods served as the No-go stimuli. In the second block, Most-Tasty foods served as the Go stimuli and the Least-Tasty foods served as the No-go stimuli. The Go and No-go stimuli in the first and second blocks were switched for the third and fourth blocks respectively. There were 100 trials in each block. In each block, Go foods were presented in 75% of the trials and No-go foods were presented in 25% of the trials. At the start of each block, instruction text indicated to the participants which food categories served as the Go and No-go stimuli for the block. Next, the participants were shown a series of food images and were asked to make a response via keyboard press as quickly as possible to the Go foods and to withhold the response to the No-go foods. A fixation cross was presented for 1 s between trials. Block order was randomised for each participant.

3.3.3.4 Paired Food Choice Task. To assess people's preferences across foods that differed in attributes (e.g., healthiness and tastiness), participants selected which food they would prefer to eat more out of pairs of foods they had previously indicated they would be willing to eat. Stimuli selection was carried out for each individual participant, using their attribute ratings from Session 1. Out of the food images that had been rated over 50 (scale: 0-100) on willingness to eat in

Session 1, 25 food images were selected. If fewer than 25 food images had been rated over 50 on willingness to eat, the subsequent highest rated food images were included in the stimuli to bring the total number of food images to 25.

Participants completed five blocks of the paired food choice task. There were 60 trials in each block. In each trial, participants were presented with two food images on the left and right side of the screen. Participants indicated which food they would prefer to eat more with a keyboard press ('z' to select the left food and 'm' to select the right food). Every possible pairwise combination of the 25 food images was presented once, totalling 300 trials. A fixation cross was presented for 1 s between each trial.

3.3.3.5 Questionnaires. Participants' dietary styles, food motivations, general motivational tendencies, and hedonism were measured using self-report scales. Dietary styles were assessed using the Dutch Eating Behaviour Questionnaire[34] and the Three Factor Eating Questionnaire Revised 21-Item[33,44]. Food-related motivations were assessed using the relevant subscales of the Food Choice Questionnaire (Health, Mood, Sensory Appeal, Natural Content, Weight Control, and Familiarity subscales)[42] and the Eating Motivation Survey Brief (Liking, Habits, Need and Hunger, Health, Pleasure, Natural Concerns, Weight Control, Affect Regulation subscales)[41]. Motivational tendencies were measured using the Behavioural Inhibition and Behavioural Activation System Scales[45] and hedonism was assessed using the Present Time Orientation Scale[46]. The descriptive statistics for the survey measures are presented in Table 1.

Table 1. Summary statistics for survey measures of dietary style, food motivations, general motivational tendencies, and hedonism. Mean, standard deviation, and range of individual participants' mean scores for the subscales of Food Choice Questionnaire, the Eating Motivations Survey – Brief, Three Factor Eating Questionnaire, Dutch Eating Behaviour Questionnaire, Behavioural Inhibition and Behavioural Activation System Scales, and Present Time Orientation Scale are reported.

Scale	Subscale	Mean	SD	Min	Max
Food Choice Questionnaire	Health	3.40	0.77	1.17	5
	Mood	3.55	0.77	1.50	5
	Sensory appeal	3.81	0.67	2	5
	Natural content	2.77	1.08	1	5
	Weight control	2.56	0.99	1	5
	Familiarity	2.64	0.94	1	5
The Eating Motivations Survey - Brief	Liking	5.93	0.73	4.33	7
	Habits	4.63	1.22	1	7
	Need and hunger	5.42	0.93	3	7
	Health	4.61	1.06	2	7
	Pleasure	5.16	0.98	2.67	7
	Natural concerns	3.75	1.48	1	7
	Weight control	3.23	1.34	1	6.33
	Affect regulation	2.95	1.44	1	6.67
Three Factor Eating Questionnaire	Cognitive restraint	2.24	0.60	1	3.67
	Emotional eating	2.07	0.71	1	4
	Uncontrolled eating	2.21	0.56	1.11	3.78
Dutch Eating Behaviour Questionnaire	Restrained	2.63	0.85	1	4.75
	Emotional	2.42	0.89	1	4.83
	External	3.36	0.67	1.80	5
Behavioural Inhibition and Behavioural Activation System Scales	Punishment sensitivity	1.84	0.49	1	3.29
	Drive	2.16	0.53	1	3.75
	Reward responsiveness	1.50	0.40	1	2.60
	Fun seeking	2.01	0.61	1	3.75
Present Time Orientation Scale	Hedonism	3.40	0.62	1.67	4.67

3.3.3.6 Online Food Attribute Ratings. A separate sample of participants completed the online rating task. Participants recorded their current hunger ("How hungry are you currently?") and satiety ("How full are you currently?") level on a sliding scale from 'Not at all' to 'Very much' and indicated how much time has elapsed since they had consumed food ("How long ago did you last eat food?") from one of the following options: 'Less than an hour ago', '1-3 hours ago', '3+ hours ago', and 'I do not know'. Each participant rated a third of the full set of food images (40 out of the 120 images) on 12 (out of 22) food attributes. Each individual food image was evaluated by 204-212 participants on healthiness, tastiness, and willingness to eat. Each image was rated by 134-145 participants on calorie content, level of transformation, edibility, positive and negative valence, arousal, previous exposure, recognisability, and typicality, and by 66-70 participants on emotional properties (happiness, disgust, surprise, craving, and guilt) and taste properties (sweetness, saltiness, bitterness, sourness, and savouriness). Individual participants' responses and summary statistics for each attribute and each food image (mean, SD, and range) are provided in the Ratings directory on the Open Science Framework repository[55]. For each participant, both the sequence in which food images appeared and the order in which each image's attributes were evaluated were randomised. Table 2 displays the full list of food attributes and the corresponding prompts and additional information presented to the participants. Participants indicated their rating for each attribute on a sliding scale (0-100) using a computer mouse.

Table 2. Food attribute ratings and corresponding prompts. Ratings on 22 food attributes across five categories (nutritive, hedonic, familiarity, taste, and emotional properties) were collected for the food image stimuli using the corresponding prompt for each food image. For edibility, level of transformation, and arousal, additional information was displayed alongside the prompt (in italics).

	Food attribute	**Prompt**
Nutritive properties	Healthiness	How healthy is the food represented in the image?
	Calorie content	How much calorie content is in the food represented in the image?
	Edibility	How much work WILL BE required to bring the food represented in the image ready to eat? *For example, raw chicken will require more work (i.e., more steps, long time, many ingredients) to get it ready to eat compared to an apple (i.e., less steps, short time, few ingredients).*
	Level of transformation	How much work WAS required to prepare the food represented in the image? *For example, a cake required more work (i.e., more steps, long time, many ingredients) to prepare than rice (i.e., less steps, short time, few ingredients).*
Hedonic properties	Tastiness	How tasty is the food represented in the image?
	Willingness to eat	How much would you like to eat the food represented in the image?
	Negative valence	How negatively do you view the food represented in the image?
	Positive valence	How positively do you view the food represented in the image?
	Arousal	How emotionally arousing is the food represented in the image? *Less emotionally arousing foods are calming/relaxing, and more emotionally arousing foods are stimulating/energising.*
Familiarity	Exposure	How often do you encounter the food represented in the image?

	Recognisability	How easy is it to identify the food represented in the image?
	Typicality	How typical is the food represented in the image?
Taste properties	Sweet	How much of the following taste is elicited by the food represented in the image?
	Salty	
	Bitter	
	Sour	
	Savoury (umami)	
Emotional properties	Happiness	How much of the following emotion is elicited by the food represented in the image?
	Disgust	
	Surprise	
	Craving	
	Guilt	

3.4 Data Records

All data and code are publicly available. The raw and processed EEG recordings and behavioural data are hosted in the Brain Imaging Data Structure (BIDS) standard[61,62] on OpenNeuro[63] (https://doi.org/10.18112/openneuro.ds007012.v1.1.1). The raw EEG recordings are provided in BioSemi data format (.bdf) and the cleaned continuous EEG files are provided in EEGLAB data format (.set). Custom code, food image stimuli, survey data, and normative ratings are available from the Open Science Framework[55] (https://doi.org/10.17605/OSF.IO/Y9PMF).

At the root level of the OpenNeuro repository[63], several sidecar files are provided to document metadata that apply to all of the lower levels of the repository. The participant-related TSV file records demographic and descriptive information such as participant ID, age, gender, whether they are suggested to be excluded from analyses, and any additional notes. The accompanying JSON

sidecar file provides column-level metadata describing the meaning and units in the TSV file. A dataset description JSON file provides top-level information about the entire dataset, including its name, the BIDS version it conforms to, author information, and links to associated publications or data repositories. An EEG JSON file contains metadata for the EEG recording, including task name, the number of EEG channels, the amplifier and electrode system used, the type of EEG reference and ground electrode, hardware and software filter settings, the recording institution, and the recording type. The events JSON files serve as data dictionaries for the accompanying TSV files containing the raw event-related data. Within each subject folder, data are organised by modality into datatype subdirectories. EEG recordings are stored under eeg/, while the behavioural data from the food go/no-go and paired food choice tasks are stored under beh/. Each subject's EEG directory contains the raw EEG data file alongside TSV files containing details of all experimental events that occurred during the recording. The derivatives folder contains the cleaned continuous recordings for all subjects.

The Open Science Framework repository[55] is organised into six top-level directories: Derivatives, Experiment, Questionnaires, Ratings, Stimuli, and Validation. The Derivatives directory stores the code used to process the raw EEG data into cleaned continuous data. The Experiment directory contains the code used to run the three experimental tasks, organised into three subdirectories (food categorisation task, food go/no-go task, and paired food choice task). Self-report questionnaire materials, individual participant responses, and summary statistics are provided in the Questionnaires directory. The Ratings directory contains the

food attribute ratings for the 120 food image stimuli, organised into two subdirectories. The in-person subdirectory stores ratings collected from the in-person participants at the end of Session 1, while the online subdirectory stores the ratings collected from the online sample. Demographic information for online participants, survey instruments, and summary statistics are provided in the online subdirectory. The Stimuli directory contains the 120 food images used across all experimental tasks. Of these, 91 were drawn from the Food-pics database[23] available for non-commercial research use under a CC BY-NC-SA licence, and 29 were sourced from online sources. The code used in the technical validation analyses and copies of the figures are included in the Validation directory. See the readme file in the Open Science Framework repository for further details.

3.5 Technical Validation

3.5.1 EEG Data Validation

For technical validation of the current dataset, we used two complementary analyses to demonstrate that both binary categorisations and continuous ratings on food attributes covary with patterns of EEG data. We examined EEG responses following food image onset to assess whether event-related potential (ERP) waveforms differed across different food items that categorically varied in attributes (e.g., Healthy versus Not-Healthy foods). Furthermore, we used MVPA to demonstrate that fine-grained information about food attributes is also present in the EEG signals.

3.5.1.1 Data Processing. We processed the EEG data using EEGLAB v2022.1[64] interfacing Matlab (R2022a). Channels with excessive noise were

identified via visual inspection (mean number of bad channels = 0.26, range 0–5) and omitted from average reference calculations and independent component analysis (ICA). Data segments containing excessive noise were also identified through visual inspection and removed. Five participants were excluded from the analyses due to noisy data or missing trials. Two additional participants were excluded due to high incongruence between their responses in the food categorisation task and their subsequent continuous food attribute ratings. The participant-related TSV file in the OpenNeuro repository indicates which participants are suggested to be excluded. The data were referenced to the average of all channels, excluding those that were excessively noisy. We removed one channel (AFz) to address the rank deficiency introduced by average referencing. A 30 Hz low-pass filter was applied to the EEG data (EEGLAB Basic Finite Impulse Response Filter New, default settings). Next, a copy of the dataset was created for the purpose of ICA, to which a 0.1 Hz high-pass filter (EEGLAB Basic Finite Impulse Response Filter New, default settings) was applied to improve stationarity. ICA was performed on this copied dataset using the RunICA extended algorithm[65]. The resulting independent component information was subsequently copied to the original dataset[66]. Independent components associated with eye movement artifacts (blinks and saccades) were identified and removed in accordance with established protocols[67]. We interpolated the excessively noisy channels and AFz using spherical spline interpolation. EEG data were segmented into epochs spanning -100 ms to 1000 ms relative to food image onset, and each epoch was baseline-corrected using the data from the 100 ms time window preceding food image

presentation. Epochs from trials in which the participant's response time exceeded 5 s, or in which the amplitude at any channel exceeded ±150 μV, were excluded from further analyses. On average, 346 out of 360 trials were retained per participant (range 283-360).

3.5.1.2 Event-Related Potentials. We demonstrate that ERP waveforms closely resemble those observed in previous work using visual food stimuli[6,8,11,68–70], and that differences in ERPs can be observed across food images that vary categorically in attributes of interest (e.g., Healthy versus Not-Healthy, Tasty versus Not-Tasty foods). Figure 2 shows group-average ERPs measured at occipital electrodes (Oz, O2, O1, and Iz) and at parietal electrodes (Pz, P1, P2, CPz, and POz) following food image onset. For each participant, we split the trials according to the participants' responses during the food categorisation task on healthiness and tastiness trials (Healthy versus Not-Healthy, Tasty versus Not-Tasty). We then averaged EEG responses across trials to derive ERPs for each choice condition. ERPs were averaged over electrodes within each region of interest (occipital and parietal) to further improve the signal-to-noise ratio. We compared ERPs following Tasty and Not-Tasty food images, and Healthy and Not-Healthy food images, using cluster-based permutation tests to correct for multiple comparisons (10,000 permutation samples, cluster forming alpha = .01, family-wise alpha = .05) using functions from the Decision Decoding Toolbox v1.1.5[71,72].

We observed typical patterns of visual evoked ERPs at occipital channels, including the visual P1, N1 and P2 components that occur within the first 250 ms following food image presentation[11,68,69]. We also observed a later, sustained

positivity at parietal channels, resembling the P3 or Late Positive Potential that has been measured in prior work[6,68,69,73]. At occipital electrodes, we observed more negative-going ERP waveforms both for tasty and healthy foods between approximately 150-600 ms (Figure 2A, 2B). At parietal channels, amplitudes were more positive-going between approximately 300-550 ms following Tasty compared to Not-Tasty foods (Figure 2D) as also reported in prior work[6,68,69]. This demonstrates that EEG responses evoked by food images do broadly differ across food attribute decision outcomes, and that they could be used to test more targeted hypotheses relating to food-evoked ERPs.

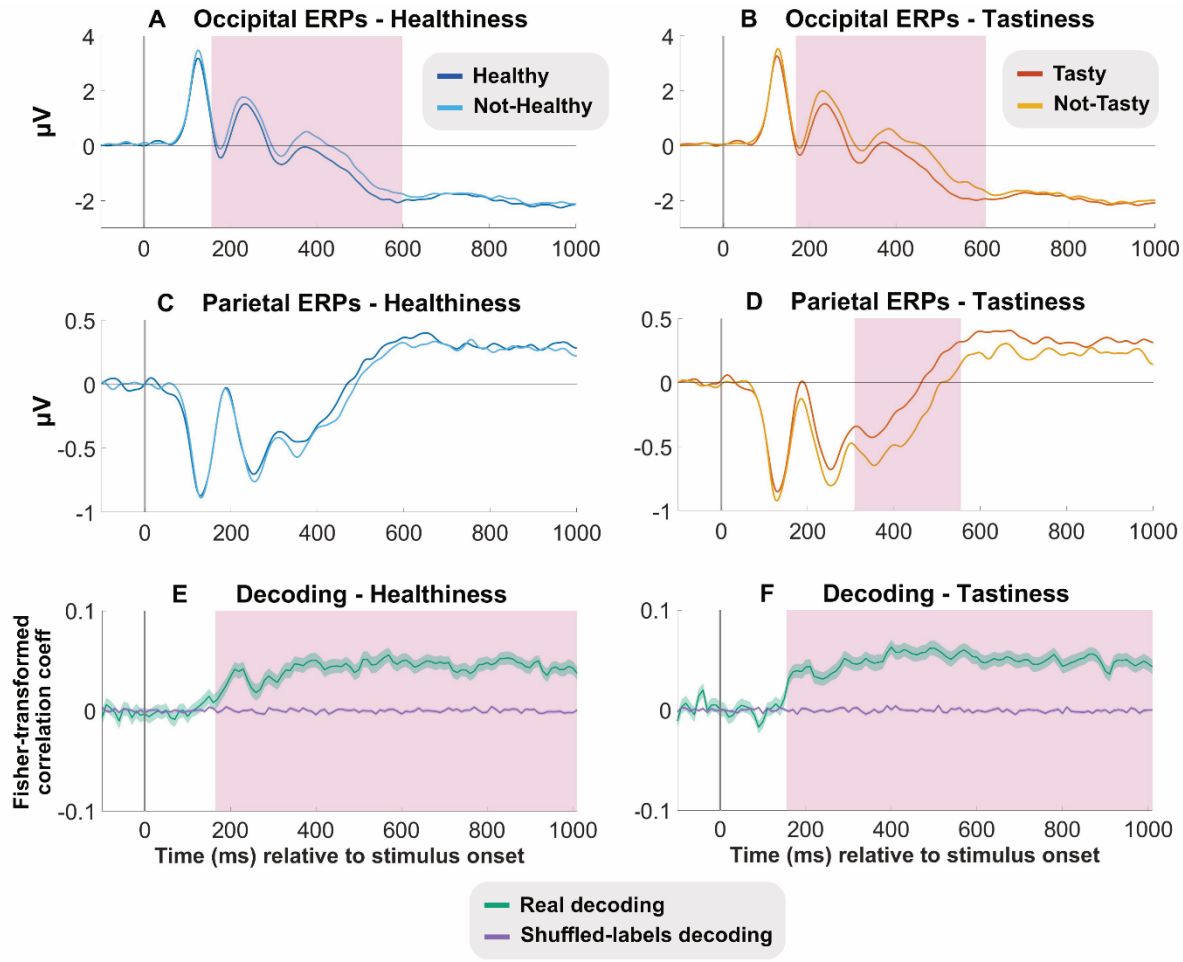

Figure 2. Group-average ERPs and decoding results following food image onset. The top row shows ERPs evoked at occipital (Oz, O2, O1, and Iz)

electrodes by A) Healthy (dark blue) and Not-Healthy (light blue) foods and by B) Tasty (red) and Not-Tasty (yellow) foods. The second row displays ERPs evoked at parietal (Pz, P1, P2, CPz, and POz) electrodes by C) Healthy and Not-Healthy foods and by D) Tasty and Not-Tasty foods. For the ERPs, pink shaded areas indicate the time windows at which the mean amplitudes between conditions significantly differed after applying multiple comparisons corrections. The third row shows the decoding results. Using support vector regressions, E) healthiness and F) tastiness ratings were predicted from the EEG data from the time relative to food image onset. Green lines indicate the real decoding results (Fisher transformed correlation coefficients between predicted and true attribute ratings) and purple lines indicate the shuffled-labels decoding results (empirical chance distribution). Shaded areas around the green and purple lines indicate the standard error of the mean. For the decoding results, pink shaded areas indicate the time windows at which the real decoding results significantly differed from the shuffled-labels decoding results and after applying multiple comparisons corrections.

3.5.1.3 Multivariate Pattern Analysis. We demonstrate using MVPA that fine-grained food attribute information beyond binary categorisations is also decodable from the current dataset. Multivariate analysis methods (e.g., MVPA, representational similarity analysis) are becoming more widely used in neuroimaging studies, due to high sensitivity that allows for the detection of distributed patterns of neural activity. Previous work has shown that such methods are useful for investigating the fine-grained neural time-courses of food attribute

processing[3–5]. The MVPA results suggest that there are patterns in the EEG data that covaried with continuous food attribute ratings and reveal that the current dataset is suitable for multivariate analysis techniques.

Linear support vector regression (SVR) models were implemented using the Decision Decoding Toolbox v1.0.5[72] to examine whether continuous food attribute ratings were decodable from the EEG signals during food viewing. A "moving window" approach was implemented to divide each epoch of the EEG data into 10 ms segments, which served as analysis time windows. These were moved through the data in steps to derive a fine-grained time-course of decoding performance. The regression model was trained to predict the continuous ratings (ranging from 0-100) for a given food attribute from the spatial brain activity patterns in each time window following the food image onset. A linear SVR model (cost parameter C = 0.1, interfacing LIBSVM[74]) was trained on 90% of the data, then tested on the held-out 10% of the data for each time window and for each participant. We repeated this process independently using a 10-fold cross-validation procedure so that all data sets had been used as test data once while training on all other datasets. We repeated this cross-validation process 10 times using newly selected random data to derive a conservative estimate of decoding performance for the time window, calculated as the correlation coefficient between the actual and predicted continuous ratings for the food images, averaged across the 10 × 10 iterations and Fisher transformed. Results for each time window were obtained independently of any other time windows. We used cluster-based permutation tests as described above to correct for multiple tests.

Continuous healthiness and tastiness ratings were decodable from the EEG data (Figure 2E, 2F) from around 150 ms after food image onset, and remained significant until the end of the 1 s analysis window. These findings suggest that there are patterns of activity in the EEG signals that contain fine-grained information about healthiness and tastiness of foods from around 150 ms onwards. Together with the ERP analyses, they show that the FOODEEG dataset is suitable for tracking the first 1000 milliseconds of neural responses to visual food cues.

3.6 Code Availability

All custom code used to produce the technical validation analyses and figures in the manuscript are available from the Open Science Framework[55] (https://doi.org/10.17605/OSF.IO/Y9PMF).

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Chapter 4: Characterising the Neural Time-Courses of Food Attribute Representations

The following chapter presents the empirical study in which we investigated the temporal dynamics of food attribute appraisals during dietary decisions. To this end, we used the normative ratings for 12 of the 22 food attributes collected as part of the FOODEEG dataset. These attributes include nutritive properties (healthiness, calorie content, edibility, and level of transformation), hedonic properties (tastiness, willingness to eat, negative and positive valence, and arousal), and familiarity (previous exposure, recognisability, and typicality). This study was published in *Appetite* on 01/02/26 and is presented in its published format.

Characterising the Neural Time-Courses of Food Attribute Representations

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4.1 Abstract

Dietary decisions involve the consideration of multiple, often conflicting, food attributes that precede the computation of an overall value for a food. The differences in the speed at which attributes are processed play an important role; however, it is unknown whether different attributes are processed over distinct time windows. We mapped the neural time-courses of 12 choice-relevant food attributes. Participants (*N* = 110) viewed food images while we recorded brain activity using electroencephalography (EEG). A separate group of participants (*N* = 421) rated the same images on nutritive properties (healthiness, calorie content, edibility, and level of transformation), hedonic properties (tastiness, willingness to eat, negative and positive valence, and arousal), and familiarity (previous exposure, recognisability, and typicality). Using representational similarity analysis, we quantified differences in patterns of multivariate EEG signals across foods and assessed whether the structure of these differences was correlated with differences in attribute ratings. We observed similar correlation time-courses for many attributes. There was an early window of correlations (~200 ms from image onset), followed by sustained windows of correlation from ~400-650 ms. Using principal component analysis, we identified a set of broader constructs that accounted for variance in ratings across multiple attributes, and were also correlated with the EEG data. Our results indicate that food attributes important for choice are represented rapidly and in parallel, over similar time windows. Furthermore, we reveal that broad dimensions underlying individual attributes are also represented in the neural activity with distinct time-courses, indicating a

multilevel structure of food attribute representations.

Keywords: food choice; electroencephalography; representational similarity analysis; healthiness; tastiness; calories

4.2 Introduction

We make dietary decisions frequently throughout each day. These are complex decisions involving the rapid processing of multiple, often conflicting, food attributes. The processing of healthiness, tastiness, and calorie content of foods have been studied extensively in behavioural and neuroimaging studies (Duraisingam et al., 2021; Harris et al., 2013; Lim et al., 2018; Meule et al., 2013; N. Sullivan et al., 2015; Toepel et al., 2009). However, it is less known how other key features of foods are represented in the brain. Here, we aimed to shed light on the neural representations of a wide range of food attributes that are important for dietary choice.

A growing body of neuroimaging research suggests that dietary decision making involves two processes: the appraisal of the decision option in relation to multiple relevant attributes (e.g., the healthiness and tastiness of a food) and the integration of these representations into an overall value signal that determines one's choice (e.g., to eat the food or to not eat the food; Hare et al., 2011; Hutcherson et al., 2012). Previous work has shed light on related aspects of food cognition, such as food-related inhibitory control (measured using food go/no-go tasks; e.g., Allen et al., 2022; Carbine et al., 2017), attention (assessed using food oddball tasks; e.g., Babiloni et al., 2009), and associative learning (measured using conditioning paradigms; e.g., Franken et al., 2011). For a methodological review of food-related EEG studies, see Zsoldos et al. (2022). Here, we focus on the appraisal of food options on relevant attributes that occurs prior to the integration of choice-relevant value signals. There are numerous decision-relevant

food attributes (Chen & Antonelli, 2020; Schulte-Mecklenbeck et al., 2013), and it is unknown whether these attributes are processed over similar time windows relative to the presentation of a food item. Behavioural evidence indicates that food attributes can differ in how quickly they are integrated into one's value signals, leading to the over-weighting of attributes thought to be processed more quickly (e.g., tastiness) and the under-weighting of attributes thought to be processed more slowly (e.g., healthiness) in food choice (Lim et al., 2018; N. Sullivan et al., 2015). To explain these findings, it has been proposed that when presented with a food choice, basic attributes relevant in the short-term (e.g., tastiness) are represented more easily and quickly than abstract attributes relevant in the long-term (e.g., healthiness; Liberman & Trope, 2008). However, the existing neuroimaging evidence is mixed, with some studies reporting neural correlates of healthiness information emerging earlier than those of tastiness (Harris et al., 2018; Schubert, Rosenblatt, et al., 2021).

Food attributes, along with features of other highly biologically relevant stimuli such as faces, animals, and tools, are likely represented in neural signals within several hundred milliseconds after image onset (Carlson et al., 2013; Collins et al., 2018; Grootswagers, Robinson, & Carlson, 2019). An ideal method for examining such rapid neural processes is electroencephalography (EEG), a non-invasive method used to record electrical activity in the brain using electrodes placed on the scalp. EEG has a high temporal resolution that allows one to disambiguate events that occur over short time windows of tens or hundreds of milliseconds. Event-related potentials (ERPs; averaged EEG responses time-

locked to an event) can be used to assess the time-courses of neural activity following food image or food cue presentation. Commonly, ERPs evoked by two classes of stimuli (e.g., healthy versus unhealthy foods) are compared. Differences in ERP amplitudes over a given time window have been interpreted as the neural activity in that time window reflecting information about the food attribute (in this case, healthiness of the foods). Previous studies have reported that key food attributes are reflected in both early ERP components (~100-200 ms after food image onset), thought to be relevant for attentional modulations during early sensory processing, as well as later, more sustained ERP components (~300-700 ms after food image onset) implicated in higher-level evaluative processes. Multiple studies have found this pattern of results for healthiness (Harris et al., 2013; Rosenblatt et al., 2018), tastiness (Harris et al., 2013; Schubert, Smith, et al., 2021; Schwab et al., 2017), and calorie content (Duraisingam et al., 2021; Meule et al., 2013; Toepel et al., 2009). However, ERP analyses typically focus on signals at a single electrode (or an average of nearby electrodes). Consequently, signals that are distributed across other channels may be missed. Multivariate methods, which assess distributed patterns of neural activity across multiple channels, can address these limitations. Multivariate methods are more sensitive to subtle, distributed differences in neural activity (Hebart & Baker, 2018) and therefore are better suited for examining the fine-grained time-courses of food attribute representations. Using multivariate pattern analysis, one study found that healthiness, tastiness, and willingness to eat information were decodable from patterns of EEG activity from around 500-800 ms after food image onset

(Schubert, Rosenblatt, et al., 2021).

As outlined above, most existing work on food choice have focused on healthiness, tastiness, and calorie content as the main attributes that drive choice (e.g., Harris et al., 2013; Schubert, Rosenblatt, et al., 2021; Schubert, Smith, et al., 2021; Sullivan et al., 2015; Toepel et al., 2009). However, there are many other features of foods that may be relevant to dietary decisions. Emerging evidence suggests that the level of transformation (i.e., how much work was required to prepare the food) and edibility are also encoded in the neural activity during food viewing (Coricelli et al., 2019; Moerel et al., 2024). Coricelli et al. (2019) presented participants with images of processed and unprocessed foods matched for calorie content. ERP amplitudes differed as early as 130 ms after food image onset between the two classes of foods, suggesting that similarly to calorie content, level of processing of foods is represented in early neural signals. Familiarity is an important influence on food choice (Blechert, Meule, et al., 2014; Foroni et al., 2013; Steptoe et al., 1995), but few studies have examined the neural processing of food familiarity in healthy individuals. One study did not observe differences in ERPs evoked by familiar and unfamiliar foods, however they only examined later time windows (500-1000 ms after food image onset; Stuldreher et al., 2023). Whether food familiarity is reflected in the neural signals in earlier time windows (e.g., reflecting early attentional capture for either novel or familiar foods) is yet to be investigated. It is also important to consider different aspects of food familiarity that may differentially influence dietary decisions: frequency of exposure in daily life, recognisability, and how typical the food is of a broader category. Emotion-

related attributes such as valence and arousal also differ among foods and likely influence choice (Blechert, Meule, et al., 2014; Foroni et al., 2013; Schacht et al., 2016). Consistent with findings for other key food attributes, valence is thought to be reflected in early (~100 ms) and later, more sustained (~300-700 ms) ERP components (Schacht et al., 2016), but these findings are limited to foods that are positive in valence. Taken together, this evidence suggests that the neural representations of numerous food attributes are important for dietary choice. However, these neural representations are yet to be comprehensively investigated.

One major issue in delineating the neural time-courses of different food attributes is that ratings of many food attributes are strongly correlated. For example, foods perceived to be lower in calories tend to be viewed as healthier, while foods that are thought to be tastier tend to also be judged as more positive in valence. This makes it difficult to determine whether the neural activity is reflecting information about a single food attribute independently of other correlated attributes. Previous work has attempted to decorrelate these food attributes by careful balancing of stimuli (e.g., Schubert, Rosenblatt, et al., 2021) and statistically controlling for effects of correlated attributes (Moerel et al., 2024), however this is difficult when evaluating a broad range of attributes. Another issue is the limited variance in some food attributes within a stimulus set. People tend to perceive foods to be tasty, positive in valence, and desirable for the most part. To increase the variance in these dimensions, some studies have included rotten or mouldy foods, half-eaten foods, or foods that have snails or ants on them (e.g.,

Piqueras-Fiszman et al., 2014). However, it is possible that these stimuli may not be perceived as foods at all, and instead perceived as inedible (Becker et al., 2016). Few studies have examined foods that are edible but unappetising or unfamiliar. Increasing the variance of these attributes in a stimulus set may improve our ability to map the neural time-courses of these attributes. Lastly, most studies did not control for low- or mid-level visual features (e.g., colour, silhouette) that may correlate with the food attributes of interest and evoke reliable differences in the neural activity. Patterns of EEG responses that correspond to such visual features can often be decoded using multivariate classifiers (Grootswagers et al., 2024; Grootswagers, Robinson, Shatek, et al., 2019). For instance, more green foods may tend to be healthier, and colour can be decoded from EEG responses across a range of latencies from stimulus onset (Grootswagers et al., 2024). Consequently, the effects of colour may produce differences in ERPs or multivariate classification performance between healthy and unhealthy foods.

Recently, Moerel et al. (2024) demonstrated a novel approach for uncovering the time-courses of multiple food attributes using representational similarity analysis (RSA). RSA is a multivariate method that can be used to look for encoded information in neural activity by comparing between neural and behavioural data based on shared structure in their representational dissimilarity matrices (RDMs). Participants viewed food images at rapid presentation rates (~100 ms per image) while EEG activity was recorded. Food attribute RDMs were constructed using normative ratings from a separate sample of participants

(Foroni et al., 2013). Importantly, Moerel et al. (2024) controlled for the effects of low- and mid-level visual features by constructing visual feature RDMs to include in the partial correlation analyses between the neural RDMs and the food attribute RDMs. Level of transformation, immediate edibility, and calorie content of foods were found to be encoded in the patterns of EEG activity within the first second. On the other hand, there was no strong evidence that valence and arousal were encoded in the neural activity.

Here, we replicate and extend on the work by Moerel et al. (2024) using RSA. We examined the neural time-courses of attribute representations when foods are presented for a longer, more naturalistic viewing period (2 s) using a stimulus set that included edible but unappetising foods to increase variance in key food attributes. Furthermore, we assessed novel food attributes that have not been investigated in this way previously, such as familiarity. We recruited a large sample ($N = 110$) to investigate the neural representations of 12 food attributes that broadly span nutritive properties (healthiness, calorie content, edibility, and level of transformation), hedonic properties (tastiness, willingness to eat, negative and positive valence, and arousal) and familiarity (previous exposure, recognisability, and typicality).

We recorded EEG while participants completed a food categorisation task. We carefully designed this task to separate the attribute representation and the integration processes of decisions. Ratings on 12 food attributes were collected from a separate sample of participants ($N = 421$). Using RSA, similarity structures between the EEG activity and the attribute ratings were compared to examine

whether, and importantly *when*, food attributes were represented in the neural activity, while controlling for the effects of low- and mid-level visual features. Furthermore, we aimed to disentangle highly correlated food attributes through two complementary approaches. Firstly, we applied principal component analysis (PCA) to identify shared variance dimensions and examined whether these dimensions were represented in the neural activity. Secondly, we assessed whether there were any unique contributions of each food attribute in the EEG data through partial correlation analyses controlling for the effects of all other food attributes.

4.3 Methods

Our study involved three parts. In the first session of the main experiment, participants completed a food categorisation task while EEG was recorded and subsequently provided food attribute ratings for each food image. In the second session of the main experiment, participants completed two behavioural food choice tasks and completed questionnaires probing their dietary style and food motivations. Data collected from the second session were not analysed here, and the descriptions of behavioural tasks and the questionnaires are not included. We also recruited a separate sample of participants who rated each food image with respect to the 12 food attributes. This was carried out to create models of the similarity structure between foods for each attribute. We compared EEG activity time-locked to food image presentations with the 12 food attribute models to examine whether and when neural activity covaried with each type of food attribute rating. This study was approved by the Human Research Ethics

Committee of the University of Melbourne (HREC ID 24850). Data processing and analysis code will be available via the Open Science Framework (https://osf.io/w8c9d/) at the time of publication.

4.3.1 Participants

Participants (*N* = 117) were recruited through the University of Melbourne student portal and advertising via posters around the University of Melbourne. Participants indicated that they were at least 18 years old, were fluent in written and spoken English, did not have a history of any eating disorders, were not on a calorie restriction diet, and did not have any dietary restrictions (e.g., for health or religious reasons). Participants were asked to fast for three hours prior to the start of the first and second sessions. At the end of the second session, participants were reimbursed AUD $50. Five participants were excluded as they did not meet the eligibility requirements or did not complete the study. Two additional participants were excluded due to the high incongruence in their continuous healthiness, tastiness, and willingness to eat ratings and their responses in the food categorisation task. The final sample of 110 participants had a mean age of 26.5 years (SD = 8.23, range 18-57 years). 81 participants identified as female, 28 as male, and one as other.

A separate sample of online participants (*N* = 421) were recruited through the University of Melbourne Research Experience Program. Participants indicated that they were at least 18 years old, were fluent in written and spoken English, did not have a history of any eating disorders, were not on a calorie restriction diet, did not have any dietary restrictions, and had not previously taken part in the main

experiment. The online sample had a mean age of 19.75 years (SD = 3.08, range 18-53 years). 326 participants identified as female, 92 as male, and three as other. Participants were awarded course credit at the conclusion of the experiment.

4.3.2 Stimuli

The stimuli included 120 colour images of food items presented against a white background (Figure 1A). 91 images were drawn from the Food-pics database (Blechert, Meule, et al., 2014) selected to represent a wide range of food categories (e.g., vegetables, meats, fruits, snack foods). 29 images were taken from online image hosting websites (e.g., Flickr, Adobe Stock). These were selected to be generally less appetising and less familiar foods to increase the variance in food attribute ratings.

4.3.3 Procedure

During the first session, participants completed a food categorisation task presented using Psychtoolbox (Kleiner et al., 2007) interfacing Matlab R2022a. Afterwards, participants rated each food image on healthiness, tastiness and how much they would like to eat the food (willingness to eat) using Qualtrics.

In the food categorisation task, participants viewed each food item three times: once each across the healthiness, tastiness, and willingness to eat trials while EEG was recorded (Figure 1B). Food images were presented centrally, subtending 6.6 × 3.5 degrees of visual angle on a 24.5-inch ASUS ROG Swift PG258Q monitor (1920 × 1080 pixels, 60 Hz refresh rate). Participants' heads were stabilised using a chin and forehead rest approximately 50 cm from the monitor. Each trial began with a fixation cross presented in isolation for 1 s, followed by the

food image with a fixation cross for 2 s. Next, the participants were prompted with "Healthy?" in a healthiness trial, "Tasty?" in a tastiness trial, and "Like to eat?" in a willingness to eat trial, along with a response mapping that indicated which of the left ('z') and the right ('m') keyboard keys corresponded to "Yes" and "No" responses. There was an equal chance of the left keyboard press indicating a "Yes" response (and the right keyboard press indicating a "No" response) and the reverse for each trial. For each participant, the order of healthiness, tastiness, and willingness to eat trials were randomised. The randomisation of the trial type order and response mapping ensured that participants could not pre-emptively prepare a keypress motor action during the food image presentation period. Participants were asked to respond as quickly and accurately as possible and to pay attention to the switching of the response mapping across trials. Participants completed five practice trials and indicated that they had understood the instructions before starting the main experiment. To reduce eye movement artifacts the participants were instructed to keep their eyes fixated on the fixation cross, which remained on screen throughout the duration of the experimental blocks. Response time was recorded as the time taken from the presentation of the prompt to the participant's response via keyboard press.

After the food categorisation task, participants rated each food image on healthiness ("How healthy is this food?"), tastiness ("How tasty is this food?") and how willing they were to eat it ("How much would you like to eat this food?"). Participants were asked to use a computer mouse to indicate their response on a sliding scale from "Not at all" to "Very much". We randomised image presentation

order for each participant (while ensuring that the same food image was not presented in two consecutive trials).

In the online rating task, a separate sample of participants indicated their current hunger level ("How hungry are you currently?") and satiety level ("How full are you currently?") on a sliding scale from 'Not at all' to 'Very much'. They selected the time elapsed since their last food consumption ("How long ago did you last eat food?") from one of the following options: "Less than an hour ago", "1-3 hours ago", "3+ hours ago", and "I do not know". Each participant rated a subset of the full stimulus set (40 out of the 120 images) on 12 food attributes, including nutritive properties (healthiness, calorie content, edibility, and level of transformation), hedonic properties (tastiness, willingness to eat, negative and positive valence, and arousal), and familiarity (previous exposure, recognisability, and typicality). It is worth noting that edibility and level of transformation are dissociable: edibility refers to the amount of work *required in the future* to make the food ready to eat from its current state, while level of processing refers to the amount of work *already invested* in the food in its current state. It is possible for a food to be high in edibility but low in level of transformation (e.g., fruits) or conversely, low in edibility and high in level of transformation (e.g., cocoa powder for baking). See Table 1 for the list of food attributes and the corresponding prompts and additional information presented to the participants. We randomised the image presentation order for each participant as well as the order of the food attributes for each image. Participants were asked to indicate their response to each prompt on a sliding scale (0-100) using a computer mouse.

Table 1. Food attributes spanning nutritive properties, hedonic properties, and familiarity. Ratings on 12 food attributes were collected using the corresponding prompt for each food image. For edibility, level of transformation, and arousal, additional information was displayed alongside the prompt (in italics).

	Food attribute	Prompt
Nutritive properties	Healthiness	How healthy is the food represented in the image?
	Calorie content	How much calorie content is in the food represented in the image?
	Edibility	How much work WILL BE required to bring the food represented in the image ready to eat? *For example, raw chicken will require more work (i.e., more steps, long time, many ingredients) to get it ready to eat compared to an apple (i.e., less steps, short time, few ingredients).*
	Level of transformation	How much work WAS required to prepare the food represented in the image? *For example, a cake required more work (i.e., more steps, long time, many ingredients) to prepare than rice (i.e., less steps, short time, few ingredients).*
Hedonic properties	Tastiness	How tasty is the food represented in the image?
	Willingness to eat	How much would you like to eat the food represented in the image?
	Negative valence	How negatively do you view the food represented in the image?
	Positive valence	How positively do you view the food represented in the image?
	Arousal	How emotionally arousing is the food represented in the image? *Less emotionally arousing foods are calming/relaxing, and more emotionally arousing foods are stimulating/energising.*
Familiarity	Exposure	How often do you encounter the food represented in the image?
	Recognisability	How easy is it to identify the food represented in the image?
	Typicality	How typical is the food represented in the image?

We validated whether the online experiment participants responded in a similar way to the participants in the main experiment. As both samples rated each food image on healthiness, tastiness, and willingness to eat, we compared the average healthiness, tastiness, and willingness to eat rating for each food image between the online and main samples using Pearson's correlations. Average ratings were strongly correlated for healthiness (r = .98), tastiness (r = .95), and willingness to eat (r = .94), indicating that the two samples appraised the foods similarly on the group level. We therefore opted to use the online sample's food attribute ratings in our analyses of the neural data from the main sample.

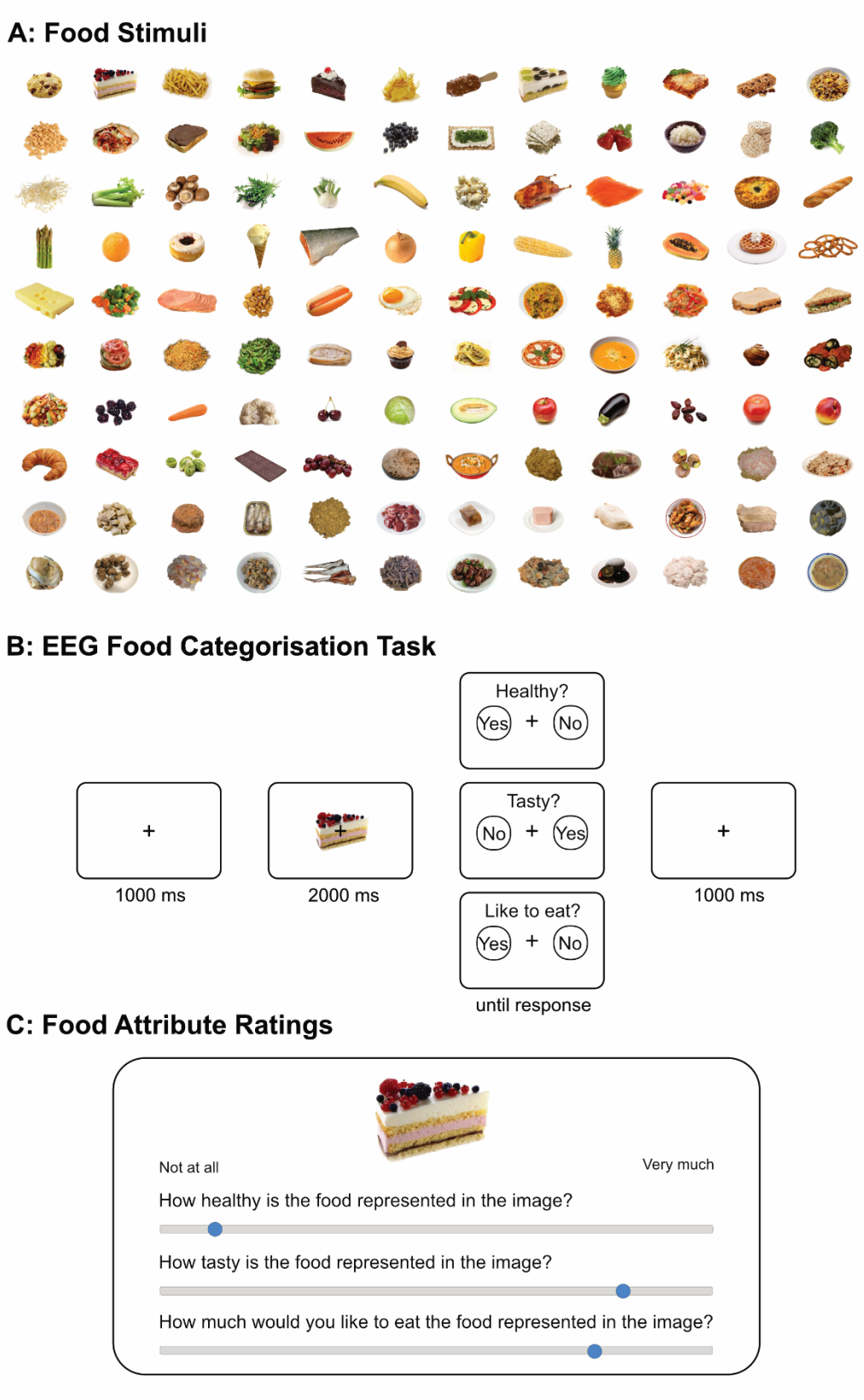

Figure 1. Stimuli and trial diagrams for the EEG and food attribute rating tasks.

A) Food stimuli. 120 food images that span a wide range of food categories on a

white background. B) EEG Food categorisation task. In each trial, participants were shown a food image for 2 s, followed by a response screen with one of three prompts (‘Healthy?’, ‘Tasty?’, ‘Like to eat?’) and one of two response mappings indicating the corresponding keyboard press for “Yes” and “No” responses (‘z’ key for “Yes” and ‘m’ key for “No”, or the reverse). Participants responded as quickly as possible. A fixation cross was displayed between trials for 1 s. C) Food attribute ratings. Participants were shown food images with three food attribute rating prompts at a time, with a sliding scale to indicate their response to each prompt. Ratings on 12 food attributes (healthiness, calorie content, edibility, level of transformation, tastiness, willingness to eat, negative and positive valence, arousal, exposure, recognisability, and typicality) were collected for each food image.

4.3.4 EEG Recording & Data Processing

EEG was recorded using a Biosemi Active II system (Biosemi, The Netherlands) with 64 channels at a sampling rate of 512 Hz using common mode sense and driven right leg electrodes (http://www.biosemi.com/faq/cms&drl.htm). We attached 64 electrodes to the cap according to the international 10-20 system. We also attached eight additional electrodes: two electrodes placed 1 cm from the outer canthi of each eye, four electrodes placed above and below the centre of each eye, and two electrodes placed above the left and right mastoids. Electrode offsets were kept within the range of ±20 μV during recording.

EEG data was processed using EEGLAB v2022.1 (Delorme & Makeig, 2004) interfacing Matlab (R2022a). Excessively noisy channels were identified through

visual inspection (mean number of bad channels = 0.26, range 0–5) and excluded from average reference calculations and independent component analysis (ICA). Excessively noisy sections or those with large amplitude artifacts were identified through visual inspection and removed. The data were referenced to the average of all channels (excluding excessively noisy channels). One channel (AFz) was removed to compensate for the rank deficiency due to average referencing. EEG data were low-pass filtered at 30 Hz (EEGLAB Basic Finite Impulse Response Filter New, default settings). A copy of the dataset was created for the purpose of ICA. A 0.1 Hz high-pass filter (EEGLAB Basic Finite Impulse Response Filter New, default settings) was applied to the copied dataset to improve stationarity for the ICA. We used RunICA extended algorithm (Jung et al., 2000) to perform the ICA. The resulting independent component information was copied to the original dataset (e.g., as done by den Ouden et al., 2023). Independent components associated with eye blinks and saccades were identified and removed in line with guidelines in (Chaumon et al., 2015). Next, we interpolated the excessively noisy channels and AFz using spherical spline interpolation.

EEG data were segmented from -100 ms to 1000 ms relative to food image onset. Segments were baseline-corrected using the data from the 100 ms time window prior to each food image presentation. Segments from trials where the participant took longer than 5 s to respond or those containing amplitudes exceeding ±150 μV at any channel were excluded from the analyses. We chose ±150 μV as the amplitude threshold, as RSA is unlikely to be biased by large amplitude signals compared to ERP analyses, in which trial-averaged ERP

measures are more susceptible to large artifacts. On average, 346 out of 360 trials were retained (range 283 – 360).

4.3.5 Representational Similarity Analysis

We analysed the data using RSA (Kriegeskorte et al., 2008; Kriegeskorte & Kievit, 2013). Compared to traditional ERP analysis, RSA had distinct advantages given that our research question focussed on characterising the neural time-courses of representations for a broad array of food attributes. This type of analysis allowed for a much more fine-grained examination of the time-points at which the food attribute RDMs were correlated with the neural activity. Furthermore, we could control for the influence of low- and mid-level visual features using partial correlation analyses. For each participant, we created time-varying representational dissimilarity matrices (RDMs; Grootswagers et al., 2017) that characterised the dissimilarity in the neural activity recorded while viewing the food images, for all possible pairs of food images. Next, we created models for the food attributes using the ratings from the online sample. For each food attribute, we created RDMs that characterised the dissimilarity in the group average food attribute ratings for all possible pairs of food images. As low- and mid-level visual features of the images, such as colour and shape, may correlate with the food attributes, we sought to control for the effects of such image features. For example, the colour green may be positively correlated with the healthiness of foods and negatively correlated with calorie content. We created RDMs that encoded the similarity structure regarding such low- and mid-level visual features between our food stimuli. Using partial correlation analyses, we

accounted for patterns in the EEG activity that were explained by similarity in the visual features across the stimuli before assessing covariation between EEG signals and the food attributes. This allowed us to compare the neural RDMs to each of the food attribute RDMs to examine whether and when the food attribute information was encoded in the EEG activity, while controlling for the effects of the visual features.

4.3.5.1 Constructing Representational Dissimilarity Matrices.

4.3.5.1.1 Neural RDMs. We created time-varying neural RDMs for individual participants. Each food image was presented three times to the participants during the food categorisation task, yielding three segments of EEG activity during food image presentation. After the EEG data processing steps described above, which involved rejection of trials with excessively noisy data, between zero to three segments remained for each food image. If no segments remained after trial rejection for a food image, the food image was excluded from further analyses for that participant. For each of the remaining food images, we took the average of the channel amplitudes across the retained segments for each of the 64 channels. For all pairwise combinations of food images, we computed the dissimilarity between the averaged channel amplitudes for all 64 channels at each time-point of the segment. Dissimilarity for each food image pair was measured as 1 minus the correlation coefficient, with 0 indicating the lowest dissimilarity (i.e., highest similarity) and 2 indicating the highest dissimilarity (i.e., lowest similarity). We repeated this process for data at each time-point relative to food image onset to create time-varying RDMs for each participant.

4.3.5.1.2 Food Attribute RDMs. To create the food attribute RDMs, we firstly calculated the group-average food attribute rating for each food image using the data collected during the online rating task. Group-average ratings were rank transformed for each food attribute across the 120 images. We calculated the dissimilarities as the Euclidean distance between the rank transformed group-average ratings for all pairwise combinations of food images to create a rating-based RDM for each food attribute: healthiness, calorie content, edibility, level of transformation, tastiness, willingness to eat, negative and positive valence, arousal, exposure, recognisability, and typicality. A visualisation of this process is displayed in Figure 2C.

4.3.5.1.3 Visual Feature RDMs. Six visual feature RDMs were created to model the low- and mid-level visual features of the food images. The silhouette RDM used vectorized images and measured dissimilarity as the Jaccard distance between binary alpha layers for all possible pairwise image combinations. The pixel-wise colour RDM was based on CIELAB colour values of vectorized images, using correlation as the distance measure. Similarly, the pixel-wise luminance RDM used greyscale values of vectorized images, with correlation as the distance measure. For these conversions, we used the rgb2lab function in Matlab, assuming a D65 white point and an sRGB colour space. The mean luminance RDM calculated dissimilarity across the entire image using the mean greyscale values of the stimuli, with the mean difference as the distance measure. The root mean square contrast RDM was based on the standard deviation of greyscale values across the entire image, also using the mean difference as the distance measure.

Lastly, we used a pretrained neural network to model visual similarity (AlexNet; Krizhevsky et al., 2012) in order to control for image features such as shape and complexity. We extracted activations at layer fc8 (the final fully connected layer) and calculated the Euclidean distance for each image pair.

4.3.5.1.4 Similarities Among Food Attribute and Visual Feature RDMs. We assessed the similarities among the food attribute and visual feature RDMs by running pairwise correlation analyses for all pairwise combinations of the RDMs (Figure 2A). The similarities between the food attribute RDMs are visualised in the model multidimensional scaling plot (Figure 2B). We included this to examine whether and which food attributes were strongly correlated, as attribute correlation can make it difficult to infer whether the neural activity reflects information about a single food attribute independently of other correlated attributes. We were also interested in examining whether any visual feature RDMs were correlated with the food attribute RDMs, which may indicate a potential confounding effect of image properties that drive visual effects. Tastiness, willingness to eat, negative and positive valence, exposure, recognisability, and typicality RDMs were found to be positively correlated with each other. Healthiness, calorie content, and level of transformation RDMs were found to be positively correlated with each other. From the visual feature RDMs, mean luminance and contrast RDMs were found to be positively correlated with each other.

4.3.5.2 Comparing Representational Dissimilarity Matrices. We compared similarities over time between neural RDMs and each food attribute

RDM using partial correlation analyses, controlling for the effects of visual features. Using correlations to compare RDMs across modalities (e.g., neural, behavioural) is considered standard practice for RSA (Grootswagers et al., 2017; Kriegeskorte et al., 2008; Kriegeskorte & Kievit, 2013) and has been widely used (e.g., Cichy et al., 2014; Grootswagers et al., 2024; Grootswagers, Robinson, Shatek, et al., 2019; Moerel et al., 2024). We first extracted the partial correlation coefficients for each participant between each food attribute RDM and their neural RDMs at each time-point relative to food image onset, controlling for the effects of six visual feature RDMs. Correlations between the visual feature RDMs and the neural RDMs are presented in the Supplementary Figure 1.

4.3.5.2.1 Statistical Analyses. To assess whether the neural data and the food attribute RDMs were correlated at a level above chance at the group level, we used a combination of Bayesian and frequentist analyses. Taking the partial correlation coefficients between the food attribute RDMs and each participant's neural RDMs, we computed Bayes factors using Bayesian one-sample t-tests to determine evidence for above-chance positive partial correlations (i.e., correlation coefficient above 0) at each time-point. For the alternative hypothesis of above-chance positive partial correlations, a half-Cauchy prior was used with a scale factor of .707 (Teichmann et al., 2022). Bayes factors greater than 1 indicate evidence preferentially supporting the alternative hypothesis (positive partial correlation), while Bayes factors less than 1 indicate evidence preferentially supporting the null hypothesis (no positive partial correlation). Specifically, we considered Bayes factors greater than 10 as substantial evidence for the

alternative hypothesis, and Bayes factors less than 1/10 as substantial evidence in favour of the null hypothesis (Jeffreys, 1998; Wetzels et al., 2011).

Additionally, we used cluster-based permutation tests (Maris & Oostenveld, 2007; 10,000 permutation samples, cluster forming alpha = .01, family-wise alpha = .05) using functions from the Decision Decoding Toolbox v1.1.5 (Bode et al., 2019) to correct for multiple tests across analysis time windows. For each permutation sample, the sign of the correlation coefficient were flipped for a subset of participants. One-sample t-tests (single-tailed) were then conducted on this permuted data at each time-point. Clusters were formed from sets of adjacent t-values corresponding to *p*-values less than .01. The sum of t-values within each cluster was defined as the cluster's "mass". The largest cluster masses from each of the 10,000 permutation samples were used to estimate the null distribution. The cluster masses from the original dataset, where correlation coefficients were not swapped, were then compared to this null distribution. The percentile rank of each cluster mass relative to the null distribution was used to calculate the *p*-value for each cluster. This approach controls for the weak family-wise error rate while retaining sensitivity to detect effects in temporally autocorrelated EEG data (Maris & Oostenveld, 2007).

In the current study, we considered time-points that were statistically significant after application of the cluster-based permutation test and at which Bayes factors exceeded 10 as evidence for a positive partial correlation.

4.3.5.2.2 Similarity Among the Time-Courses of Correlations. We used dynamic time warping to measure the similarity between the time-courses of

correlations with the neural RDMs for each of the food attributes. Dynamic time warping is an algorithm that measures the similarity between two temporal sequences, even if they vary in speed or length. This method is shape-based and is therefore suitable for comparing time series data that may not be perfectly aligned temporally (Aghabozorgi et al., 2015). Previous work has used this method to quantify similarity between time-courses of representations derived using RSA (Teichmann et al., 2024). We used this method to measure the distance (Euclidean) between the correlations over time for all pairwise combinations of food attributes. Smaller distance indicates more similar time-courses of correlations between the food attributes and the neural RDMs.

4.3.6 Investigating Covariation Among Food Attributes

We observed that many food attributes covaried with each other (Figure 2A, 2B) which likely contributed to the similarity in the time-courses of correlations with the EEG data (Figure 5). To shed light on this, we took two complementary approaches.

4.3.6.1 Capturing Broad Underlying Dimensions. We performed PCA using the group-average ratings for each of the food images for all 12 food attributes. The rating data was rank transformed for consistency with the food attribute RDMs and then standardised (M = 0, SD = 1) for each attribute prior to extracting components. Components with eigenvalues greater than 1 were retained (Kaiser's rule; Kaiser, 1960). The final solution retained two components, which explained 85.5% of the total variance.

We created principal component RDMs for each of the first two

components. We used the Euclidean distance between the component loadings for all pairwise combinations of food images as the dissimilarity measure. To assess whether the underlying dimensions captured by the principal components were represented in the EEG signals, each principal component RDM was correlated with each participant's neural RDMs at each time-point, using partial correlation analyses to control for the six visual feature RDMs. We tested for above-chance positive partial correlations at the group level using Bayesian and frequentist t-tests as described above.

4.3.6.2 Unique Contributions to the Correlations Between the Neural RDMs and the Food Attribute RDMs. To assess whether any of the food attributes explained any variance in the neural data not accounted for by other food attributes or visual features, we performed partial correlation analyses to measure the correlation between each food attribute RDM and the neural RDMs controlling for all other food attributes and the visual features. For example, neural RDMs were correlated with the healthiness RDM for each time-point and for each participant, using partial correlations to control for the other 11 food attribute RDMs and the six visual feature RDMs. We tested for above-chance positive partial correlations at the group level using Bayesian and frequentist t-tests as described above.

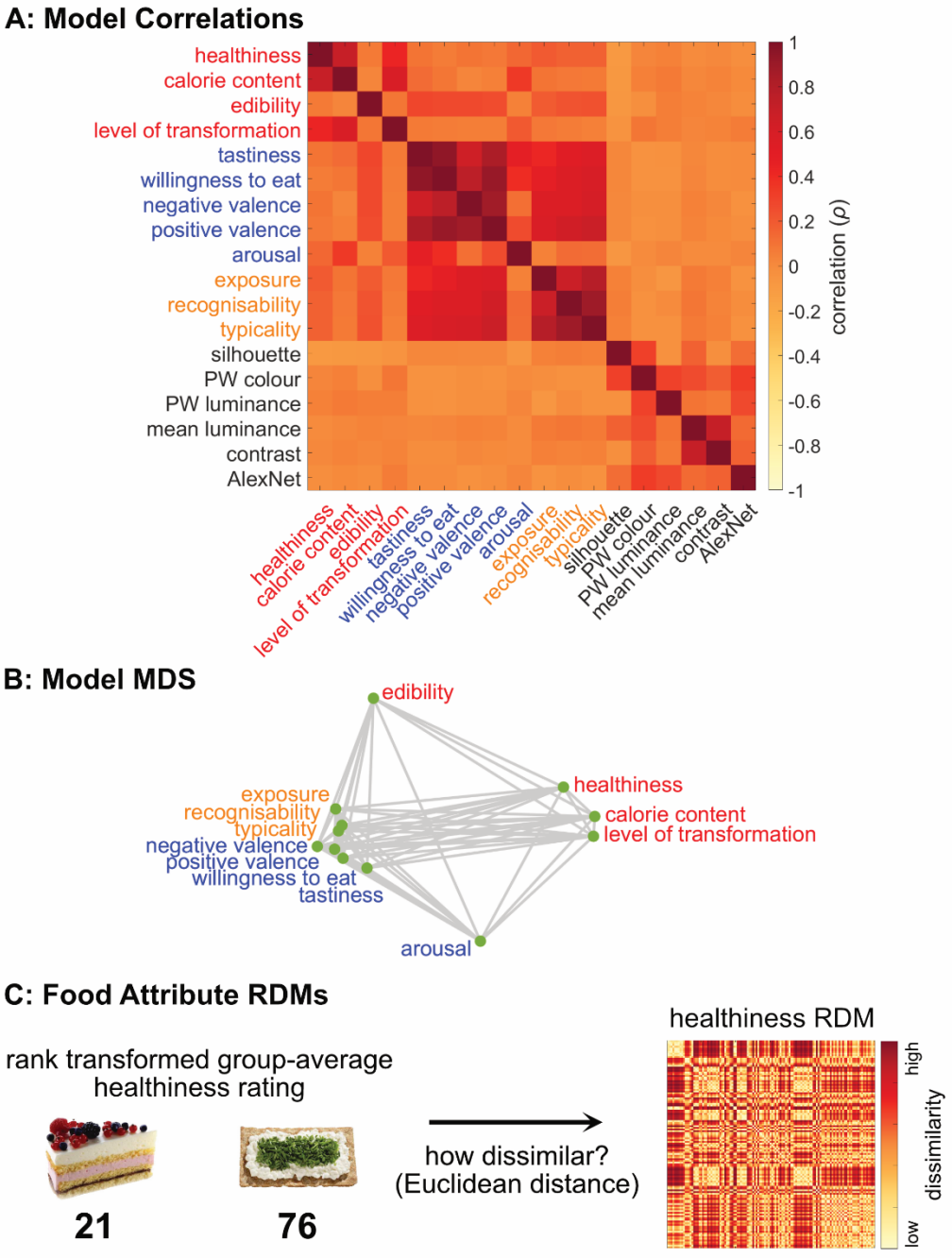

Figure 2. Models used in the representational similarity analysis. A) Model correlations. Correlations between 12 food attribute RDMs and six visual feature RDMs. The food attributes included nutritive properties, hedonic properties, and familiarity. Red indicates positive correlations (i.e., higher similarity) and yellow indicates negative correlations (i.e., lower similarity) between models. B) Model multidimensional scaling. Model correlations between the 12 food attribute RDMs

depicted in 2-dimensional space. Smaller distances between the models indicate stronger correlation. C) Food attribute RDMs. Food attribute RDMs were created by calculating the dissimilarity (as measured by Euclidean distance) between the rank transformed group-average attribute rating between all pairwise combinations of food images. For example, we calculated the dissimilarity between the rank transformed group-average healthiness ratings for all possible food pairs (e.g., 21 vs 76) to construct the healthiness RDM.

4.4 Results

We examined the neural time-courses of food attribute representations during the appraisal of foods. We used representational similarity analysis (RSA; Kriegeskorte et al., 2008; Kriegeskorte & Kievit, 2013) to create models of the EEG activity and food attributes. We used partial correlation analyses to determine the time-points at which the EEG signals and the food attribute ratings were correlated, while controlling for the low- and mid-level visual features. To further our understanding of the covariation between food attributes, we took two different approaches. Firstly, we performed PCA to examine whether the covariation between ratings could be captured in components, and whether these components also covaried with the EEG data. Furthermore, we used partial correlation analyses to determine whether there were time-points at which the food attributes were uniquely correlated with the EEG activity after controlling for the rest of the food attributes and the visual features.

4.4.1 Time-Courses of Food Attribute Representations

We examined the correlations between the neural RDMs and the food

attribute RDMs at each time-point, using partial correlation analyses to control for the six visual feature RDMs. Positive correlations between the neural RDMs and the food attribute RDMs indicate that the representational geometries, estimated by the dissimilarities between all possible food pairs, were similar on the neural level and on the level of food attribute judgements. This can be interpreted as the neural patterns reflecting food attribute information. The strength of the correlation indicates how similar the neural RDMs and the food attribute were, with peaks in correlations indicating the time at which there was the highest level of similarity.

We found that for many food attributes, there was an early peak in correlations with the neural RDMs around 200 ms from food image onset and a later, more sustained window of correlations starting from around 400 to 650 ms onwards. Taking healthiness as an example (Figure 3A), the top plot shows the correlation between the neural RDMs and the healthiness RDM over time, with 0 ms indicating the time of the food image onset. Positive correlation indicates that the neural RDM is similar to the healthiness RDM, which indicates that healthiness information is present in the neural activity at that time.

4.4.1.1 Nutritive Properties. The correlations for healthiness, calorie content, and level of transformation displayed an early peak (at 227 ms, 248 ms, and 223 ms respectively; Figure 3A, 3B, 3D). For calorie content and level of transformation, there was one sustained window of correlations (starting from 140 ms and 137 ms respectively) that lasted until the end of the analysed time range. Healthiness was found to be correlated from around 152 ms and in later,

sustained windows starting from 375 ms and lasting until the end of the analysed time range. Edibility was found to be correlated later than the other nutritive properties, from 648 ms (Figure 3C). Nutritive properties, with the exception of edibility, appeared to be correlated with the early EEG signals (from 100-150 ms) in a sustained manner throughout the analysed time range, with a peak (indicating the time at which there was the highest similarity) around 200-250 ms.

4.4.1.2 Hedonic Properties. The valence attributes were found to be correlated with the neural data from 189 ms for negative valence and 193 ms for positive valence, with an early peak at 209 ms for both attributes (Figure 3G, 3H). Additionally, the negative and positive valence attributes were correlated in later, more sustained windows from 545 ms and 640 ms respectively and lasting until the end of the analysed time range. Tastiness and willingness to eat were correlated later, from 670 ms and 654 ms respectively and sustained until the end of the analysed time range (Figure 3E, 3F). For arousal, there were some time-points at which the BFs exceeded 10 and the cluster-based permutation test for multiple comparisons returned significant results; however, these windows were very small (Figure 3I). Hedonic properties, with the exception of arousal, appeared to be correlated with the later neural activity (from 600-650 ms) in a sustained manner until the end of the analysed time range. For the valence attributes, there was an additional small window of correlations around 200 ms.

4.4.1.3 Familiarity. Exposure, recognisability, and typicality displayed an early peak at 213 ms, 207 ms, and 205 ms respectively, and a later, more sustained window of encoding starting from 377 ms, 457 ms, and 451 ms

respectively and lasting until the end of the analysed time range (Figure 3J-L). Familiarity attributes displayed the highest similarity with the EEG activity around 200 ms, as indicated by the peaks in correlations, and were also correlated with later EEG activity (from 350-450 ms) in a sustained manner until the end of the analysed time range.

4.4.1.4 Similarities Among Time-Courses. As many of the food attributes shared similarities in their time-courses of encoding, we used dynamic time warping to measure these similarities. In general, attributes within groups were found to share similar time-courses of encoding, as evidenced by smaller distances between the time-courses of correlations (Figure 5). Visual inspection of the plot revealed distinct clusters of attributes that were more similar in their time-courses of correlations, as evidenced by the clustering of yellow cells. Note that we did not use a specific threshold to distinguish high from lower similarity, as the absolute Euclidean distance values are not individually informative. Instead, we used the colour gradients to describe the similarity structure across all pairwise combinations of the correlation time-courses. Out of the nutritive attributes, healthiness and calorie content, as well as calorie content and level of transformation, were found to be similar in their time-courses of encoding. Encoding of many of the hedonic properties (tastiness, willingness to eat, negative and positive valence, but excluding arousal) were also found to be similar over time. Furthermore, the time-courses of encoding for all three familiarity attributes (exposure, recognisability, and typicality) were found be similar. Interestingly, time-courses of encoding for the majority of the hedonic properties (tastiness,

willingness to eat, negative and positive valence) were found to be similar to that for familiarity (recognisability and typicality, and exposure). The model correlation matrix (Figure 2A) and the dynamic time warping matrix (Figure 5) were found to be strongly (negatively) correlated (Spearman's rho = -.94), indicating that the two matrices are structurally similar.

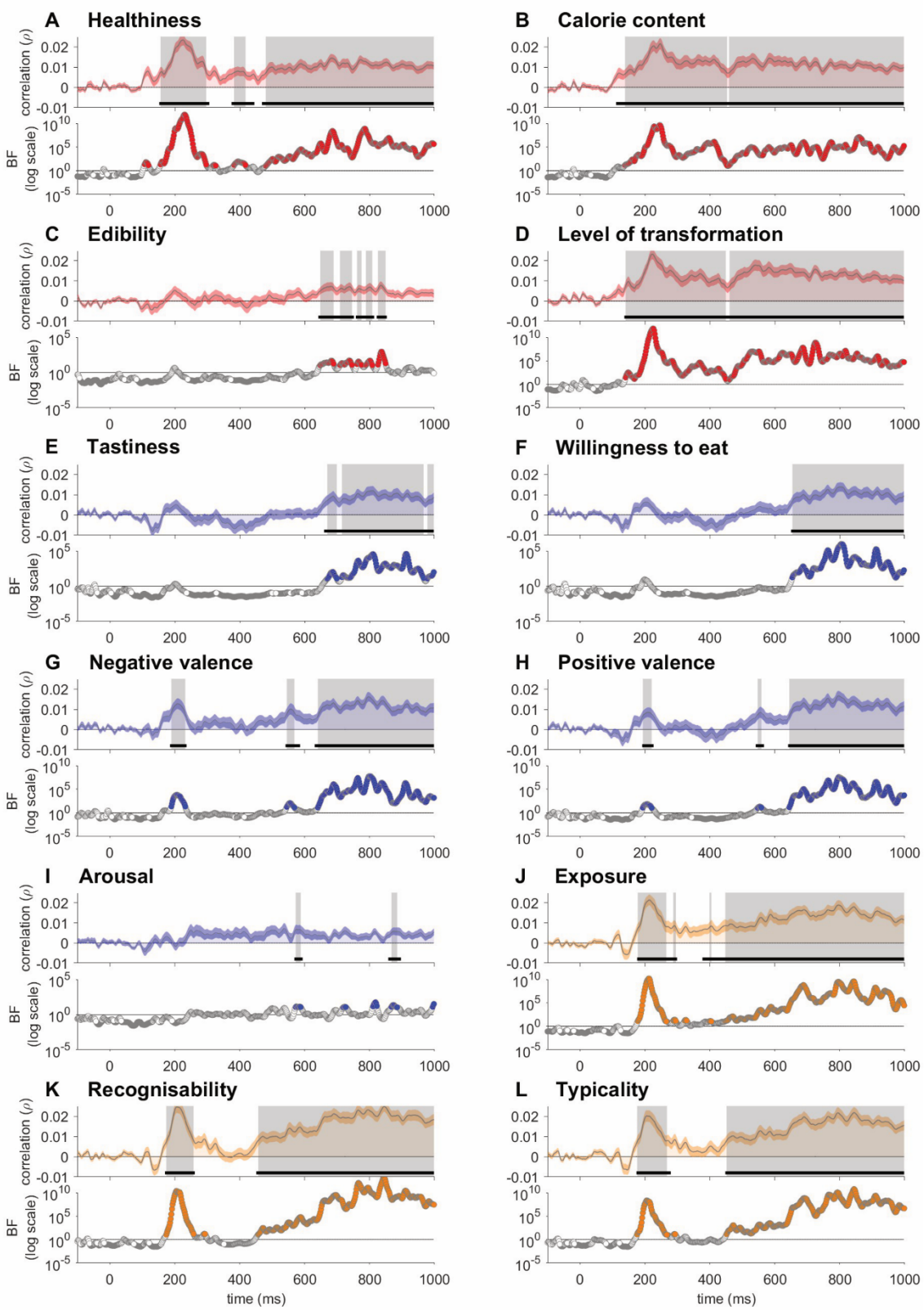

Figure 3. Correlations between the EEG and the food attributes while controlling for visual features. Partial correlations between the 12 food attribute

RDMs and the neural RDMs, controlling for the six visual feature RDMs. Nutritive properties (A-D) include healthiness, calorie content, edibility, and level of transformation. Hedonic properties (E-I) include tastiness, willingness to eat, negative valence, positive valence, and arousal. Familiarity attributes (J-L) include exposure, recognisability, and typicality. The shaded area around the plot lines shows the standard error of the mean. The horizontal black lines indicate time windows with statistically significant above-zero correlations after applying multiple comparisons corrections. The coloured circles indicate the time-points at which the Bayes factors (BFs) were greater than 10, while grey circles indicate the time-points at which the BFs were less than 1/10, and the white circles indicate the time-points at which the BFs were between 1/10 and 10. The grey shaded areas indicate the time windows at which the BFs were greater than 10 and there were statistically significant above-zero correlations after applying multiple comparisons corrections.

4.4.2 Identifying Broad Underlying Dimensions

We used PCA to identify broad underlying dimensions that explained substantial amounts of variance in food attribute ratings. To assess whether the information captured in these principal components were present in the neural activity, we examined the correlations between each of the principal component RDMs and the neural RDMs over time, using partial correlation analyses to control for the six visual feature RDMs.

4.4.2.1 PCA Results. Eigenvalues were used to determine the number of components to retain. According to Kaiser's rule (eigenvalues > 1), two

components were extracted. The first principal component had an eigenvalue of 7.01, explaining 58.4% of the variance, while the second component had an eigenvalue of 3.26, explaining 27.2% of the variance. Together, these two components accounted for 85.5% of the total variance. Factor loadings are presented in Table 2. The first component had large positive loadings for tastiness, willingness to eat, positive valence, and the familiarity attributes (exposure, recognisability, typicality), and a large negative loading for negative valence. The first component also had a negative loading for edibility (for this attribute, low scores indicate high edibility and high scores indicate low edibility). This component likely reflects how appetising the food is, and also maps onto the largest cluster in the model multidimensional scaling plot (Figure 2B). The second component had large positive loadings for calorie content, level of transformation, and arousal, and a large negative loading for healthiness. This component likely taps into how processed the food is, and maps onto the second largest cluster in the model multidimensional scaling plot (Figure 2B).

4.4.2.2 Broad Underlying Dimensions. The first and second principal component RDMs were correlated with neural signals and showed distinctive time-courses (Figure 4). Both components displayed an early peak at 215 ms and 248 ms respectively. For the first component, this was followed by a sustained window of correlations starting from 642 ms. For the second principal component, correlations were sustained across a large window from 141 ms until the end of the analysed time range. We examined the similarities in the time-courses of encoding between the principal components and the individual food attributes

using dynamic time warping (Figure 5). The first principal component shared similar time-courses of encoding with the attributes that relate to how appetising the food is (tastiness, willingness to eat, valence, exposure, recognisability, and typicality), while the second principal component shared similar time-courses of encoding with the attributes that relate to how processed the food is (healthiness, calorie content, level of transformation, and arousal).

Table 2. Factor loadings for principal components 1 and 2 based on principal component analysis performed with food attribute ratings. Loadings above .3 or below -.3 are deemed large loadings and are in boldface.

Food attribute	Factor loadings	
	PC1	PC2
Tastiness	**0.352**	0.160
Willingness to eat	**0.360**	0.109
Negative valence	**-0.361**	0.036
Positive valence	**0.368**	0.023
Exposure	**0.340**	-0.114
Recognisability	**0.349**	-0.032
Typicality	**0.358**	-0.032
Edibility	-0.248	0.002
Arousal	0.182	**0.418**
Healthiness	0.128	**-0.489**
Calorie content	-0.024	**0.541**
Level of transformation	-0.059	**0.489**

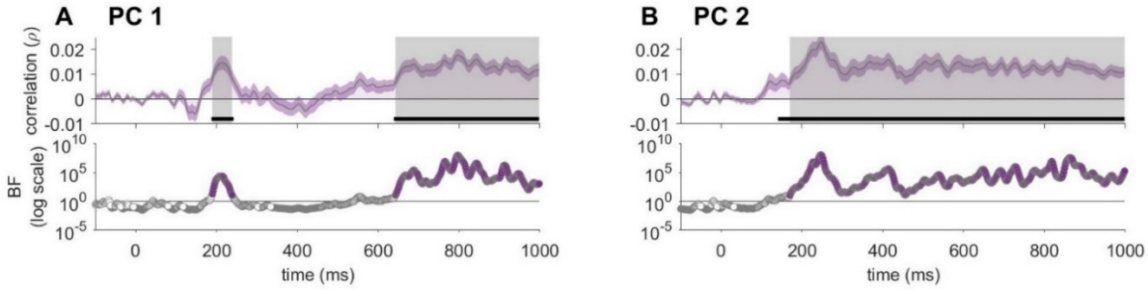

Figure 4. Correlations between the EEG and the principal components while controlling for visual features. Partial correlations between the first (A) and second (B) principal component RDMs and the neural RDMs, controlling for the six visual feature RDMs. The shaded area around the plot lines shows the standard error of the mean. The horizontal black lines indicate time windows with statistically significant above-zero correlations after applying multiple comparisons corrections. The coloured circles indicate the time-points at which the BFs were greater than 10, while grey circles indicate the time-points at which the BFs were less than 1/10, and the white circles indicate the time-points at which the BFs were between 1/10 and 10. The grey shaded areas indicate the time windows at which the BFs were greater than 10 and there were statistically significant above-zero correlations after applying multiple comparisons corrections.

4.4.3 Unique Contributions to the Variance in Neural Activity

We next examined whether any food attributes accounted for any variance in the neural data outside of the shared variance explained by other food attributes or visual features. We performed partial correlations with the neural RDMs and each of the food attribute RDMs while controlling for the other 11 food attribute RDMs and the visual feature RDMs. This allowed us to evaluate the unique

variance in EEG data explained by each food attribute while controlling for the influence of all other food attributes, as well as the visual features. We found that a subset of food attributes across nutritive properties (healthiness, calorie content, and level of transformation), hedonic properties (negative valence and arousal), and familiarity (recognisability) explained unique variance in the neural data.

4.4.3.1 Nutritive Properties. Healthiness, calorie content, and level of transformation explained variance in the neural data after controlling for all other food attributes and visual features (Figure 6A, 6B, 6D). All three attributes were found to be correlated early (from 195 ms for healthiness, 244 ms for calorie content, and 197 ms for level of transformation). Encoding of healthiness and level of transformation displayed an early peak around 203 ms and 221 ms respectively. For level of transformation, there was an additional later window of correlations starting from around 502 ms onwards that was sustained until the end of the analysed time range.

4.4.3.2 Hedonic Properties. Negative valence and arousal accounted for unique variance in the neural activity (Figure 6G, 6I). Negative valence was correlated from 154 ms, with an early peak at 209 ms, as well as subsequent windows of correlations from 346 ms. In contrast, arousal was correlated from 377 ms.

4.4.3.3 Familiarity. Out of the familiarity attributes, only the recognisability model explained some unique variance in the EEG data (Figure 6K). There was an early peak at 207 ms and later, sustained windows of correlations starting from

574 ms and lasting until the end of the analysed time range.

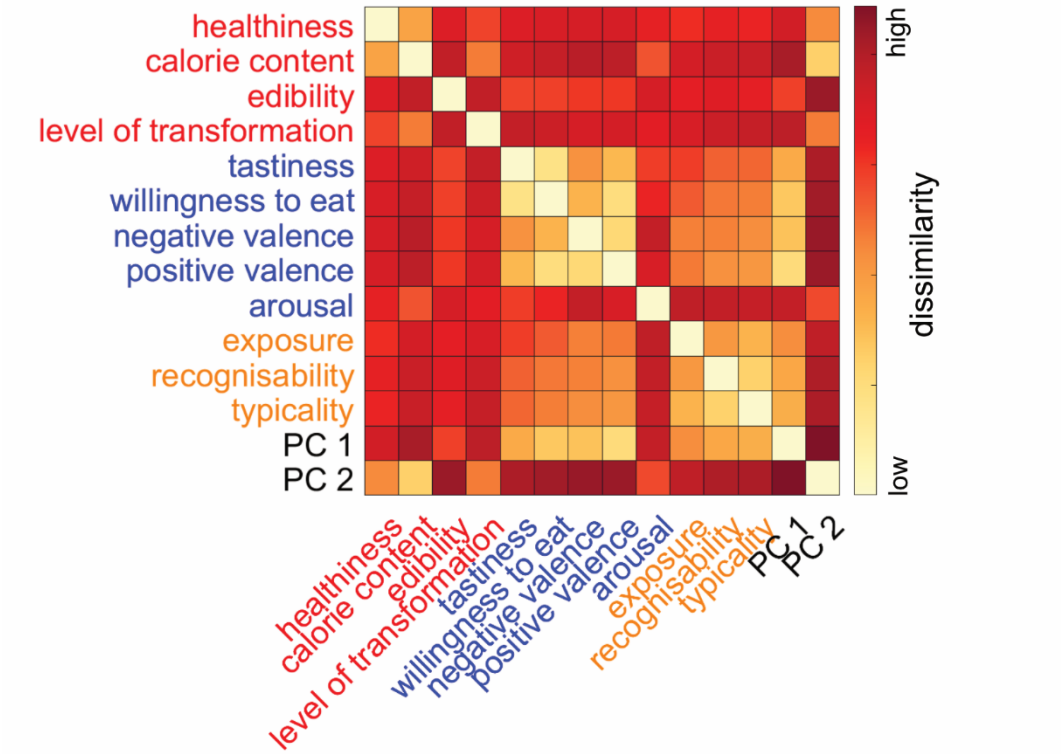

Figure 5. Dynamic time warping to compare similarities between the neural time-courses of food attribute representations. Dissimilarity (measured in Euclidean distance) between the partial correlations over time between the neural RDMs and each of the food attributes, controlling for visual features. Cell colour indicates dissimilarity, with yellow cells indicating lower dissimilarity and red cells indicating higher dissimilarity.

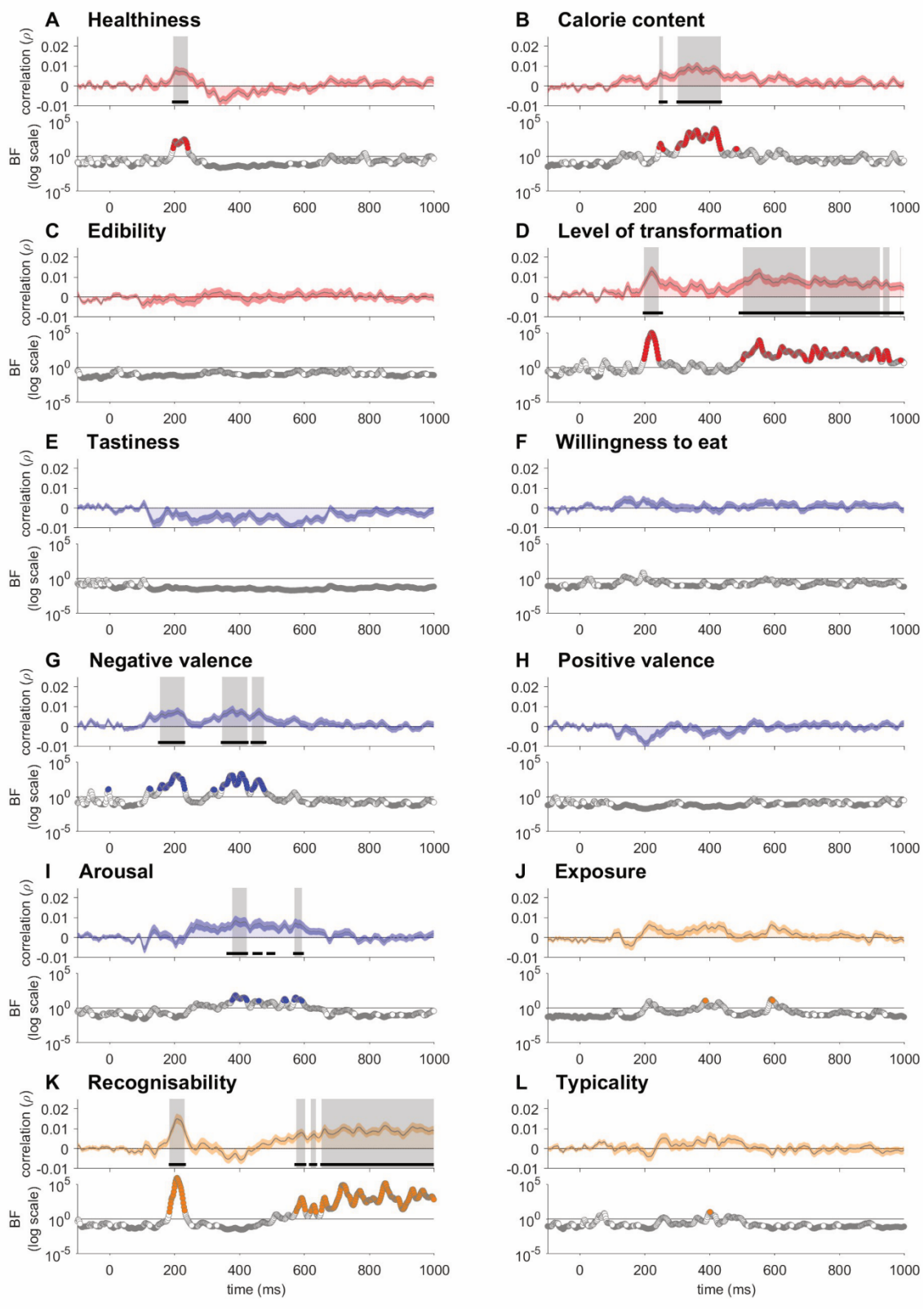

Figure 6. Correlations between the EEG and the food attributes while controlling for all other food attributes and visual features. Partial correlations

between the food attribute RDMs and the neural RDMs, controlling for the other 11 food attribute RDMs and the six visual feature RDMs. Nutritive properties (A-D) include healthiness, calorie content, edibility, and level of transformation. Hedonic properties (E-I) include tastiness, willingness to eat, negative valence, positive valence, and arousal. Familiarity attributes (J-L) include exposure, recognisability, and typicality. The shaded area around the plot lines shows the standard error of the mean. The horizontal black lines indicate time windows with statistically significant above-zero correlations after applying multiple comparisons corrections. The coloured circles indicate the time-points at which the BFs were greater than 10, while grey circles indicate the time-points at which the BFs were less than 1/10, and the white circles indicate the time-points at which the BFs were between 1/10 and 10. The grey shaded areas indicate the time windows at which the BFs were greater than 10 and there were statistically significant above-zero correlations after applying multiple comparisons corrections.

4.5 Discussion

We comprehensively examined how patterns of EEG signals covary with food attribute judgements. Participants viewed food images while their EEG activity was recorded, and ratings on food attributes related to nutritive properties, hedonic properties, and familiarity were collected from a separate sample. Using RSA, we assessed the neural time-courses of each food attribute individually, while controlling for potential confounds associated with low- and mid-level visual features. We reveal that food attributes were represented in the neural activity

rapidly and in parallel, in contrast to the idea that certain attributes are processed more quickly than others. Our findings suggest that decision-relevant features of foods may capture early attention and facilitate rapid appraisal processes. In light of the substantial covariation between the food attributes, we examined the broad underlying dimensions of foods using PCA and the unique contributions of individual attributes using partial correlation analyses. We found that the broad dimensions underlying individual attributes (how appetising and how processed the food is) were also represented in early neural signals. On the other hand, the neural activity also reflected information unique to a subset of individual attributes. These findings highlight that the structure and time-courses of food attribute representations can be mapped at multiple levels. Furthermore, we demonstrate the utility of examining the time-courses of neural representations in EEG activity by coupling a large EEG dataset and attribute ratings collected from a separate sample.

4.5.1 The Neural Time-Courses of Individual Food Attributes

We found that many food attributes shared similarities in their time-courses of correlation with the EEG signals. For many attributes, we observed an early peak in the correlation (~200 ms from food image onset) as well as later, more sustained windows of encoding (from ~400-650 ms). These findings are consistent with previous findings that some key food attributes are reflected in early (~100-200 ms) and later, more sustained (~300-700 ms) ERP components (Duraisingam et al., 2021; Harris et al., 2013; Meule et al., 2013; Rosenblatt et al., 2018; Schubert, Smith, et al., 2021; Toepel et al., 2009). Previous work has

suggested that differences in ERP amplitudes evoked by foods may reflect differences in initial attention allocation (see review by Carbine et al., 2018). In line with this, early windows of encoding in neural activity (~100-200 ms) may be reflective of early attentional processes evoked by foods that differ in decision-relevant features. On the other hand, activity related to stimulus value signals are thought to emerge later (~400-500 ms from stimulus onset) in food decisions (Harris et al., 2013). We hypothesise that the later, sustained windows of encoding may reflect parallel appraisal of attributes before the integration of information towards a decision. While it has been well established that key food attributes (e.g., tastiness, healthiness, and calorie content) are reflected in the neural activity over these time windows when explicitly judging the foods on these attributes, we demonstrate that a wide array of attributes may be processed in parallel during food viewing. Taken together, salient features of foods may capture early attention, facilitating rapid valuation of the food on relevant attributes.

Researchers have speculated that activity related to decision-relevant food attributes occur in the ventromedial prefrontal cortex in these temporally dissociable windows (Harris et al., 2011, 2013). The ventromedial prefrontal cortex is widely thought to be involved in the encoding of stimulus value across many different types of value-based decision-making (Hare et al., 2009; Kable & Glimcher, 2007; Rangel & Clithero, 2014). In dietary self-control literature, this later window (~400-650 ms) is thought to be when stimulus value is modulated to exert self-control (e.g., increased weighting of healthiness; Harris et al., 2013). Our findings are in line with the idea that food attributes are represented and used by

the brain for decision-making during these later time windows; however, our findings do not give us information about the specific brain regions involved in these processes.

Furthermore, we corroborate and extend on findings by Moerel et al. (2024) by applying a similar multivariate approach to map the neural time-courses of representations for a different, overlapping set of food attributes. Consistent with Moerel et al. (2024), we found that nutritive properties are represented in EEG activity earlier (~100-350 ms) for level of transformation and calorie content and later (~650 ms) for edibility. On the other hand, we found evidence for the representation of hedonic properties in the neural activity, while Moerel et al. (2024) did not find strong evidence for the representation of valence and arousal. We observed a later onset (~600-650 ms) of the sustained window of encoding for hedonic properties, which may explain why Moerel et al. (2024) did not find strong evidence for the representation of these attributes at very rapid presentation rates (e.g., ~100 ms per image). While numerous studies have shown that features of objects are represented in the EEG signals even at very rapid presentation rates (Contini et al., 2020; Grootswagers, Robinson, Shatek, et al., 2019; Marti & Dehaene, 2017; Mohsenzadeh et al., 2018), unlike early neural responses (<150 ms), later processing may be influenced by presentation rate (Grootswagers, Robinson, & Carlson, 2019). Representations at very rapid presentations rates (~50 ms per image) were weaker and lasted for shorter durations compared to slower presentation rates (~200 ms per image), potentially due to the increase in presentation duration leading to further consolidation of representations

(Grootswagers, Robinson, & Carlson, 2019). Future studies may opt for an extended presentation duration (e.g., in the order of seconds) when investigating the appraisal of foods. Different stimulus sets used in the studies may be another contributing factor to this discrepancy. Selecting food stimuli to include edible but less appetising foods ensured that we were able to obtain sufficient variance in the hedonic properties. Achieving sufficient variance in the attributes of interest may be especially crucial for multivariate analyses that rely on fine-grained information to train a classifier or construct meaningful RDMs. Taken together, these findings shed light on the methodological differences (e.g., viewing duration, stimuli selection) that influence the mapping of the neural representations of different types of food attributes. Furthermore, we reveal the neural time-courses of a novel class of food attributes (familiarity), which appear to share similarities with the time-courses of hedonic properties. We add to a growing body of knowledge showing that key food features are rapidly represented in neural activity and highlight the importance of experimental design when assessing subtle patterns of neural activity.

Our findings do not support the idea that tastiness information is processed more quickly compared to healthiness information when viewing foods, revealing that the latter can in fact be represented in the EEG activity earlier than the former. This is consistent with some findings reported by Schubert, Rosenblatt, et al. (2021), where the decoding onset of healthiness ratings preceded the decoding onset of tastiness ratings when participants were not explicitly evaluating the foods on healthiness or tastiness. Categorising attributes

in terms of their level of abstraction or short- or long-term relevance may pose a problem for food attributes, especially given the intercorrelated structure of these attributes. For example, calorie content can be conceptualised as an attribute with long-term relevance as it plays a role in nutrition, but also signals short-term tastiness due to its close relationship with the fat and sugar content of foods. For other attributes, such as typicality, recognisability, emotional arousal, or level of processing, their level of abstraction and relevance to short- or long-term goals is less clear and may be situational. In the context of a typical food cognition study that uses food images as stimuli rather than real foods, in which real food choice is not imminent, attributes may not differ so much in their short- or long-term relevance. When there is a real food choice at stake (e.g., when participants are aware that they will have to consume one of the foods that they choose in the experiment), we may observe that more immediately relevant attributes are indeed processed more quickly (e.g., Sullivan et al., 2015). Our results show that in typical lab settings, healthiness and other attributes that are more ambiguous in their level of abstraction can be processed rapidly. These findings lend support for the parallel encoding of multiple relevant attributes that inform a food choice.

4.5.2 Understanding Food Attribute Covariation

We took a novel approach to address the issue of food attribute covariation, which historically has made it difficult to draw conclusions about the time-courses of correlations for individual food attributes. Previous studies have been limited in examining only one or a few food attributes at a time and proposing that any differences in neural activity reflected information about that food

attribute without considering covarying attributes that may also contribute (Coricelli et al., 2019; Harris et al., 2013; Meule et al., 2013; Rosenblatt et al., 2018; Schacht et al., 2016; Schubert, Smith, et al., 2021; Stuldreher et al., 2023; Toepel et al., 2009). We collected ratings for a wide range of food attributes, which allowed us to explicitly investigate the structure of attribute covariation and conduct further analyses to examine the broader dimensions that may underlie individual attributes. In a complementary approach, we also assessed whether there were unique contributions from the individual attributes not shared with the other attributes.

We identified that the 12 food attribute ratings were clustered into a few groups that were strongly positively correlated (Figure 2B). The largest cluster included familiarity attributes (exposure, recognisability, and typicality) and many of the hedonic properties (tastiness, willingness to eat, negative and positive valence). The second largest cluster included many nutritive properties (healthiness, calorie content, and level of transformation). Arousal and edibility were each found to be relatively distinct from the other attributes. Consistent with this, the time-courses of correlations with the EEG signals were similar within the clusters (Figure 5), indicating that the covariation among food attributes were reflected in the neural signals over time. This suggests that shared underlying dimensions may be driving the covariation between the food attributes, and these dimensions may be encoded in the neural activity.

Using PCA, we demonstrated that two broad underlying dimensions can capture most of the variance in multiple correlated attributes. We further showed

that these dimensions display two distinct time-courses of representations. The first dimension, reflective of how appetising the food is, appears to be processed in two stages, with an early brief window (~200 ms) followed by a later, more sustained window (~600 ms and onwards). This is consistent with findings by Carbine et al. (2018) that reported that foods, in comparison to neutral cues or less palatable foods, elicit greater ERP amplitudes that reflect early attentional allocation (e.g., increased P2). The early window in our results may reflect early attentional allocation toward foods that are more appetising, while the later window may correspond to higher-level appraisal processes. In contrast, the second dimension, reflective of how processed the food is, appears to be represented in a sustained manner from ~150 ms onwards. We found distinct time-courses of representations for the two dimensions, most notably in the onset time for the sustained window of encoding. One potential explanation for this difference may be that appraising foods on how appetising it is involves cognitive processes such as memory retrieval of past eating experiences, interoception (e.g., evaluation of one's current hunger level), or mental simulation, while appraising foods on how processed it is may not involve such processes to the same degree.

We demonstrate a novel way to get closer to the dimensions most salient for the brain, using principal components rather than individual attributes. The brain may map representations of foods on dimensions that correlate with, but are not exactly, the attributes we choose for our studies. On the other hand, we also show that half of the food attributes (healthiness, calorie content, level of

transformation, negative valence, arousal, and recognisability) explained some amount of unique variance in the neural data not shared with any other attribute. In particular, level of transformation and recognisability explained unique variance in later, more sustained time windows. Our approach highlights the multilevel structure of food representations, revealing that how appetising and how processed the food is may broadly capture many decision-relevant attributes and are represented by the brain, while at the same time, the neural signals also contain information uniquely relevant to certain individual attributes.

Future work examining the neural correlates of food attribute processing should carefully consider possible multilevel, correlated structures of food attribute representations. For example, attribute ratings may be used to derive a food stimulus set with minimal correlations across targeted sets of attributes, or decorrelated stimulus sets may be curated for each individual participant. Alternatively, food attribute ratings could be collected first before selecting a subset of food stimuli that are not strongly correlated on relevant attributes to investigate the neural correlates of specific food attributes. Our approach using PCA may be particularly useful for identifying and mapping patterns of shared variance across food attributes.

4.5.3 A Novel Approach Combining EEG Recordings With Online Food Attribute Ratings

We demonstrate a novel approach for examining food representations in the human brain. We showed that attribute ratings collected from a separate sample can be used in conjunction with EEG data to examine the neural time-

courses of representations. Future studies may consider using available datasets containing EEG data recorded during food viewing to examine representations of foods. For example, future work can involve collecting ratings on novel food attributes from a separate sample and applying RSA to examine whether these novel attributes are represented in the EEG signals in an available dataset. As EEG data acquisition can be time-consuming and expensive, this approach provides a potentially more efficient way to study the neural processing of foods.

4.5.4 Conclusion

In this study, we coupled food attribute rating data with a large EEG dataset. We delineate the neural time-courses of food attribute representations at different levels, from individual attributes to broad underlying dimensions. Our findings suggest that salient food features may capture early attention, facilitating rapid and parallel appraisal of foods on multiple relevant attributes over similar time-courses. Beyond the neural time-courses of individual attributes, we reveal that broad underlying dimensions of how appetising and how processed the food is are also represented in the neural activity with distinct time-courses. Future studies may leverage available EEG datasets to explore the neural correlates of novel food attribute processing or consider alternative methods for parsing out representations of highly covarying attributes.

4.6 Authorship Contribution Statement

Violet J. Chae: Conceptualisation, Data curation, Formal analysis, Writing – original draft, Writing – review and editing.

Tijl Grootswagers: Methodology, Supervision, Conceptualisation, Writing – review

and editing.

Stefan Bode: Conceptualisation, Supervision, Funding acquisition, Methodology, Writing – review and editing.

Daniel Feuerriegel: Project administration, Supervision, Conceptualisation, Methodology, Writing – review and editing.

4.7 Ethical Statement

The experiment was approved by the Human Research Ethics Committee (ID 24850) of the University of Melbourne.

4.8 Declaration of Competing Interest

All authors have no conflicts of interest to report.

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4.10 Data Availability

Data used for the analyses reported here are available via the Open Science Framework (https://osf.io/w8c9d/).

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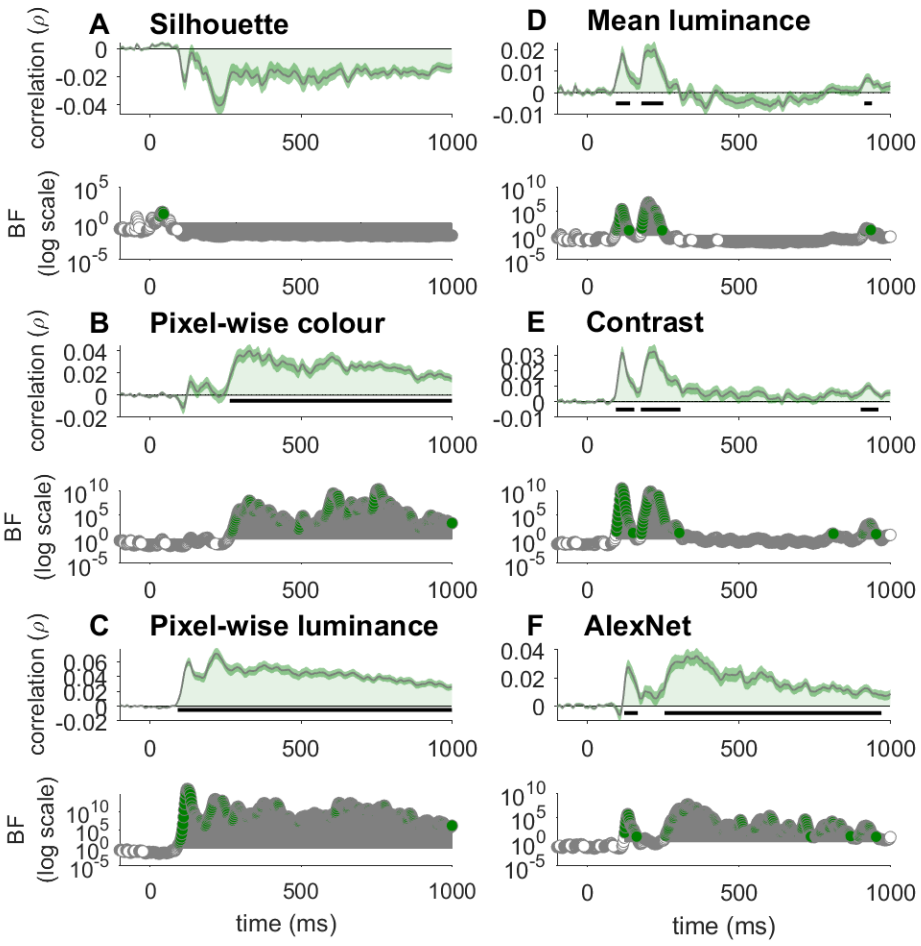
4.12 Supplementary Material



Supplementary Figure 1. Correlations between EEG signals and low- and mid-level visual features. Correlations between the silhouette (A), pixel-wise colour (B), pixel-wise luminance (C), mean luminance (D), contrast (E), and AlexNet (F) models and the neural RDMs. The shaded area around the plot lines shows the standard error of the mean. The coloured circles indicate the time-points at which the BFs were greater than 10. The horizontal black lines indicate time windows with statistically significant above-zero correlations after applying multiple comparisons corrections.

Chapter 5: The Centroparietal Positivity Traces the Path of Evidence Accumulation During Dietary Decisions

The following chapter presents a study in which we characterised a neural correlate of evidence accumulation during the choice phase of dietary decisions. This chapter is presented as a manuscript which is currently under review at *Open Mind* and is accessible as a preprint on *bioRxiv*.

The Centroparietal Positivity Traces the Path of Evidence Accumulation During Dietary Decisions

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5.1 Abstract

Each day we make dozens of decisions about food. These choices are informed not only by information that we receive from our senses, but also by our memories, values, cultural norms, and goals. Evidence accumulation models have been proposed to explain how we transform these disparate sources of information into dietary choices and their corresponding motor actions. These models describe decisions arising from a noisy integration of decisional evidence until a criterion is reached. We investigated whether the centroparietal positivity (CPP), an event-related potential component proposed as a neural correlate of evidence accumulation during perceptual judgements, also traces accumulation trajectories during dietary decisions. Participants (N = 110) made speeded Yes/No judgements about food images relating to three attributes (healthiness, tastiness, and willingness to eat) while electroencephalography was recorded. They subsequently provided continuous ratings for each attribute. After applying signal deconvolution techniques, CPP waveforms exhibited a close correspondence to hypothesised evidence accumulation trajectories, showing steeper amplitude build-up rates for both faster decisions and continuous ratings more strongly in favour of one's categorical choice. Our findings provide clear support for a neurally instantiated evidence accumulation process that integrates multiple sources of information to produce dietary decisions.

5.2 Introduction

When faced with a restaurant menu, how do we decide what to eat? According to models of dietary decision-making (Rangel, 2013), we evaluate food items on relevant attributes to calculate an overall value for each option, and use these value representations to select the option with the higher overall value. Similarly, when confronted by a single food option – to eat or not eat the last slice of cheesecake – a decision may be reached by comparing the food's representational value to an internal decision criterion.

Substantial progress has been made in understanding how our brains evaluate food items. Relevant food attributes (e.g., healthiness, tastiness, calorie content) are rapidly appraised (Chae et al., 2026; Meule et al., 2013; Moerel et al., 2024, 2026; Schubert et al., 2021; Toepel et al., 2009) and integrated into value signals in key regions, such as the ventromedial prefrontal cortex (Hare et al., 2009, 2011; Hutcherson et al., 2012). However, the food cognition literature has focused predominantly on this appraisal stage and very little is known about how the brain transforms value representations into choices and actions. Understanding this process is essential for a complete account of how dietary decisions unfold in the brain.

In perceptual decision-making research, sequential sampling models characterise decision making as the accumulation of noisy evidence towards a choice and action outcome. The diffusion decision model (DDM; Ratcliff, 1978; Ratcliff & Smith, 2004) is the most widely applied sequential sampling model and accounts for well-established behavioural phenomena, such as the speed-

accuracy trade-off and the characteristic shapes of response time (RT) distributions in perceptual tasks (Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998). In the DDM, decisions arise from the noisy accumulation of evidence towards a response boundary. The drift rate describes the average rate and direction of evidence accumulation and reflects the combined strength of external sensory and internal mnemonic evidence (Ratcliff et al., 2016). During decision formation, accumulated evidence is continuously perturbed by stochastic noise, causing evidence to fluctuate towards or away from the response boundary. This means that on average, higher drift rates produce faster and more accurate responses, while within-decision noise produces trial-to-trial RT variability.

In humans, the centroparietal positivity (CPP), a positive-going event-related potential (ERP) component recorded using electroencephalography (EEG) over midline posterior scalp electrodes, has been identified as a neural signature of evidence accumulation in perceptual decision tasks (Kelly & O'Connell, 2013; O'Connell et al., 2012). The CPP exhibits two critical properties predicted by sequential sampling models. First, the amplitude build-up rate (waveform slope) prior to a motor response scales with RT and stimulus quality (steeper slopes for faster RTs and higher quality sensory evidence; Feuerriegel et al., 2021; Kelly & O'Connell, 2013; O'Connell et al., 2012; Twomey et al., 2015). Second, the amplitude just prior to the response remains approximately constant across RTs and stimulus quality conditions, consistent with accumulation to a fixed decision threshold (Kelly & O'Connell, 2013; O'Connell et al., 2012; Twomey et al., 2015). Establishing the CPP as a neural correlate of evidence accumulation provides a

critical link between computational models and brain activity, revealing how the brain transforms sensory information into perceptual choices.

Sequential sampling models have been successful in accounting for speeded perceptual decisions based on sensory input, where the decision-relevant information is well defined (Bowman et al., 2012; Brunton et al., 2013; Ossmy et al., 2013; Ratcliff et al., 2009; van Vugt et al., 2012). These models have also been successfully applied to account for choice proportions and RT distributions in value-based decision tasks, such as choosing foods (Krajbich et al., 2010; Krajbich & Rangel, 2011; Milosavljevic et al., 2010) and consumer goods (Krajbich et al., 2012; Philiastides & Ratcliff, 2013), which additionally draw from endogenous sources of information (e.g., memories, knowledge, and personal preferences). This indicates that noisy evidence accumulation may serve as a general decision-making process that extends beyond perceptual choices (Kable & Glimcher, 2009).

Consistent with this idea, the CPP has been found to trace evidence accumulation dynamics during memory-based decisions (van Ede & Nobre, 2024), preference-based decisions (Fong et al., 2026), and crucially, two-option dietary decisions (Pisauro et al., 2017). Pisauro and colleagues presented participants with pairs of food items while recording EEG. They reported a centroparietal signal showing ramping-to-bound dynamics, with a build-up rate that was steeper for faster RTs and for trials with higher subjective value differences between the two foods. Taken together, these findings raise the possibility that evidence accumulation may be a domain-general decision-making mechanism indexed by a

common neural marker, extending to dietary choice.

However, whether the CPP robustly reflects evidence accumulation during value-based and dietary decisions remains contested. Frömer et al. (2024) recorded EEG while participants made value-based choices between sets of consumer goods and food items. They found that, although a CPP-like ramping signal was observed, its properties did not align with the predictions of evidence accumulation models. The authors argued that the observed RT-dependent modulation of CPP slopes and waveform amplitudes can arise artifactually from the temporal overlap between stimulus-locked and response-locked EEG signals, rather than reflecting a genuine evidence accumulation signal. When they applied a deconvolution technique to separate these overlapping components, they could no longer detect waveform amplitude differences across fast and slow RT conditions that resemble CPP slope modulations. Frömer et al. also reanalysed EEG datasets from previously published studies, including the dietary choice study by Pisauro et al. (2017). By applying the same deconvolution procedure, they similarly attenuated or abolished waveform amplitude differences across fast and slow RT trials in those datasets.

While this study raised valid concerns regarding EEG signal overlap, the deconvolution-based analysis methods they used may not be suitable for identifying ramping evidence accumulation signals, and can artifactually prevent their detection (for a detailed critique see O'Connell et al., 2025). Resolving this debate requires studies that apply more appropriate methods to account for component overlap when characterising neural signals of evidence accumulation

during dietary choice tasks.

An additional challenge when studying dietary decisions is that some valuation processes, such as attribute appraisal, may temporally overlap with choice-related processes, potentially hindering our ability to isolate the latter in the neural signals. When food images are presented, numerous attributes (e.g., healthiness, tastiness, edibility, familiarity) are rapidly represented by the brain with overlapping time-courses during the first second of viewing (Chae et al., 2026; Moerel et al., 2024; Schubert et al., 2021). In typical dietary and value-based decision paradigms, participants are presented with decision options (e.g., food images) and immediately make speeded choices (e.g., Frömer et al., 2024; Pisauro et al., 2017). This means that the appraisal of relevant attributes and the conversion of this information into action likely occurs in parallel, making it difficult to disentangle neural correlates of appraisal and choice.

One approach to better isolate evidence accumulation processes is to temporally separate attribute appraisal from choice, by presenting decision options first and then prompting a decision after a delay. In such a paradigm, the appraisal of each option can begin earlier and there is time to process decision-relevant attributes. The subsequent choice process draws primarily on endogenous memory representations rather than ongoing sensory processing. Previous work has used this approach to demonstrate that the CPP exhibits characteristic accumulation dynamics during working memory-based decisions (van Ede & Nobre, 2024). However, they did not use signal deconvolution to account for choice prompt stimulus-locked EEG signals, which largely overlapped

in time with their response-locked waveforms.

We investigated whether the CPP exhibits signatures of evidence accumulation during dietary decisions, extending this framework beyond perceptual choices. Our aim was to extend an account developed primarily in the perceptual domain to food choice, a domain in which the processes leading up to choice have not yet been clearly characterised. Participants viewed food images and gave binary (Yes/No) responses according to whether the food was healthy, tasty, or whether they were willing to eat it, while EEG was recorded. These decisions (single-item choice and healthiness/tastiness judgements) differ from the two-choice food preference decisions studied previously (Pisauro et al., 2017). Nevertheless, such choices are frequently made in everyday life and may recruit domain-general evidence accumulation mechanisms. Our paradigm separated attribute appraisal processes from the subsequent conversion of this information into choice. We first presented the food image in isolation and then prompted participants to make one of the three possible categorisation decisions after a delay (Figure 1A). This design allowed us to better isolate the neural mechanisms underlying the processes leading up to the decision and corresponding motor action. After applying an appropriate deconvolution method to account for EEG signals time-locked to stimulus onset, we assessed whether the CPP consistently displayed the hallmark characteristics of evidence accumulation across these three types of dietary judgements.

5.3 Methods

The experiment consisted of two sessions. In the first session,

participants completed a food categorisation task while EEG was recorded and subsequently provided food attribute ratings for each food image. In the second session, participants completed two behavioural food choice tasks and answered questionnaires regarding their dietary style and food motivations. Data collected from the second session were not analysed in this study, and the behavioural tasks and the questionnaires are described in Chae et al. (2025). This study was approved by the Human Research Ethics Committee of the University of Melbourne (HREC ID 24850).

5.3.1 Participants

Participants (*N* = 117) were recruited through the University of Melbourne student portal and advertising via posters. Participants indicated that they were at least 18 years old, were fluent in written and spoken English, did not have a history of any eating disorders, were not on a calorie restriction diet, and did not have any dietary restrictions (e.g., for health or religious reasons). Participants were asked to fast for three hours prior to the start of both in-person sessions. At the end of the second session, participants were reimbursed AUD $50. Five participants were excluded due to excessively noisy data or incomplete participation. Two additional participants were excluded due to the high incongruence in their continuous healthiness, tastiness, and willingness to eat ratings and their responses in the food categorisation task. The final sample of 110 participants had a mean age of 26.5 years (SD = 8.23, range 18-57 years). 81 participants identified as female, 28 as male, and one as other.

5.3.2 Procedure

Participants completed a food categorisation task presented using Psychtoolbox (Kleiner et al., 2007) interfacing Matlab R2022a. After the task, participants rated each food image on healthiness, tastiness and how much they would like to eat the food (willingness to eat) using Qualtrics.

5.3.2.1 Food Categorisation Task. Participants viewed each food item three times: once each across the healthiness, tastiness, and willingness to eat trials (Figure 1A). Food images were presented centrally, subtending 6.6 × 3.5 degrees of visual angle on a 24.5-inch ASUS ROG Swift PG258Q monitor (1920 x 1080 pixels, 60 Hz refresh rate). Participants' heads were stabilised using a chin and forehead rest approximately 50 cm from the monitor.

Each trial began with a fixation cross presented in isolation for 1 s, followed by the food image with a fixation cross for 2 s. Next, the participants were prompted with "Healthy?" in a healthiness trial, "Tasty?" in a tastiness trial, and "Like to eat?" in a willingness to eat trial, along with a response mapping that indicated which of the left ("z") and the right ("m") keyboard keys corresponded to Yes and No responses. There was an equal chance of the left keyboard press indicating a Yes response (and the right keyboard press indicating a No response) and the reverse for each trial. For each participant, the order of healthiness, tastiness, and willingness to eat trials were randomised. The randomisation of the trial type order and response mapping ensured that participants could not pre-emptively prepare a keypress motor action during the food image presentation period.

Participants were asked to respond as quickly and accurately as possible

and to pay attention to the switching of the response mapping across trials. Participants completed five practice trials and indicated that they had understood the instructions before starting the main experiment. To reduce eye movement artifacts the participants were instructed to keep their eyes fixated on the fixation cross, which remained on screen throughout the duration of the experimental blocks. RT was recorded as the time taken from the presentation of the prompt to the participant's response via keyboard press. We randomised image presentation order for each participant (while ensuring that the same food image was not presented in two consecutive trials).

5.3.2.2 Continuous Ratings. Participants rated each food image on healthiness ("How healthy is this food?"), tastiness ("How tasty is this food?") and how willing they were to eat it ("How much would you like to eat this food?"). Participants were asked to use a computer mouse to indicate their response on a sliding scale from "Not at all" to "Very much" (Figure 1B). The order of image presentation was randomised. Participants' categorisation responses were compared against their corresponding continuous ratings by counting the number of trials on which a participant gave a "Yes" response despite a continuous rating below 50, or a "No" response despite a rating above 50. Two participants showed outlier levels of incongruent responses (165 out of 360 trials) and were excluded on this basis.

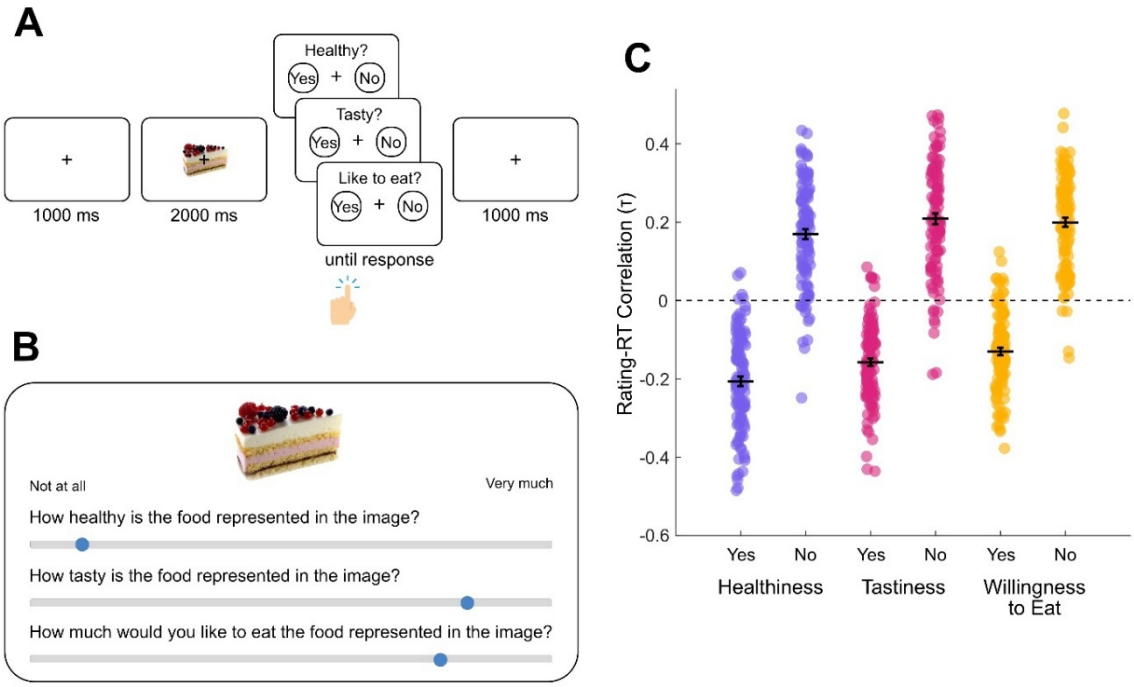

Figure 1. Trial diagrams and correlations between continuous ratings and categorisation task RTs. A) EEG food categorisation task. In each trial, participants viewed a food image (2 s), followed by a response screen displaying one of three decision prompts (healthiness, tastiness, or willingness to eat) and one of two keyboard press response mappings ('z' key for Yes and 'm' key for No, or the reverse). Participants were instructed to respond as quickly as possible. B) Continuous rating task. Participants provided continuous ratings for each food image for the three attributes (healthiness, tastiness, willingness to eat) using sliding scales ranging from 0 ("Not at all") to 100 ("Very much"). C) Participants' rating-RT correlations. Kendall's tau-b correlation coefficients between continuous ratings and RTs for Yes and No trials separately within the three decision types, shown for individual participants (dots) and group means (horizontal black lines). Error bars denote standard errors.

5.3.3 Behavioural Data Analyses

To verify whether choices and RTs in the categorisation task reflected stable judgements of each food attribute, we assessed correlations between RTs and the continuous ratings provided for each food, for Yes and No choices separately. Kendall's tau-b correlations were chosen to account for rank ties in the continuous ratings. Correlation coefficients were obtained for each participant and attribute and are plotted in Figure 1C.

5.3.4 EEG Recording & Data Processing

EEG was recorded using a Biosemi Active II system (Biosemi, The Netherlands) with 64 channels at a sampling rate of 512 Hz using common mode sense and driven right leg electrodes (http://www.biosemi.com/faq/cms&drl.htm). We attached 64 electrodes to the cap according to the international 10-20 system. We also attached eight additional electrodes: two electrodes placed 1 cm from the outer canthi of each eye, four electrodes placed above and below the centre of each eye, and two electrodes placed above the left and right mastoids. Electrode offsets were kept within the range of ±20 μV during recording.

EEG data was processed using EEGLAB v2022.1 (Delorme & Makeig, 2004) interfacing Matlab (R2022a). Excessively noisy channels were identified through visual inspection (mean number of bad channels = 0.26, range 0–5) and excluded from average reference calculations and independent component analysis (ICA). Excessively noisy sections or those with large amplitude artifacts were identified through visual inspection and removed. The data were referenced to the average of all channels (excluding excessively noisy

channels). One channel (AFz) was removed to compensate for the rank deficiency due to average referencing. EEG data were low-pass filtered at 30 Hz (EEGLAB Basic Finite Impulse Response Filter New, default settings). A copy of the dataset was created for the purpose of ICA. A 0.1 Hz high-pass filter (EEGLAB Basic Finite Impulse Response Filter New, default settings) was applied to the copied dataset to improve stationarity for the ICA. We used RunICA extended algorithm (Jung et al., 2000) to perform the ICA. The resulting independent component information was copied to the original dataset (e.g., as done by den Ouden et al., 2023). Independent components associated with eye blinks and saccades were identified and removed in line with guidelines in (Chaumon et al., 2015). Next, we interpolated the excessively noisy channels and AFz using spherical spline interpolation.

EEG data were initially segmented from -1300 to 4200 ms relative to food image onset and baseline corrected using the data from the 200 ms time window prior to the food image onset. Epochs containing amplitudes exceeding ±200 μV at any scalp channel were excluded from the analyses.

5.3.4.1 EEG Signal Deconvolution. In tasks where stimuli and responses are separated by variable intervals, ERP components time-locked to stimulus onset can overlap temporally with response-locked neural activity, potentially confounding estimates of pre-response signals such as the CPP. To mitigate this, we applied Residue Iteration Decomposition (RIDE; Ouyang et al., 2015) to separate stimulus-locked contributions from response-locked and variable latency EEG signals. RIDE decomposes single-trial EEG data into distinct

subcomponents based on their temporal alignment to different events within each epoch, making it suitable for recovering latency-variable and response-locked signals (Ouyang et al., 2015). This approach addresses concerns raised by Frömer et al. (2024) regarding artifactual RT-dependent CPP slope differences arising from overlapping stimulus- and response-locked activity, and has been validated for use with ramping evidence accumulation signals in prior work (Fong et al., 2026; Steinemann et al., 2018).

We decomposed the stimulus-locked single-trial EEG data for each participant into three subcomponents using the following time windows: a stimulus-locked (S) subcomponent estimated from 0 to 1000 ms post-stimulus onset, a response-locked (R) subcomponent estimated from −600 to −100 ms relative to response onset, and a time-varying (C) subcomponent estimated from 500 to 1000 ms post-stimulus, which captures neural activity with a latency that varies across trials and is not strictly tied to either the stimulus or response. We took a conservative approach to estimating and removing stimulus-locked EEG activity, using an extended estimation window for the S subcomponent beyond the default recommendations of Ouyang et al. (2015), following Sun et al. (2024) and Fong et al. (2026). This was done to minimise the risk that response-locked signals reflecting genuine decision processes, such as evidence accumulation, might be confounded by residual stimulus-evoked activity. The estimated S subcomponent was subsequently subtracted from each stimulus-locked single trial epoch prior to extracting stimulus- and response-locked epochs, such that the resulting waveforms more selectively

capture time-varying and response-locked neural dynamics underlying decision formation. R and C subcomponent estimates were included to improve decomposition accuracy in our estimation of the S subcomponent but were not otherwise used in subsequent analyses.

Following S subcomponent subtraction, we created response-locked epochs spanning −1300 to 200 ms relative to response onset. Epochs were baseline-corrected using the 100 ms window preceding food image onset, preserving the pre-stimulus baseline for response-locked ERP analyses.

5.5.4.2 Current Source Density Transformation. After deriving response-locked epochs, we applied a current source density (CSD) transformation to the response-locked data using the CSD Toolbox (Kayser & Tenke, 2006; m-constant = 4, λ = 0.00001 following Feuerriegel et al., 2021; Fong et al., 2026). CSD transformation estimates the second spatial derivative of the scalp-recorded potential, enhancing the spatial resolution of the EEG signal by emphasising local cortical sources and attenuating the contribution of spatially diffuse signals. This step was particularly important for isolating the CPP measured at posterior electrodes from co-occurring signals generated at more anterior frontal and central sites (e.g., motor preparatory activity) which can spread to parietal electrodes via volume conduction (Feuerriegel et al., 2022; Fong et al., 2026; Kelly & O'Connell, 2013).

5.3.5 Event-Related Potential Analyses

We examined the relationship between the pre-response CPP component and both RTs and continuous attribute ratings using two complementary

approaches: analyses focused on established pre-response analysis windows, and mass-univariate analyses spanning the full response-locked epoch.

5.3.5.1 Deriving CPP Measures. Pre-response CPP slope and amplitude measures were extracted from response-locked epochs at electrode Pz. Slopes were estimated by fitting a linear regression to each single-trial waveform within a window spanning −300 to −70 ms relative to response onset. Pre-response amplitude was defined as the mean signal within −130 to −70 ms relative to response onset. This time window was chosen to capture the amplitude of the CPP around the onset time of motor execution prior to completion of the keypress (in line with previous work, e.g., Feuerriegel et al., 2022; Fong et al., 2026; Steinemann et al., 2018).

5.3.5.2 Window Analyses Involving RT. We used linear mixed effects models to test whether RT predicted CPP slope and amplitude. Models were fit separately for each decision type (healthiness, tastiness, and willingness to eat). Prior to modelling, RTs were log-transformed to reduce positive skew and then z-scored within each participant to remove between-participant differences in RT scale, allowing inference to focus on within-participant variance (as done by Fong et al., 2026). We specified a maximal random-effects structure that included participant random intercepts and random slopes for the predictor of interest:

$$CPP_{measure} \sim 1 + RT + (1 + RT \mid pID)$$

Where the maximal model produced a singular fit or convergence failure (e.g., due to insufficient trial counts, near-zero variance components, or collinearity), the random slope was removed and only a random intercept was

retained (Bates et al., 2015). We compared models with and without the fixed effect of RT but with identical random effects structures using likelihood ratio tests under maximum likelihood estimation. We report regression coefficients (β) from the best-fitting model that converged without singularity. Full likelihood ratio test statistics and regression coefficients are reported in Supplementary Tables 2 and 3, respectively.

5.3.5.3 Window Analyses Involving Continuous Attribute Ratings. We used rank correlation analyses (Kendall's tau-b) to test for ordinal relationships between the pre-response CPP measures and continuous attribute ratings. Correlation analyses were run for Yes and No trials separately for each decision type (healthiness, tastiness, willingness to eat). Note that there were more Yes trials than No trials for most participants, particularly for tastiness and willingness to eat decisions. The descriptive statistics for the trial counts in each condition are reported in the Results. If there were fewer than 20 trials available for the correlation analyses, the participant was excluded from further analyses for that decision type. All participants (N = 110) were retained for Yes trials for all decision types. We retained 109 participants for healthiness No trials, 105 participants for tastiness No trials, and 106 participants for willingness to eat No trials.

5.3.5.4 Mass-Univariate Analyses for RT and Continuous Ratings. To examine the relationships between RT/continuous ratings and CPP measures beyond the fixed analysis windows, we performed complementary mass-univariate analyses to test for associations across the full response-locked epoch. At each time-point, CPP slope was estimated as the linear slope of a 300 ms

window centred on that time-point; time-points within 150 ms of the epoch boundaries were excluded as a full 300 ms window could not be constructed. Amplitude at each time-point was taken as the instantaneous signal value.

For RT, we fit linear regression models at each time-point to predict the CPP slope and amplitude values using RT as the predictor, yielding time series of β coefficients. This was carried out separately for each decision type (healthiness, tastiness, willingness to eat). One-sample t-tests were performed to compare the distributions of the resulting β values against 0. To correct for multiple comparisons, we used cluster-based permutation tests (10,000 permutations, cluster-forming threshold: $p < .01$), implemented in the Decision Decoding Toolbox (Bode et al., 2019; Maris & Oostenveld, 2007). Significant clusters were identified as those whose summed t-value exceeded the 97.5^{th} percentile of the permutation-derived null distribution ($\alpha = .05$, two-tailed). For continuous ratings, we calculated the Kendall's rank correlation coefficient (tau-b) at each time-point between the CPP slope and amplitude values and continuous ratings, yielding time series of τ coefficients. This was carried out for Yes and No trials separately for each decision type (healthiness, tastiness, willingness to eat). Correlation coefficients were Fisher transformed and one-sample, single-tailed t-tests were performed to compare whether the distributions of the transformed τ values were above zero (Yes trials) or below zero (No trials). To correct for multiple comparisons, we used cluster-based permutation tests as outlined above.

Bayes factors (BF_{10}) were also computed for each time-point using the BayesFactor toolbox v3.0 (Krekelberg, 2024) using default Cauchy priors (r = 0.707;

Rouder et al., 2017). Bayes factors are reported here solely as a descriptive index showing where evidence supports the presence versus absence of an effect at each time point.

5.4 Results

Participants (N = 110) completed a food categorisation task in which they viewed food images and made speeded binary (Yes/No) choices relating to one of three food attributes (healthiness, tastiness, and willingness to eat; Figure 1A). Participants indicated their choice via keypress with their left or right index finger and EEG was recorded throughout the task. In a separate phase conducted without EEG recording, participants rated each food image on the same three attributes on a continuous sliding scale, with 0 indicating "Not at all" and 100 indicating "Very much" (Figure 1B).

We first assessed whether categorisation task performance was associated with the subjective continuous attribute ratings. Participants responded faster for foods with higher ratings (closer to "Very much") for Yes trials (healthiness: mean τ = -.21, SD = .13, $t(109) = -17.32$, $p < .001$; tastiness: mean τ = -.16, SD = .10, $t(109) = -16.23$, $p < .001$; willingness to eat: mean τ = -.13, SD = .10, $t(109) = -13.55$, $p < .001$) and for foods with lower ratings (closer to "Not at all") for No trials (healthiness: mean τ = .17, SD = .13, $t(108) = 13.54$, $p < .001$; tastiness: mean τ = .01, SD = .09, $t(104) = 15.03$, $p < .001$; willingness to eat: mean τ = .02, SD = .09, $t(105) = 16.83$, $p < .001$) for all three decision types (Figure 1C). These results demonstrate that the ratings reflect stable food evaluations and that the speed of participants' choices reflected the strength of their internal representations for

each attribute, validating our approach of linking retrospectively collected ratings to trial-level neural activity.

5.4.1 CPP Morphology Is Consistent With Evidence Accumulation Dynamics During Dietary Choices

The CPP is defined as an ERP component with a clear parietal locus and a ramping-to-threshold signal morphology. We applied current source density (CSD) transformation, a spatial filtering technique that enhances the spatial resolution of EEG signals (Kayser & Tenke, 2006). This was done to better isolate signals at parietal electrodes and disambiguate them from concurrent EEG signals at more anterior and posterior sites, which can bias CPP waveform measurements (as done by Feuerriegel et al., 2021, 2022; Fong et al., 2026; Kelly et al., 2021; Kelly & O'Connell, 2013; Steinemann et al., 2018). We also applied a signal deconvolution technique (RIDE; Ouyang et al., 2015) to account for effects of stimulus-locked EEG signals (i.e., locked to decision prompt onset) that may temporally overlap with ramping evidence accumulation signals (Fong et al., 2026; Steinemann et al., 2018). Early sensory evoked EEG components may overlap more substantially with signals of interest for trials with faster as compared to slower RTs (Frömer et al., 2024), leading to spurious findings of a ramping-to-bound morphology (but see O'Connell et al., 2025). We used RIDE to isolate the stimulus-locked component of the EEG signal for each decision type separately. We then subtracted this stimulus-locked component from the single trials of EEG data for that decision type to better isolate time-varying, decision-related EEG activity such as ramping evidence accumulation signals.

ERPs at parietal electrode Pz, shown in Figure 2, were highly consistent with a ramping-to-threshold morphology. As visible in Figure 2C, ERP amplitudes immediately prior to the motor response showed a clear parietal positivity for all three decision types, consistent with the observed topography of the CPP in CSD-transformed data (Kelly & O'Connell, 2013; Feuerriegel et al., 2021; Fong et al., 2026).

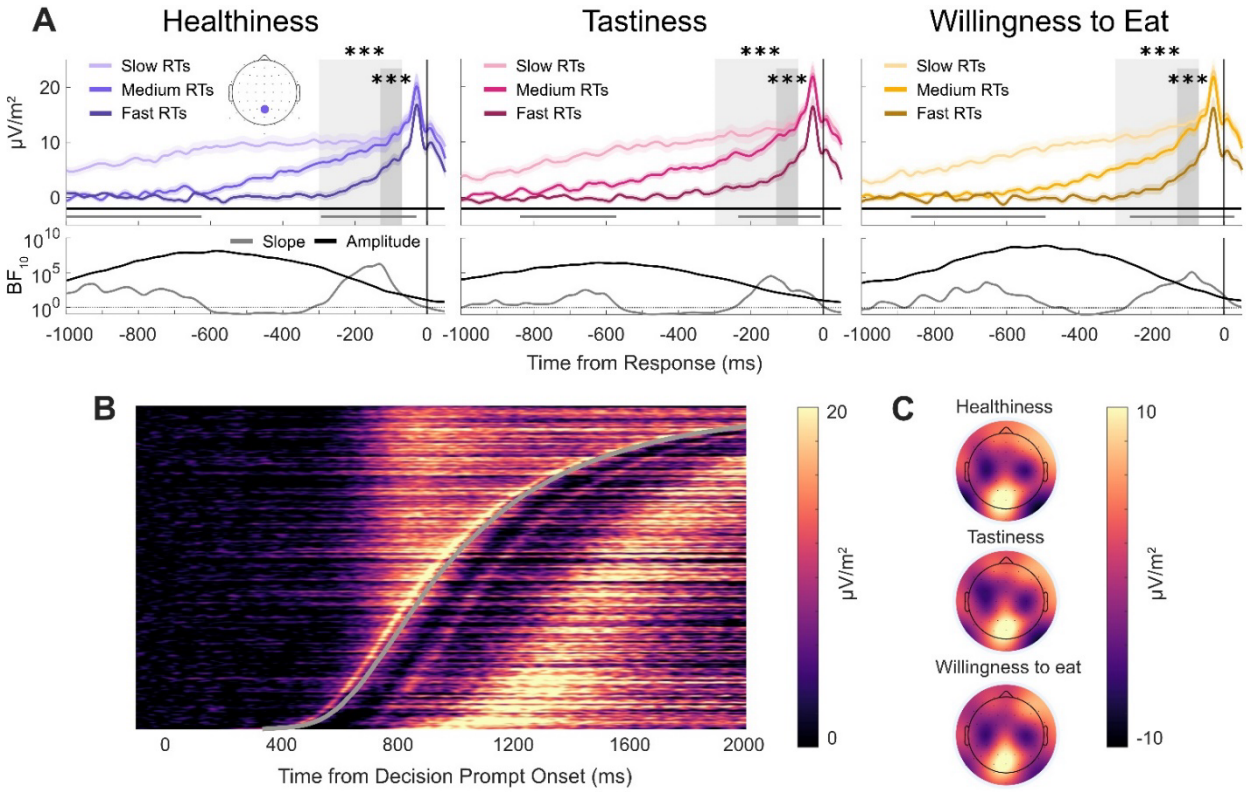

Figure 2. Associations between RT and CPP slope and amplitude for food-related decisions. A) Group-averaged response-locked ERP waveforms for healthiness, tastiness, and willingness to eat decisions, plotted by RT tertile (fast/medium/slow). Shaded areas denote standard errors. Pre-response analysis windows are denoted with light grey shading for slope analyses (−300 ms to −70 ms relative to response onset) and dark grey shading for amplitude analyses (−130 ms to −70 ms). Asterisks indicate statistically significant associations between RT

and CPP slope and amplitude within the respective pre-response windows (*** indicates $p < .001$). Horizontal grey and black lines in the upper plots indicate the time windows with statistically significant associations between RT and CPP slope and amplitude respectively, derived from mass-univariate analyses. In the lower plots, grey and black lines indicate Bayes factors (BFs) at each time point for associations between RT and CPP slope and amplitude respectively. B) Single-trial ERP amplitudes locked to decision prompt onset for all decision types, pooled across all participants and sorted by RT (fast RT below). Data were smoothed over 300 trial bins using a sliding Gaussian-weighted moving average filter. RTs are indicated by the grey line. C) Scalp topographies for healthiness, tastiness, and willingness to eat decisions, averaged across a pre-response analysis window (-130 ms to -70 ms relative to response onset).

Consistent with a ramping evidence accumulation signal, we found that CPP slopes across several hundred milliseconds leading up to the response were steeper for trials with faster decisions. Figure 2A shows the group-averaged response-locked waveforms for the three decision types, split into RT tertiles (fast, medium, and slow) for each participant and averaged across participants. Faster RTs were associated with steeper slopes across all decision types (healthiness: $\beta = -0.02$, $SE = 0.003$, $t(104.55) = -5.68$, $p < .001$; tastiness: $\beta = -0.01$, $SE = 0.003$, $t(102.57) = -3.88$, $p < .001$; willingness to eat: $\beta = -0.01$, $SE = 0.003$, $t(12538.33) = -4.97$, $p < .001$).

Outside of the pre-response analysis window, we found additional evidence for effects of RT on ERP slopes that were consistent with a ramping-to-bound

morphology. We performed mass-univariate analyses to examine associations between CPP slope and RT across the full response-locked epoch. For each decision type, we identified two windows in which RTs were associated with CPP slopes, as denoted by horizontal grey lines in Figure 2A. In the earlier window, slower RTs were associated with steeper CPP slopes, consistent with a ramping evidence accumulation signal starting further back in time from the response in trials with slower decisions (from -1000 ms to -629 ms for healthiness, from -838 ms to -574 ms for tastiness, and from -863 ms to -492 ms for willingness to eat decisions). By contrast, faster RTs were associated with steeper CPP slopes in a later window that overlapped with the pre-response analysis window, extending to around the time of the response (from -295 ms to -29 ms for healthiness, from -235 ms to -8 ms for tastiness, and from -260 ms to +29 ms for willingness to eat decisions).

To further visualise the CPP waveform dynamics, we generated a heatmap of single-trial ERPs locked to decision prompt onset at electrode Pz (Figure 2B). Trials were sorted by RT (faster trials at the bottom) and were pooled across participants. As all decision types showed similar ERP dynamics and comparable pre-response amplitudes, we also pooled data across decision types. Consistent with gradual evidence accumulation towards a decision threshold (Fong et al., 2026; O'Connell et al., 2012), the heatmap reveals that CPP amplitudes build gradually with similar onset latencies across trials, and then converge to comparable amplitudes near the time of the response (curved grey line).

If the CPP traces evidence accumulation to a fixed criterion, pre-response

amplitudes should not substantially vary across RTs, as all decisions terminate at the same threshold regardless of accumulation speed. However, we observed that faster RTs were associated with lower amplitudes consistently across all three decision types. Faster RTs were associated with lower amplitudes for all decision types (healthiness: $\beta = 2.14$, $SE = 0.63$, $t(111.09) = 3.41$, $p < .001$; tastiness: $\beta = 2.85$, $SE = 0.80$, $t(110.83) = 3.57$, $p < .001$; willingness to eat: $\beta = 3.26$, $SE = 0.79$, $t(109.52) = 4.12$, $p < .001$). As visible in Figure 2A, pre-response CPP amplitudes were attenuated in trials with fast RTs, visible as lower amplitudes for the fast RT tertile bin. By comparison, there were no clearly visible differences between the medium RT and the slow RT tertile bins. Plots of amplitudes by RT using finer-grained quantile bins (displayed in Supplementary Figure 1) revealed that amplitudes were lowest for trials with the fastest RTs and gradually increased across quantiles with longer RTs up to 1 s, after which amplitudes appeared to be relatively stable.

Follow-up mass-univariate analyses similarly revealed that faster RTs were associated with lower amplitudes for the full second leading up to the time of response, including the pre-response analysis window, for all three decision types (black horizontal lines in the upper plots in Figure 2A; cluster $p < .001$ for healthiness, tastiness, and willingness to eat decisions). While earlier amplitude differences are expected due to the differences in CPP build-up rates, amplitude modulations immediately prior to the response are not in line with evidence accumulation to a fixed threshold.

We suspected that this amplitude decrement for the fastest trials may be

due to some proportion of choices made prematurely, where computer keys were pressed without a corresponding evidence accumulation process that would be comparable to decisions in slower RT trials. These fast contaminant responses are well-documented in perceptual decision-making research (Ratcliff & Kang, 2021; Ratcliff & Tuerlinckx, 2002) and can arise due to a build-up of preparatory motor activity that precedes the onset of evidence accumulation, also resulting in reduced pre-response CPP amplitudes for very fast RTs (Kelly et al., 2021). We reasoned that if such responses were prevalent in fast RT trials, then there would be a substantially weaker correspondence between the continuous attribute ratings and categorical choices as compared to slower RT trials. This is analogous to observations of low accuracy in perceptual decision tasks for trials with very fast RTs (e.g., Kelly et al., 2021; Ratcliff & Kang, 2021).

To examine this possibility, we calculated differences in continuous attribute rating scores across Yes and No trials for each attribute across faster and slower RT quantiles (shown in Supplementary Figure 2). Large average rating differences between Yes and No trials indicate a high degree of choice consistency. Lower rating differences indicate a higher proportion of random responding, similar to low-accuracy, very fast RT trials in perceptual tasks. On average, we did not observe a substantial drop in continuous rating differences for the fastest RT trials, indicating that such contaminant responses were not prevalent in our data, and that even very fast choices were generally congruent with participants' continuous attribute ratings.

By also performing additional simulation analyses (detailed in

Supplementary Figure 3), we found that the amplitude differences by RT may be attributable to the deconvolution procedure used to isolate the CPP from overlapping stimulus-locked EEG signals. The CPP is a ramping signal that begins a short period after stimulus onset (O'Connell et al., 2025). Consequently, deconvolution procedures such as RIDE may erroneously attribute a portion of the ramping signal to the stimulus-locked component of the data, which is subtracted from single trials of EEG data prior to analyses (for examples of comparable artifacts see Frömer et al., 2024; O'Connell et al., 2025). By simulating stimulus-locked and ramping EEG signals and applying RIDE, we observed this misestimation of stimulus-locked signals.

As the signals captured by the stimulus-locked component fall closer to the time of the response for faster RT trials, the reduction in waveform amplitudes around the time of the response is expected to be greater in those trials. As this attenuation disproportionately affects faster responses, it may artificially generate the observed modulation of pre-response amplitude by RT. This pattern was also visible in our simulations, where amplitudes around the response were disproportionately attenuated for fast RT trials (Supplementary Figure 5). Consistent with this, the RT-amplitude association in our EEG data appears to be mostly driven by a drop in amplitude for the fastest trials (dark coloured lines; Figure 2A) rather than a general, linear difference in amplitude across RTs (similar peaks for medium and lighter coloured lines; Figure 2A). In addition, the time-course of pre-response CPP amplitude decrements observed in our data closely mirrored the amplitude profile of the RIDE-estimated stimulus-locked component

(Supplementary Figure 4).

In summary, while the RIDE deconvolution procedure appeared to recover differences in ramping accumulator signals well, and is required to account for biasing effects of stimulus-locked ERPs, the biases observed in the simulations provide a plausible reason for the amplitude differences in our data.

5.4.2 CPP Build-Up Rates Covary With Continuous Attribute Ratings

We also tested whether the CPP displayed build-up rates that were modulated by subjective attribute values, estimated using the continuous attribute ratings. This approach parallels how stimulus quality is operationalised in perceptual tasks. Just as higher motion coherence in random dot motion tasks provides higher stimulus quality for a direction judgement and produces higher evidence accumulation rates (drift rates; Kelly & O'Connell, 2013), more extreme attribute ratings indicate stronger representations for categorical judgements about a given food and correspondingly higher drift rates. For foods categorised as Yes, higher ratings indicate relatively stronger evidence favouring the Yes response, whereas for foods categorised as No, lower ratings indicate stronger evidence favouring the No response. Ratings further from the participant's subjective category boundary should correspond to higher drift rates and steeper CPP build-up.

Examination of the RT distributions across continuous rating tertiles (Figure 3) revealed patterns consistent with differences in drift rates. The fastest trials (10th RT percentile) did not differ substantially between high, medium, and low continuous ratings. On the other hand, the slowest trials (90th RT percentile)

exhibited the greatest rating-dependent variation. The influence of ratings on RT increased across faster to slower quantiles, consistent with trial-level changes in drift rate (Ratcliff & McKoon, 2008). Stronger representations (indexed by higher ratings for Yes trials and lower ratings for No trials) produce faster evidence accumulation, an effect that compounds over time and becomes most pronounced in the slowest responses within each rating tertile.

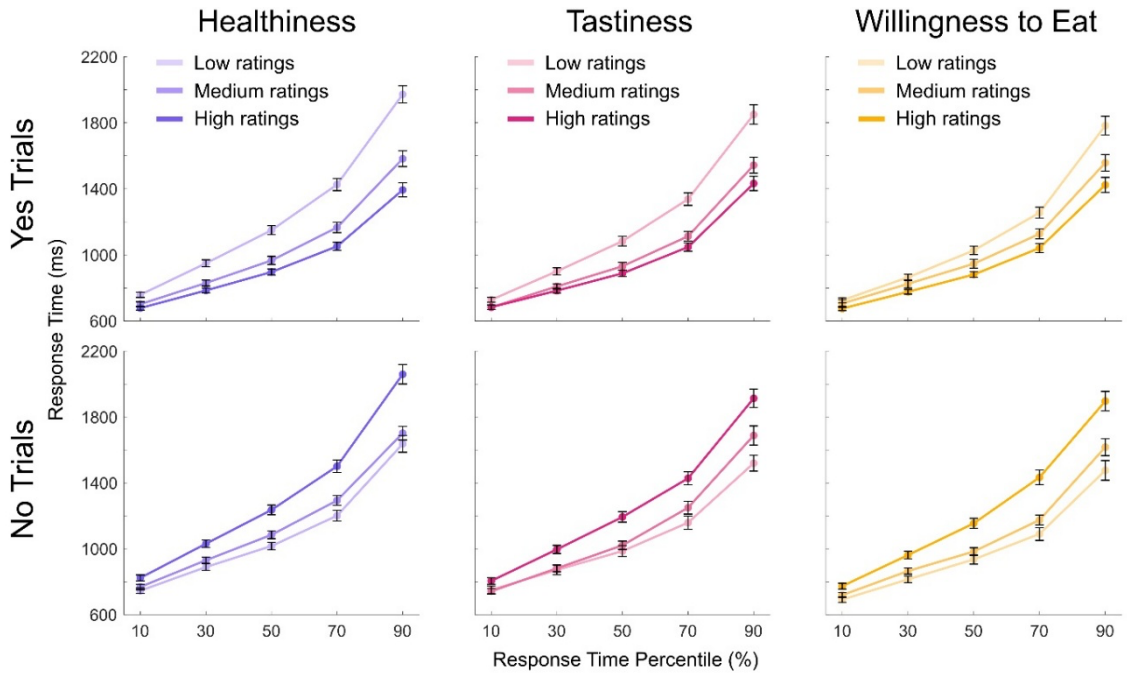

Figure 3. RT distributions stratified by continuous ratings. RT distributions at 10th, 30th, 50th, 70th, and 90th percentiles for continuous rating tertiles (low, medium, and high), for Yes and No trials. Continuous ratings were divided into tertiles for each participant and decision type, then RT percentiles were calculated from the corresponding trial subsets before averaging across participants. Coloured circles represent group mean RTs for each percentile. Black error bars denote standard errors. The increasing separation between rating tertiles from fast to slow RT percentiles reveals that subjective attribute value (indexed by continuous ratings)

has minimal influence on rapid decisions but substantial influence on slower decisions, consistent with drift rate modulation in evidence accumulation models.

Assuming that continuous ratings are correlated with single-trial drift rates, we expected to observe steeper pre-response CPP slopes in trials with higher ratings for Yes trials, and steeper slopes in trials with lower ratings for No trials, for all decision types. Importantly, we expected these associations to be more subtle than those between RT and CPP slope. The CPP is described as tracing the path of evidence accumulation in each trial, which includes both the influence of systematic drift and within-trial decision noise as specified in the DDM. The noise component substantially contributes to RT variability, so that even when drift rates differ on average, there can be substantial overlap in RT distributions and single-trial evidence accumulation profiles across lower and higher drift rate conditions, reflected in the RT percentile plots in Figure 3. In our data, there is high RT variability within each rating tertile but relatively small average RT differences across tertiles (in contrast to Kelly & O'Connell, 2013). In addition, the continuous ratings are unlikely to perfectly correspond to drift rates during the categorisation task due to changes-of-mind or decision noise influencing choices/ratings in each task, and we cannot reasonably assume a linear linking function between rating values and drift rates. Our large sample allowed us to test for these subtle associations using ordinal rank correlation analyses.

Figure 4 shows group-averaged response-locked waveforms for Yes and No trials for the three decision types, split by continuous rating tertile (high, medium, and low) for each participant and averaged across participants. Participants'

ratings were positively correlated with pre-response CPP slopes for Yes trials for all decision types (healthiness: mean τ = .04, *SD* = .09, $t(109) = 4.25$, $p < .001$; tastiness: mean τ = .01, *SD* = .09, $t(109) = 1.71$, $p = .045$; willingness to eat: mean τ = .02, *SD* = .09, $t(109) = 2.94$, $p = .002$). As expected, these associations were more subtle than those between CPP slope and RT, as visible in Figure 4. Ratings were negatively correlated with CPP slopes for No trials for healthiness decisions (mean τ = -.02, *SD* = .13, $t(108) = -1.71$, $p = .045$). However, we did not find clear evidence that ratings were associated with CPP slopes for No trials for tastiness and willingness to eat decisions.

We also performed mass-univariate analyses to test for rank correlations between ratings and CPP slopes across the full response-locked epoch. For the Yes trials in healthiness and willingness to eat decisions, ratings were significantly correlated with CPP slopes in a window that overlapped with the pre-response analysis window, as denoted by horizontal grey lines in the upper plots (healthiness: from -231 ms to +49 ms, willingness to eat: -278 ms to +25 ms; Figure 4). Within these windows, ratings were positively correlated with CPP slopes, indicating that stronger representations were associated with steeper slopes.

The less consistent slope effects for No trials compared to Yes trials may partly arise from reduced measurement precision due to relatively fewer observed No responses. Across participants, Yes responses were more frequent than No responses for all three decision types, with the discrepancy being more pronounced for tastiness (Yes trials: mean number of trials = 75, *SD* = 13, range = 37-102; No trials: mean = 38, *SD* = 13, range = 2-73) and willingness to eat

decisions (Yes trials: mean = 73, *SD* = 13, range = 40-100; No trials: mean = 41, *SD* = 14, range = 5-73). By comparison, healthiness decisions were more balanced between Yes and No responses (Yes trials: mean = 62, *SD* = 62, range = 44-93; No trials: mean = 52, *SD* = 10, range = 19-72). The rating-dependent slope effects for No trials in tastiness and willingness to eat decisions should therefore be interpreted with caution, as reduced trial counts in these conditions would attenuate our ability to detect effects of comparable magnitude to those observed for Yes trials. Consistent with this interpretation, we found a statistically significant negative correlation between continuous ratings and CPP slope for No trials in healthiness decisions within the pre-response analysis window.

We did not find evidence that pre-response CPP amplitudes were associated with subjective attribute values, consistent with an evidence accumulation trajectory to a fixed decision threshold. We did not observe statistically significant associations (Kendall's tau-b) between CPP amplitudes in the pre-response window and ratings for any of the three decision types. Mass-univariate results did not reveal any statistically significant clusters of correlations between CPP amplitudes and ratings across the response-locked epoch for all decision types.

We did not find evidence that CPP amplitude was associated with representational strength, consistent with an evidence accumulation trajectory to a fixed decision threshold. We found no statistically significant correlations (Kendall's tau-b) between CPP amplitudes in the established pre-response window and ratings for any of the three decision types. Mass-univariate results revealed no

statistically significant clusters of correlations between CPP amplitudes and ratings across the response-locked epoch for all decision types.

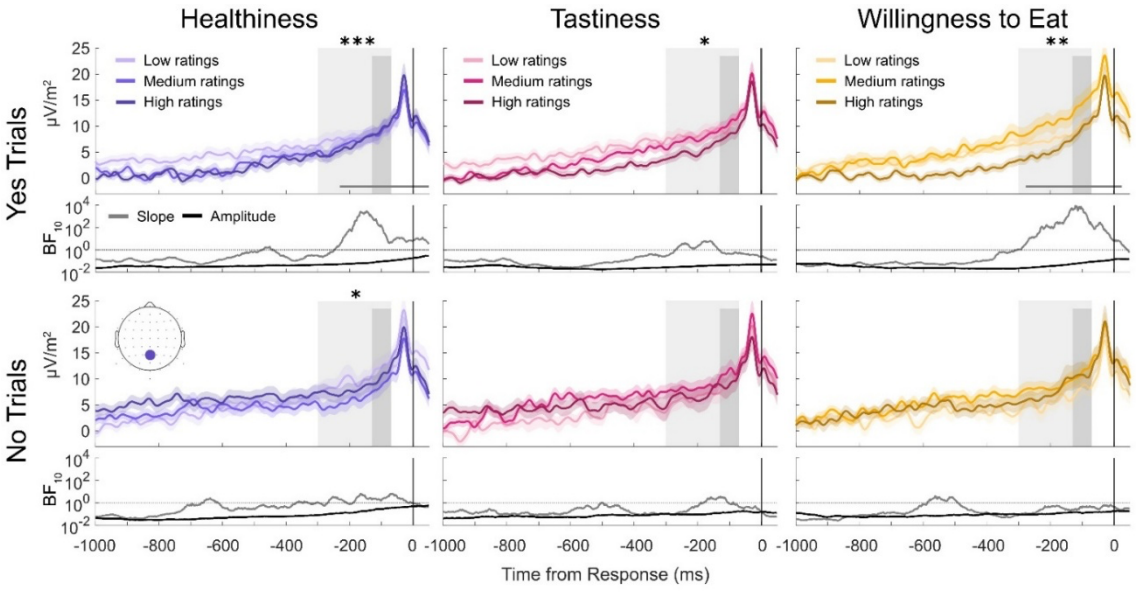

Figure 4. Associations between continuous ratings and CPP slope and amplitude. Group-averaged response-locked ERP waveforms for Yes and No trials in healthiness, tastiness, and willingness to eat decisions, split by attribute rating tertiles. The shaded areas around the plot lines show standard errors of the mean. Pre-response analysis windows are denoted with light grey shading for slope (−300 ms to −70 ms relative to response onset) and dark grey shading for amplitude (−130 ms to −70 ms). Asterisks indicate statistically significant associations between ratings and CPP slope and amplitude within the respective pre-response windows (* indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$). The horizontal grey lines in the upper plots indicate the time windows with statistically significant associations between ratings and CPP slope. In the lower plots, grey and black lines indicate the BF over time for the associations between ratings and CPP slope and amplitude respectively.

5.5 Discussion

The CPP is posited as a neural correlate of evidence accumulation in perceptual decisions, exhibiting two key characteristics: steeper build-up rates that are associated with faster RTs and higher stimulus quality (reflecting higher drift rates) and pre-response amplitudes that remain relatively constant across trials (reflecting a fixed decision boundary). We tested whether this neural signature is also observed during dietary decisions. Our task design also allowed us to disentangle neural correlates of decision formation from those underlying attribute appraisal processes.

In our large (N = 110) sample, we observed steeper pre-response CPP slopes in trials with faster RTs across all three decision types (healthiness, tastiness, and willingness to eat). Although pre-response amplitudes were smaller (i.e., less positive-going) for trials with fast RTs, this appears to be a consequence of our deconvolution method. In addition, we found that patterns of categorical choice RTs differed across lower and higher continuous attribute rating trials in a manner consistent with drift rate changes. CPP slopes were also steeper when ratings more strongly accorded with participants' categorical choices for Yes responses, congruent with changes in drift rate. We did not observe evidence that pre-response amplitudes covaried with continuous ratings for any decision type, consistent with a fixed decision boundary. Taken together, our findings provide converging evidence that the CPP traces the path of evidence accumulation during multiple types of dietary decisions.

These findings further support the extension of evidence accumulation

frameworks to investigate the neural processes underlying dietary choice. While substantial research has examined attribute appraisal and subjective value computation (Chae et al., 2026; Hare et al., 2009; Meule et al., 2013; Moerel et al., 2024; Schubert et al., 2021; Toepel et al., 2009), the neural mechanisms that transform these value representations into choices and motor responses have remained largely unexamined. Sequential sampling models provide a computational account of this transformation through noisy evidence accumulation toward a decision boundary in perceptual decisions (Ratcliff & McKoon, 2008; Ratcliff & Smith, 2004), and our findings support the idea that this framework can be extended to a wide range of decision types (Kable & Glimcher, 2009; Shadlen & Shohamy, 2016). Our findings establish that the CPP, a neural marker of evidence accumulation in multiple decision domains (Fong et al., 2026; Pisauro et al., 2017; van Ede & Nobre, 2024), exhibits the same accumulation-to-bound dynamics during dietary decisions.

Previous work has identified neural signatures of evidence accumulation when participants choose between two food items in a value-based comparative judgement task (Pisauro et al., 2017). We make two key extensions to this work. First, we demonstrate that the same accumulation dynamics may underlie decisions about single food items (i.e., choosing whether to eat a specific food). Second, we show that the CPP also traces decision processes for attribute judgements, during which participants evaluate individual foods on healthiness or tastiness rather than making consumption decisions. These extensions are theoretically important, as single-item and attribute-based decisions differ

fundamentally from binary choice tasks. When choosing between two foods (e.g., an avocado versus a tomato), participants compare relative subjective values, potentially considering multiple attributes weighted according to importance depending on the specific options presented. In contrast, single-item willingness-to-eat decisions require comparing a food's subjective value against an internal criterion, which is a structurally different evaluation (e.g., one might choose an avocado over a tomato, yet decline to eat the avocado when it is presented in isolation). Similarly, attribute judgements require evaluating each food on a consistent, specified dimension (healthiness or tastiness) rather than a combination of subjectively important features.

Despite these fundamental differences in decision structure, we found similar accumulation dynamics as reflected in the CPP waveforms across all three decision types. This suggests that the CPP indexes a domain-general evidence accumulation process towards a decision outcome threshold, invariant to whether the evidence constitutes relative comparisons (choice between multiple options), absolute evaluations (single-item choice), or dimension-specific judgements, or whether the source of the evidence is exogenous (sensory) or endogenous (preferences, knowledge, or memory). Our findings support the CPP as a neural correlate of a domain-general decision signal and suggest that diverse forms of decision-relevant information are translated into action via similar processes.

We also demonstrate that isolating neural correlates of evidence accumulation requires careful application of signal processing techniques. We applied CSD transformations to minimise the overlap from concurrent motor

preparation signals (Kelly & O'Connell, 2013) and used a deconvolution algorithm (Ouyang et al., 2015) to account for temporally overlapping stimulus-locked activity. Consequently, our findings address recent challenges to whether the CPP traces evidence accumulation in non-perceptual decisions. Recently, researchers have claimed that deconvolution eliminates the characteristic RT-slope association in value-based tasks (Frömer et al., 2024). However, it was shown that the deconvolution method used in that study was not appropriate for recovering an accumulation-to-bound signal as specified in sequential sampling models, which is neither strictly stimulus-locked nor response-locked but ramps from stimulus onset until just prior to the response (for further discussion see O'Connell et al., 2025). We therefore used an algorithm that allowed us to identify stimulus-locked activity and subtract this to better isolate such ramping activity (Ouyang et al., 2015).

While this method was better suited for recovering a signal that traces evidence accumulation, our simulation analyses revealed that this approach can introduce a different artifact (see Supplementary Figure 3). As the onset of the ramping CPP component is aligned to stimulus onset, some amplitude variation attributable to the CPP can be misattributed to stimulus-locked activity and subtracted during deconvolution. This attenuation is greater for faster trials, as stimulus- and response-locked components overlap more closely in time, leading to a spurious amplitude-RT effect. This artifact may have obscured the fixed pre-response amplitude predicted by evidence accumulation models. Note that this artifact produces *lower* pre-response amplitudes for faster trials, which is the

opposite pattern to the pre-deconvolution findings in the study by Frömer et al. (2024). It is also the opposite of what would be predicted by an account involving urgency signals or collapsing decision boundaries (Steinemann et al., 2018; Kelly et al., 2021), which anticipate higher, not lower, pre-response amplitude for faster trials. We consider this a necessary trade-off, as failing to adequately control for stimulus-locked activity risks misattributing overlap effects to accumulation processes, a more fundamental confound than the small amplitude artifact introduced by our deconvolution method. Importantly, we found that the CPP slope was modulated by both RT and continuous attribute ratings after deconvolution, which aligns with predictions of evidence accumulation models and provides support for accumulation processes in dietary decisions despite the amplitude artifact. Future work may develop deconvolution techniques that can better isolate accumulation signals while minimising artifactual amplitude modulation.

Our study used continuous ratings as a measure of subjective attribute value and found that ratings covaried with CPP slopes in Yes choice trials in a manner consistent with predictions of evidence accumulation models. This extends previous work demonstrating similar associations in other decision domains. In perceptual decision tasks, stimulus quality has been shown to modulate CPP slope (Feuerriegel et al., 2021; Kelly & O'Connell, 2013; Twomey et al., 2015), while in binary food choices, steeper CPP slopes have been associated with larger estimated value differences between options (Pisauro et al., 2017). Larger perceptual discriminability or value differences indicate higher quality of

evidence favouring one option over another in these tasks. We demonstrate that continuous ratings provide a comparable index of subjective attribute value for single-item willingness-to-eat decisions and attribute judgements. Higher ratings for Yes responses and lower ratings for No responses indicate evaluations that are further from one's subjective categorical boundary, corresponding to stronger representations analogous to higher discriminability in perceptual tasks, whereas middling ratings near the boundary are more ambiguous and reflect weaker evidence.

Consistent with drift rate modulations in evidence accumulation models, CPP build-up rates scaled systematically with subjective attribute value for Yes trials, with steeper slopes for trials with higher ratings. On the other hand, slope modulation by subjective attribute value for No trials was less consistent, with effects only observed in the specified pre-response analysis window for healthiness decisions. This may partly reflect differences in statistical power arising from an imbalance in trial counts between Yes and No responses for tastiness and willingness to eat decisions, potentially due to participants' general tendency to rate foods positively on these dimensions. The lack of clear evidence for slope effects for the No trials in tastiness and willingness to eat trials should therefore be interpreted cautiously, as reduced trial counts would attenuate our ability to detect effects. Future work may ensure more balanced response distributions to provide sufficient measurement precision (e.g., through careful curation of stimuli). Nevertheless, our finding that CPP slope showed weaker associations with continuous ratings than with RT aligns with predictions from

evidence accumulation models.

While drift rate, which we assumed would be higher for subjective attribute values more strongly in favour of one's choice (Polanía et al., 2014), determines the average rate of accumulation, the evidence accumulation trajectory on any given trial is substantially influenced by within-trial decision noise in the DDM. Single-trial RTs reflect this trial-by-trial variability in both drift rate and noise, whereas continuous ratings index only the systematic drift component. Similar to our results, Pisauro et al. (2017) found that CPP slope modulation by RT was greater than modulation by stimulus value differences. More generally, the relative magnitudes of RT and subjective attribute value associations will depend on the spread of RTs within each condition or subset of trials, compared to the average RT differences between them.

Our findings provide a solid foundation for future joint modelling approaches to formally quantify relationships between CPP dynamics and drift rate by simultaneously fitting behavioural and neural data (Bridwell et al., 2018; Palestro et al., 2018; Sun et al., 2025; Turner et al., 2019). Although a joint modelling venture is beyond the scope of the current study, our finding that CPP slope is modulated by RT and subjective attribute value in theoretically predicted ways forms a strong basis for formally establishing a model linking CPP build-up rates to drift rate parameters. Establishing this neural correlate will enable researchers to develop more comprehensive mechanistic accounts of how subjective value signals or attribute information are converted into action outcomes during dietary decisions.

Our analysis framework can also be applied to investigate how individual differences and contextual factors interact with the underlying computational processes driving food choice. For example, researchers may examine whether individual differences in food preferences, eating motivations, dieting status, or physiological state (e.g., hunger), or the effect of contextual manipulations (e.g., social settings, dietary interventions, or priming) manifest as changes in specific parameters of the DDM. If an intervention alters RT distributions or between-group differences in RTs are observed, joint models incorporating neural measurements can reveal which model parameters correspond to these changes (De Hollander et al., 2016; Turner et al., 2019). For example, changes in drift rate may reflect differences in stimulus quality, subjective attribute value, or attention, while differences in threshold and starting point may indicate differences in caution or response bias (Voss et al., 2004). Computational modelling of choice and RT data can clarify which parameters are affected, and incorporating neural measures provides the mechanistic link, revealing how these computational processes may be implemented by the brain. Explicitly considering evidence accumulation dynamics also affords new perspectives on patterns of speeded dietary choices. The influence of within-trial noise during evidence accumulation is expected to produce a wide range of RTs even for the same food item, meaning that the associations between single-trial RTs and subjective food item evaluations (drift rates) may be weak. Inconsistency across choices made at different times may also reflect the influence of within-trial decision noise rather than true changes in underlying choice preferences.

In conclusion, we demonstrate that the CPP exhibits signatures of evidence accumulation during multiple types of dietary decisions, with CPP build-up rate scaling with RT and subjective attribute value. Our findings indicate that diverse sources of decision-relevant information, from perceptual features to subjective attribute evaluations, are translated into action via shared accumulation mechanisms during dietary decision-making, where this accumulation trajectory is indexed by the morphology of the CPP.

5.6 Data and Code Availability Statement

Data processing and analysis code will be available via the Open Science Framework (https://osf.io/j247x/) at the time of publication. The raw and processed continuous EEG data are available via OpenNeuro (https://doi.org/10.18112/openneuro.ds007012.v1.1.1). For more detail on this experiment and EEG data, see the dataset descriptor paper (Chae et al., 2025).

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5.8 Supplementary Material 1

To evaluate whether the observed associations between centroparietal positivity (CPP) pre-response amplitude measures and response times (RTs) may have been an artifact of our deconvolution procedure, we conducted a simulation analysis in which the ground-truth signal was fully known. Similar to simulations of the CPP component by O'Connell et al. (2025), we generated simulated data containing a signal that ramps from a fixed latency after stimulus onset and peaks at a fixed amplitude at the time of response. We assessed whether the Residue Iteration Decomposition (RIDE) algorithm (Ouyang et al., 2015) systematically underestimates the peak amplitude of the ramping signal for fast RT trials under simulated conditions that are similar to our own dataset.

We generated 2,000 trials of simulated EEG data for a single channel. Each trial consisted of a 3,500 ms epoch (1,000 Hz sample rate) containing two additive signal components. The stimulus-locked component (Supplementary Figure 1B) consisted of a Gaussian-shaped waveform peaking at 500 ms from stimulus onset (peak amplitude = 5 amplitude units, SD = 150 ms). This simulated signal is comparable to the estimated S component waveform at electrode Pz derived from RIDE in the main analyses (Supplementary Figure 2). A ramping component (Supplementary Figure 1B) consisted of a linearly increasing signal beginning at 500 ms from stimulus onset that rose until the time of the response (peak amplitude = 10 amplitude units). Following the response, the signal linearly decreased back to zero over a fixed 200 ms ramp-down period, mimicking the typical morphology of the CPP component. Please note that this simulated

ramping signal cannot be cleanly categorised as either stimulus- or response-locked. Supplementary Figure 1E displays the trial-averaged combined signal with both components and Supplementary Figure 1A shows examples of the combined signal from individual simulated trials.

Trial-by-trial RTs were drawn from a gamma distribution (shape parameter = 5, scale = 200 ms, offset = 620 ms) to approximate the right-skewed RT distribution in our data (Supplementary Figure 1F). As the ramping component had a consistent peak amplitude at the time of the response irrespective of RT, the slope of the ramping signal covaried with RT. Steeper slopes occurred in simulated trials with faster RTs, as visible in plots of the ramping component that are time-locked to the response (Supplementary Figure 3A).

The RIDE algorithm was applied to the simulated data to isolate three components: a stimulus-locked (S) component estimated from 1 to 1000 ms relative to stimulus onset, a response-locked (R) component estimated from −600 to 100 ms relative to response onset, and a time-varying (C) component estimated from 500 to 2000 ms relative to stimulus onset. Deconvolution algorithm settings were comparable to what was used for our EEG analyses.

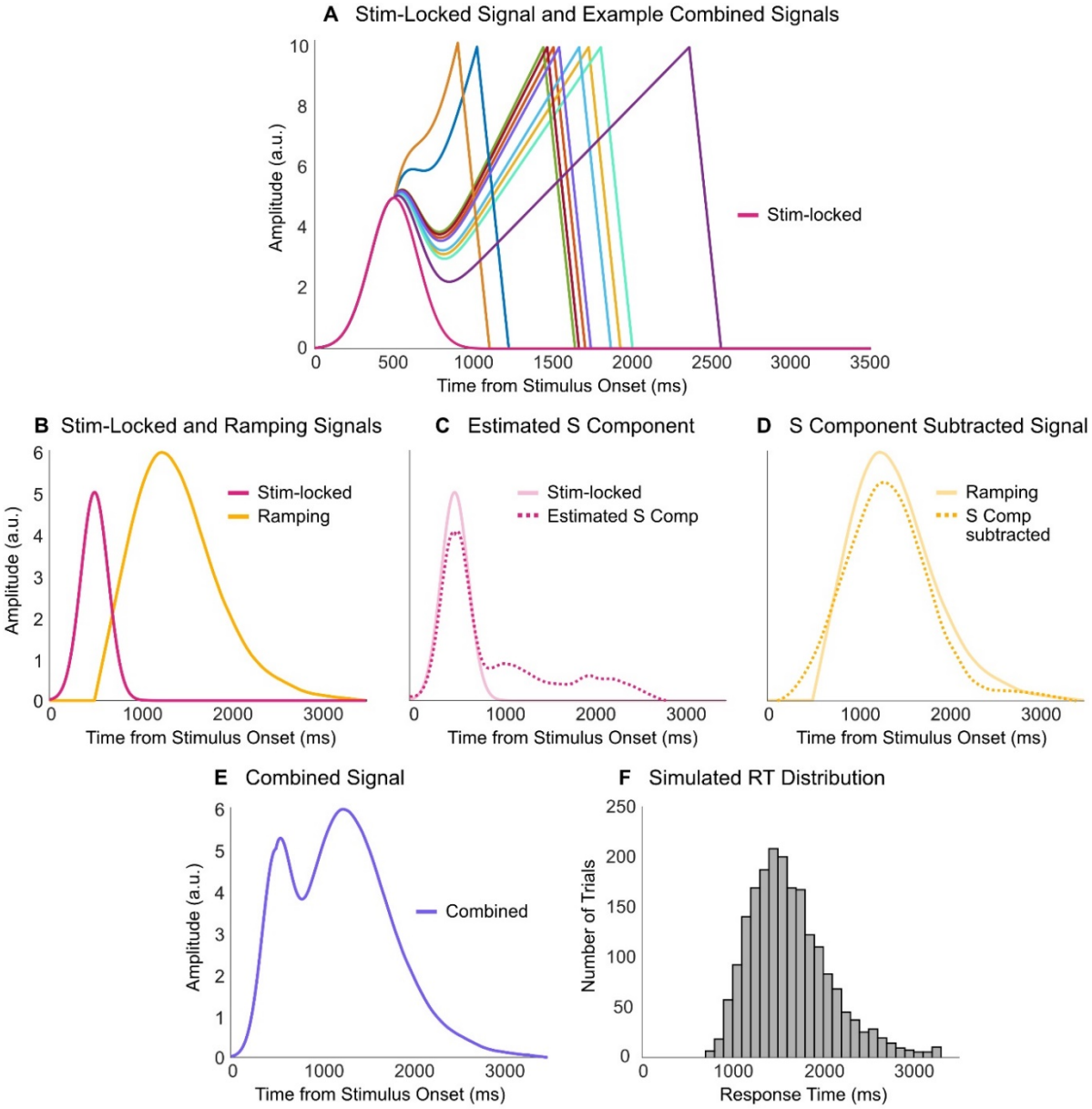
We observed that simulated EEG signals originating from ramping activity were partly misattributed to the S component when RIDE was applied. As visible in Supplementary Figure 1C, the estimated S component captured most of the stimulus-locked signal but additionally included a portion of the ramping signals that occurred outside of the stimulus-locked signal time window. Next, we subtracted the estimated S component from each trial of simulated data to

recover the ramping signal (Supplementary Figure 1D). Following S component subtraction, data were realigned to the time of the response. The response-locked recovered ramping signal was then compared to the ground-truth ramping signal (Supplementary Figure 3).

We observed an attenuation of ramping signal amplitude that was most pronounced around the time of the response for trials with fast RTs. Amplitude for the fast RT trials was attenuated to a greater degree compared to the medium and slow RT trials in the recovered ramping signal, despite the amplitude at the time of the response being fixed across faster and slower RT trials in the originally simulated ramping signals (Supplementary Figure 3). This attenuation arises because the signals associated with the early portion of the ramp, which begins at a fixed latency post-stimulus, is somewhat consistent in time relative to stimulus onset. Consequently, some of this signal is erroneously attributed to the estimated S component when applying the RIDE algorithm. As fast RT trials have shorter intervals between stimulus onset and the response, the amplitude reduction after S component subtraction near the time of the response is consequently larger compared to trials with medium and slow RT trials. For medium and slow RT trials, stimulus onset is temporally more distant from the response, and so the attenuation is smaller or primarily occurs in early time windows relative to the RT. This results in a lower amplitude around the time of the response for fast as compared to slower simulated RT trials.

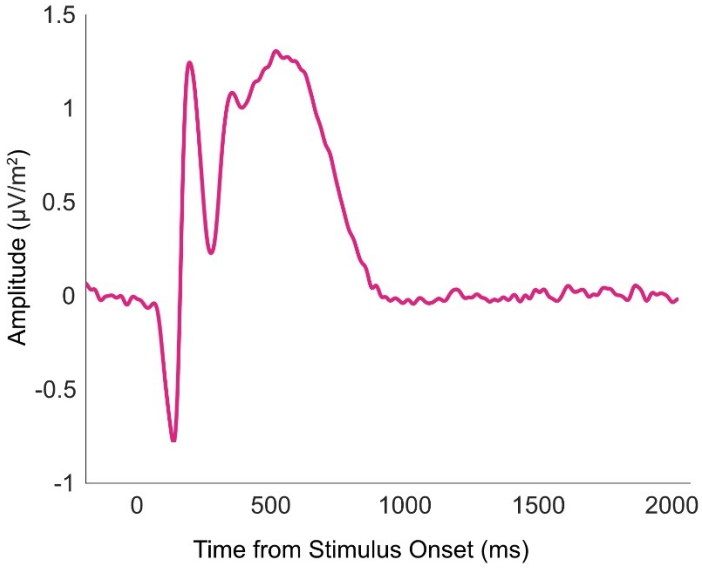
These simulations demonstrate a specific mechanism by which RIDE deconvolution can produce spurious RT-amplitude associations in ramping signals that are consistent with amplitude variation that we observed in our data.

Notably, the slope differences across RT tertiles were still visible in the RIDE S component-subtracted data. This indicates that RIDE is still a useful method for isolating stimulus-locked from latency-varying EEG signals to characterise evidence accumulation dynamics.

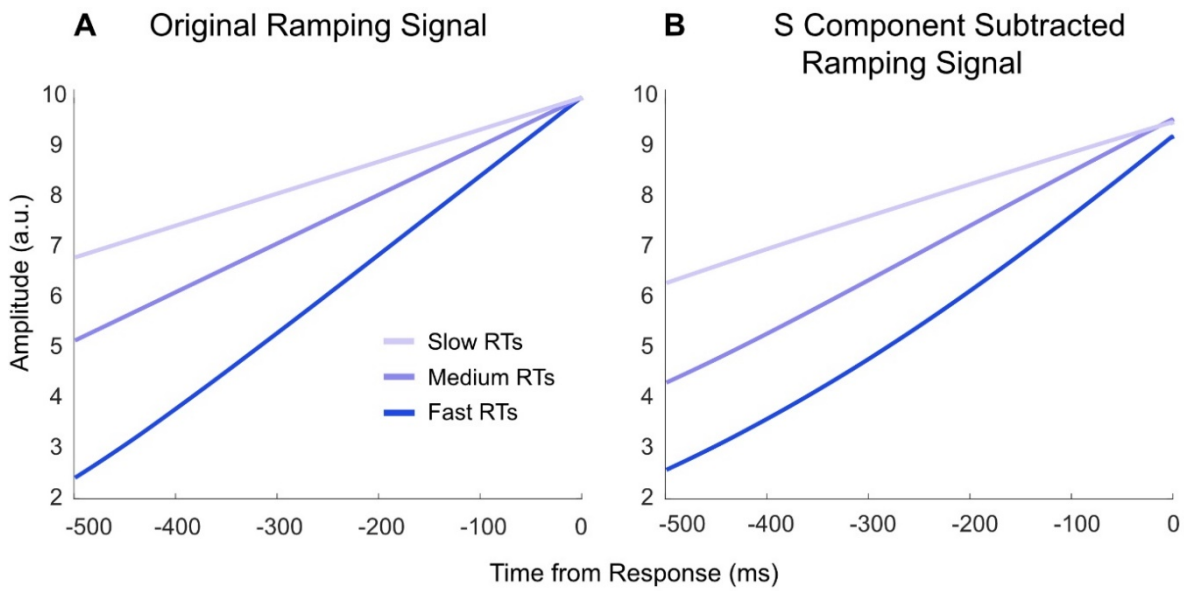


Supplementary Figure 1. Simulation of stimulus-locked and ramping signals and the simulated RT distribution. A) Trial-averaged stimulus-locked signal (solid pink) and 10 examples of the simulated signals (combined signals after adding together the stimulus-locked and ramping signals). B) Trial-averaged plots of the stimulus-locked signal (solid pink; a Gaussian-shaped waveform peaking at 500 ms from stimulus onset) and ramping signal (solid yellow; a linearly increasing signal beginning at 500 ms from stimulus onset and rising until the time of the response to a fixed amplitude). C) Estimated S component after running RIDE

deconvolution (dotted pink). Most of the ground-truth stimulus-locked signal (solid light pink) is captured by this component, but some of the ramping signal is also erroneously captured. D) S component-subtracted signal (dotted yellow) mostly captures the ramping signal (solid light yellow). E) Trial-averaged combined signal after adding together the stimulus-locked and ramping signals. F) Simulated RT distribution with a right skew.



Supplementary Figure 2. RIDE-derived group-averaged S (stimulus-locked) component waveform at electrode Pz. The estimated S component captures ERP waveform contributions strictly time-locked to stimulus onset.



Supplementary Figure 3. Effect of the RIDE deconvolution procedure on the ramping signal. A) Original ramping signals averaged over trials within fast, medium and slower RT tertile bins. B) S component subtracted data time-locked to the response. The RIDE deconvolution visibly attenuates the amplitude at the time of the response for the fast relative to medium and slow RT trials, consistent with the patterns of EEG data we observed. The modulation of slope by RT is largely preserved after deconvolution.

5.9 Supplementary Material 2

We fitted linear mixed-effects models (LMMs) using the lme4 package (Bates et al., 2015) to test whether RT predicted CPP slope and amplitude separately for each decision type (healthiness, tastiness, willingness to eat). RT was log-transformed and then z-scored within each participant. We specified a maximal random-effects structure that included participant intercepts and random slopes for the predictor of interest. If the maximal model produced a singular fit or failed to converge, we removed the random slope and retained the random intercept.

Models were compared with and without the fixed effect of RT (i.e., m4 vs m3, or m2 vs m1) using maximum likelihood and Chi-square likelihood-ratio tests with matched random-effects structures across models. Likelihood ratio test statistics are reported in Supplementary Table 1 and regression coefficients are reported in Supplementary Table 2. Models are denoted in lme4 notation as follows:

$$\text{m1: } CPP_{measure} \sim 1 + (1 \mid pID)$$

$$\text{m2: } CPP_{measure} \sim 1 + RT + (1 \mid pID)$$

$$\text{m3: } CPP_{measure} \sim 1 + (1 + RT \mid pID)$$

$$\text{m4: } CPP_{measure} \sim 1 + RT + (1 + RT \mid pID)$$

Supplementary Table 1. Chi-square likelihood ratio tests for group-level model comparisons.

Decision type	CPP measure	Chi-square	df	p	Comparison test	Best model
Healthiness	Slope	48.46	1	<.001	m1 vs m2	m4
		–	–	–	m3 vs m4	
	Amplitude	19.21	1	<.001	m1 vs m2	m4
		11.09	1	<.001	m3 vs m4	
Tastiness	Slope	18.40	1	<.001	m1 vs m2	m4
		14.21	1	<.001	m3 vs m4	
	Amplitude	36.47	1	<.001	m1 vs m2	m4
		12.02	1	<.001	m3 vs m4	
Willingness to eat	Slope	24.72	1	<.001	m1 vs m2	m2
		–	–	–	m3 vs m4	
	Amplitude	48.32	1	<.001	m1 vs m2	m4
		15.76	1	<.001	m3 vs m4	

Note. m1: null model, m2: random intercept model, m3: null random slope model, m4: random slope model. Models denoted in red produced a singular fit and failed to converge. Dashes indicate data were not reported as one or more models in the comparison test failed to converge.

Supplementary Table 2. LMM coefficients for predicting CPP pre-response amplitudes and slopes from RTs.

Decision type	CPP measure	Model	Estimate	SE	t	p
Healthiness	Slope	m2	-0.02	<0.01	-6.97	<.001
		m4	-0.02	<0.01	-5.68	<.001
	Amplitude	m2	2.10	0.48	4.39	<.001
		m4	2.14	0.63	2.41	<.001
Tastiness	Slope	m2	-0.01	<0.01	-4.29	<.001
		m4	-0.01	<0.01	-3.88	<.001
	Amplitude	m2	2.89	0.48	6.05	<.001
		m4	2.85	0.80	3.57	<.001
Willingness to eat	Slope	m2	-0.01	<0.01	-4.97	<.001
		m4	–	–	–	–
	Amplitude	m2	3.30	0.47	6.96	<.001
		m4	3.26	0.79	4.12	<.001

Note. m2: random intercept model, m4: random slope model. Models denoted in red produced a singular fit and failed to converge. Dashes indicate data were not reported as the model failed to converge.

Chapter 6: General Discussion

6.1 Summary of Thesis Chapters

This thesis makes two complementary contributions to our understanding of dietary decision-making. The first is an empirical contribution, advancing our knowledge of the neural and computational mechanisms that underlie food decisions. The findings reported in this thesis provide novel insights about the valuation phase, during which decision-relevant attributes of foods are appraised and represented in the brain (Chapter 4), and the choice phase, during which these representations are converted into an action outcome (Chapter 5). We also make a methodological contribution through the presentation of the FOODEEG dataset (Chapter 3), a large-scale, open-access resource containing neural and behavioural data collected during food cognition tasks accompanied by normative ratings on 22 food attributes, which can support a wide range of future research on food-related neurocognitive processes. In the sections that follow, I summarise the key findings from each empirical study and their implications, before considering what they reveal in combination regarding the broader architecture of dietary decision-making. Following this, I discuss potential limitations across the empirical studies and avenues for future research.

6.1.1 Rapid, Parallel, and Multilevel Representations of Food Attributes

Chapter 4 examined the structure and time-courses of food attribute representations in the brain during food appraisal. Using representational similarity analysis (RSA), we characterised the neural time-courses of food attributes spanning nutritive properties, hedonic properties, and familiarity –

moving well beyond healthiness, tastiness, and calorie content that have been the focus of prior work (Duraisingam et al., 2021; Harris et al., 2013; Lim et al., 2018; Meule et al., 2013; N. Sullivan et al., 2015; Toepel et al., 2009). We used normative ratings that capture population-level food attribute judgements, rather than participant-specific representations. Our approach of correlating attribute models derived from these normative ratings with individual participants' neural signals assumes that these shared food attribute judgements are also represented in individual participants' neural activity. This is a common approach in work using RSA (e.g., Cichy et al., 2019; Moerel et al., 2024), wherein models are typically instantiated using group-level rather than individual participants' ratings as the latter are difficult to obtain reliably at the item level within a single session. The strong correlations between the ratings obtained from the online and electroencephalography (EEG) samples indicate that these normative estimates are stable and reproducible across samples. However, the attribute time-courses should be interpreted as reflecting population-level food judgements and deviations from these in the individual participant's representations may not be captured by this approach. Most attributes were represented rapidly and in parallel, with a characteristic early peak around 200 ms after image onset and a sustained later window from approximately 400 to 650 ms onwards. Notably, healthiness was represented as early as, or earlier than, tastiness, contrary to the longstanding idea in the field that more immediately relevant or basic attributes are processed more quickly than more abstract attributes relevant in the long-term (Hofmann et al., 2009; N. Sullivan et al., 2015). Taking a data-driven approach to

address the substantial intercorrelation among food attributes, we applied principal component analysis (PCA) and identified two broad underlying dimensions (how appetising and how processed the food is) that explained the majority of the variance among individual attributes. The two broad dimensions were also represented in neural activity with distinct temporal profiles, pointing to a multilevel representational structure. We further revealed that six individual attributes had unique contributions to the neural signals over and above the shared variance, most notably recognisability and level of transformation, which may indicate that these two aspects are particularly salient. Together, we revealed that food appraisal is a rapid, parallel process in which a rich diversity of choice-relevant features is encoded simultaneously and at multiple levels within the first second of viewing a visual food cue.

6.1.2 Domain-General Evidence Accumulation Drives Food Choice

In Chapter 5, we investigated how endogenous value representations are converted into an action outcome during dietary decision-making. We aimed to determine whether a neural correlate of evidence accumulation, a process well-established in perceptual decision-making (Kelly & O'Connell, 2013; O'Connell et al., 2012), could also be identified during the choice phase of dietary decisions. Using a task designed to temporally separate attribute appraisal from choice execution, we found that the centroparietal positivity (CPP) exhibited the hallmark signatures of evidence accumulation across three types of dietary decisions, including steeper pre-response CPP slopes for trials with faster response times (RTs) and stronger representations and a relatively fixed pre-response amplitude

across RTs and representational strength estimates (Feuerriegel et al., 2021; O'Connell et al., 2012; Twomey et al., 2015). Critically, we applied signal deconvolution methods (Ouyang et al., 2015) to address concerns that CPP slope modulations observed in similar value-based decision tasks may arise artifactually from overlapping stimulus- and response-locked activity (Frömer et al., 2024). These findings extend the evidence accumulation framework beyond binary food choices (Pisauro et al., 2017) to single-item evaluations and dimension-specific attribute judgements, and beyond perceptual decisions informed by sensory input to decisions that substantively draw from endogenous or mnemonic sources of information, supporting the view that evidence accumulation is a domain-general decision mechanism. We also demonstrate that continuous ratings are a valid proxy for representational strength, modulating CPP slopes in a way that aligns with predictions from sequential sampling models. Characterising the choice process in dietary decisions in this way reframes inconsistencies in people's dietary choices as a consequence of the stochastic noise arising during the accumulation of evidence toward a decision threshold, rather than changes in underlying preferences or self-control failures (Cosme et al., 2019). This represents a mechanistically distinct account of choice inconsistency from that offered by weighted additive models commonly used to characterise food choice (Keeney et al., 1976; Payne et al., 1993), which compute choice as a weighted sum of attribute values without an explicit account of moment-to-moment noise in the underlying decision process.

6.2 General Implications

6.2.1 Building a Process Model of Dietary Decisions

We adopted a cognitivist lens to examine the processes underlying dietary decisions across the empirical chapters (Chapters 4 and 5), approaching food choice as processes to be characterised mechanistically rather than outcomes to be evaluated normatively. As outlined in Chapter 1, much of the existing research on food choice has implicit assumptions about how people *should* eat, rooted in the medical model of nutrition, longstanding cultural anxieties around dietary restraint, and the widespread conflation of body size and health (Coveney, 2006; Crotty, 1995). By contrast, the research in the current thesis does not begin from the premise that there is a universally correct way to choose foods, and instead we characterised the processes involved in how people represent food attributes (Chapter 4) and convert these value representations into a decision outcome (Chapter 5), regardless of individual goals or priorities.

Going beyond the normative assumptions allowed us to explore a broader range of attributes and discover how and when they are represented by the brain. By not presupposing that healthiness and tastiness are the main drivers of dietary decisions (Hare et al., 2009; Harris et al., 2013; Lim et al., 2018; N. Sullivan et al., 2015), we found that previous exposure, recognisability, typicality, level of transformation, edibility, valence, and emotional arousal are also rapidly and automatically represented in the neural activity during early food viewing (Chapter 4). We were able to reveal a richness and complexity in food appraisal that may be flattened by frameworks that solely focus on the trade-off between healthiness

and tastiness. The similarity in the neural time-courses of many different attributes suggests that healthiness and tastiness are not necessarily more salient than the other attributes. These findings complement our characterisation of the choice phase as an evidence accumulation process as described by sequential sampling models (Chapter 5) that allows for the consideration of multiple attributes to compute an action outcome, rather than competition between a few. While we included a relatively broad range of attributes here compared to much existing work, future researchers may investigate the neural representations of other choice-relevant attributes not considered here (e.g., ethical concerns, price, convenience). The open dataset (Chapter 3) includes rating data on taste-related attributes (e.g., sweetness, savouriness, saltiness) and emotion-related attributes (e.g., disgust, happiness, guilt), providing users with the resources to extend the present findings by characterising the neural time-courses of these as yet unexplored dimensions of food appraisal.

A further advantage of this process-focused approach is that the mechanisms we uncovered are not specific to any particular dietary goal, cultural context, or population subgroup. Because we did not impose assumptions about the "correct" way to choose foods, the attribute appraisal (Chapter 4) and evidence accumulation (Chapter 5) processes we characterised pertain to the shared neural and computational mechanisms underlying dietary decisions more generally. Delineating these processes in a sample without eating disorders provides a general framework from which differences can be identified and interpreted. We demonstrated that a shared evidence accumulation process may

underlie dietary decisions with different structures and decision criteria (attribute judgements and willingness-to-eat choices; Chapter 5). Future research can examine how cultural background (Chen & Antonelli, 2020; Djekic et al., 2021), individual differences in food motivation (Renner et al., 2012; Steptoe et al., 1995) or inhibitory control (McGreen et al., 2023), and contextual factors (e.g., priming, hunger, urgency, or social influence; Chen & Antonelli, 2020; Cruwys et al., 2015) may impact the valuation and choice processes in food decisions using our analysis framework. Distinguishing where in the decision process a given factor exerts its influence is important for building a coherent mechanistic account of how people choose what they eat.

Adopting a cognitivist lens to develop a process model of dietary decisions is also compatible with the goals of health-oriented research. Gaining a thorough understanding of the processes underlying dietary decisions is the prerequisite to developing strategies and interventions that help people make food choices to meet their individual dietary goals (Renner et al., 2012; Steptoe et al., 1995), which may include eating for health or for weight loss. The FOODEEG dataset includes measures of food-related inhibitory control, eating styles, and food motivations, and future researchers interested in clinical and public health applications may examine these individual differences in relation to the precisely characterised neural and computational processes.

6.2.2 Implications for the Dual-Process Model of Dietary Decisions

The dual-process account of dietary self-control that frames food choice as a competition between an automatic and rapid response driven by palatability and

a slower, effortful evaluation of healthiness has long been influential in the field (Cosme et al., 2019; Hare et al., 2009; Hutcherson et al., 2012). The findings of the current thesis raise challenges to this model on two fronts.

Firstly, our findings provide support for an alternative account of how these attribute representations may inform choice that does not involve competition between dual systems (Chapter 5). We demonstrate that the conversion of food evaluation into action may follow a continuous, stochastic accumulation of evidence until a decision outcome boundary is reached, a domain-general process that underlies many different kinds of decisions beyond dietary choices (Feuerriegel et al., 2021; Fong et al., 2026; O'Connell et al., 2012; Pisauro et al., 2017; van Ede & Nobre, 2024). Framed this way, inconsistencies in the way people make dietary decisions (e.g., at times choosing the healthy but less tasty food and at other times choosing the reverse; Köster, 2003) may partially be accounted for by the noise in the decision process, rather than reflecting a success or failure in willpower or self-control as posited by dual-process models (Cosme et al., 2019; Hofmann et al., 2009).

Secondly, the neural time-courses of attribute representations we uncovered (Chapter 4) are at odds with a dual-process model that reserves rapid, automatic processing for palatability-relevant attributes and longer processing times for health-relevant attributes (Hofmann et al., 2009; N. Sullivan et al., 2015). In line with previous neural decoding work (Schubert, Rosenblatt, et al., 2021), we found that healthiness was represented earlier than tastiness in the neural signals, which contradicts the predictions from the dual-process account (N. Sullivan et

al., 2015). Furthermore, we demonstrate that a broad range of food attributes, beyond only healthiness and tastiness, are represented in the neural activity in parallel and with overlapping time-courses. While we cannot directly infer which attributes are used in the subsequent choice phase, these findings are compatible with a dietary decision process that takes multiple and varied attributes into account (Cosme et al., 2019; Hutcherson & Tusche, 2022). Our findings also challenge the categorisation of attributes into basic and abstract or immediate or long-term relevance (Hare, Malmaud, et al., 2011; Liberman & Trope, 2008; Rangel, 2013; Schubert, Rosenblatt, et al., 2021; N. Sullivan et al., 2015). Many choice-relevant attributes (e.g., level of processing, typicality, recognisability, valence) are represented in the early neural signals but do not fit neatly into categorisations according to short- or long-term relevance or level of abstraction. The highly covarying structure between individual attributes also makes it difficult to draw clean distinctions between these categories that the dual-process view posits are processed by separate, competing systems.

Our data-driven approach of identifying the broad underlying dimensions that capture most of the variance across the individual attributes lends some support for the specific attributes emphasised in the dual-process model. We found that most of the variance across our 12 food attributes was explained by two components which appeared to reflect how appetising and how processed the food is, and these components were also correlated with early neural activity with distinct time-courses. We note, however, that the labels assigned to the dimensions were determined by examining how the food images were distributed

along that dimension and are open to subjective interpretation. For instance, the second principal component could be characterised as reflecting unhealthiness or calorie content, given comparable absolute loadings for these attributes. Interpreted in this way, the two dimensions may broadly capture the tastiness and healthiness of foods respectively, revealing that these may indeed be the two most salient aspects of foods during choice.

The dual-process model carries the assumption that health-relevant attributes are necessarily effortful and demanding to process (Hare, Malmaud, et al., 2011; Hofmann et al., 2009; N. Sullivan et al., 2015), but this is likely context- and individual-dependent. For individuals who find healthier foods intrinsically appealing, or for whom health motivations are strongly internalised, considering health-related attributes may require little deliberate effort. A process model grounded in evidence accumulation (Cosme et al., 2019; Hutcherson & Tusche, 2022) accommodates these individual differences, and future researchers may consider characterising these differences through formal modelling (e.g., allowing attribute weightings to vary across individuals and contexts).

6.2.3 Implications for Models of Multiattribute Choice

Behavioural work has found that simple heuristics relying on only a limited set of attributes can predict food choices as accurately as, or even better than, the classical weighted additive model that takes all relevant attributes and their respective weightings into account (Scheibehenne et al., 2007; Schulte-Mecklenbeck et al., 2013). These findings have been taken as evidence that there is a limit to the number of attributes people can appraise during multiattribute

decisions, due to constraints on time, motivation, or cognitive resources. However, our findings challenge this view.

Firstly, we demonstrate that a broad range of food attributes can be rapidly represented in the neural signals in parallel (Chapter 4). We investigated whether the neural signals contained information about 12 food attributes and found that they were represented in the neural activity within the first second of viewing. Secondly, task-irrelevant attributes were also encoded in the neural activity. Familiarity (previous exposure, recognisability, and typicality), as well as nutritive (level of transformation, calorie content, and edibility) and hedonic attributes (valence, arousal) were encoded in the early neural activity, despite no explicit prompting to consider these attributes during EEG recording. While shared variance with the task-relevant attributes may partially explain these findings, a subset of these attributes (calorie content, level of transformation, negative valence, arousal, and recognisability) also explained unique variance in the neural signals over and above all other attributes. Previous work using passive viewing paradigms with no explicit prompting to consider attributes (including designs involving much shorter viewing durations compared to our task; ~100 ms vs 2 s), has also reported that a rich array of attributes are encoded in the neural activity (Moerel et al., 2024, 2026). These results point to a rapid, automatic, and implicit food appraisal process that is not necessarily constrained by time, motivation or computational resources.

Instead, these findings are in line with a growing body of evidence that high-level features of stimuli are effortlessly and rapidly extracted by the brain upon

viewing. Research using multivariate decoding of EEG and magnetoencephalography signals has demonstrated that several ecologically important object properties emerge in neural signals within approximately 100-200 ms of stimulus onset (Carlson et al., 2013; Cichy et al., 2014; Grootswagers, Robinson, & Carlson, 2019). These include animacy (living being vs inanimate object), critical for detecting potential predators, prey, or conspecifics; humanness, which underlies rapid person perception and guides social behaviour; and naturalness (human-made vs natural objects), which may support the rapid identification of tools or foods in the environment. The rapid and automatic processing of these properties suggests that the visual system prioritises information with high behavioural relevance (Khosla et al., 2022). Foods are similarly salient stimuli important for survival, and the present findings add to a growing body of work showing that viewing foods elicits a comparably rapid and spontaneous appraisal across a wide range of attributes within the first second of viewing (Moerel et al., 2024, 2026).

Our findings indicate that the representational inputs required for a decision process that integrates across a large number of choice-relevant attributes, as posited by weighted additive models (Keeney et al., 1976; Payne et al., 1993), are available early in the neural signals. That said, the present thesis did not examine how these attribute representations are weighted or combined into an overall value signal, and it remains an open question whether and which of the encoded attributes contribute to downstream choice. Future work could address this by linking the strength or timing of individual attribute representations to

behavioural choice outcomes, thereby characterising how the brain aggregates parallel attribute information into an integrated value signal that multiattribute choice models assume. For example, systematically varying attribute values across food stimuli and applying a diffusion decision model (DDM) framework may allow researchers to infer which attributes most strongly drive both choice and RT.

6.3 Limitations

6.3.1 Covarying Information May Not Necessarily Be Used by the Brain

We used multivariate analyses to infer the neural time-courses of attribute representations in Chapters 4 and 3 respectively, but there is a key caveat to these findings. RSA and multivariate pattern analysis (MVPA) are useful techniques for examining information in distributed patterns of neural activity: RSA involves comparing the (dis)similarity structures across neural and behavioural data, while MVPA tests whether a classifier trained on neural data can reliably distinguish between conditions. A key caveat with these methods is that even when covariation is observed between neural and behavioural data or a classifier can successfully decode between conditions, there remains a gap between the information available in the neural signals and the information that the brain actually uses to produce behaviour (de-Wit et al., 2016; Gessell et al., 2021; Ritchie et al., 2019). In MVPA, a decoder may be driven by extraneous information that is correlated with the representation of interest; similarly in RSA, shared similarity structure between neural and rating data does not guarantee that this shared structure is meaningfully used by the brain. Drawing on J. Sullivan's (2010) distinction between substantive versus minimal roles for representation, Gessell

et al. (2021) differentiate between a strong sense of representation, in which a representation assumes an explanatory role regarding its content, and a weak sense, in which the same representation may only signal covariation with the underlying referent. In the strong sense, a representation is assumed to be accessible to and used by the brain (e.g., in producing relevant behaviour). In the weak sense, the representation may covary with, but may be distinct from, the information that the brain uses.

Furthermore, there is an important caveat regarding the interpretation of the unique contributions of each attribute to the neural signals, as assessed through partial correlations. The time-courses we delineate through this analysis indicate that an attribute explains variance that is relatively independent from the other attributes included in the model, and does not necessarily imply that this attribute is more important or more influential during appraisal. Conversely, an attribute that is strongly related to the neural signal but shares substantial variance with other attributes may explain little unique variance, even though it may be important in the appraisal process.

Nonetheless, the present findings are meaningful contributions to our understanding of food valuation. The time-courses of food attribute representations uncovered using RSA and MVPA point to the temporal windows in which the relevant information used by the brain can be plausibly present, providing meaningful constraints on when different food attributes are represented. Our work on tracing evidence accumulation trajectories in dietary choices in Chapter 5 takes a step toward the stronger sense of representation by

examining the associations between neural dynamics and both RTs and continuous ratings, providing a connection (although still correlational) between neural activity and behaviour.

Future work may extend upon how the neural representations uncovered through RSA or MVPA may be accessible to and used by the brain. One intuition is that if the decoded information was meaningfully associated with relevant behavioural outcomes, this may provide evidence towards the idea that the information is indeed used by the brain for the behaviour (Grootswagers et al., 2018; Ritchie & Carlson, 2016; Ritchie & Op de Beeck, 2019). If aspects of the neural time-courses derived from RSA or MVPA are meaningfully associated with relevant behavioural outcomes (e.g., RTs, choice outcomes, or individual differences in dietary style and food motivations), then this may support that we are indeed accessing neural representations that are functionally meaningful and not merely covarying with neural activity. These aspects may include the magnitude or onset of correlation or decoding performance between neural activity and food attribute ratings. Establishing an association between these features of neural representations and the behavioural outcomes will strengthen the case that these representations are functionally used by the brain.

The distance-to-bound approach offers one concrete method for linking neural representations to behaviour (Grootswagers et al., 2018; Ritchie & Carlson, 2016; Ritchie & Op de Beeck, 2019). In MVPA, the decision boundary of the decoder is a hyperplane in neural state space separating conditions. For any given stimulus, its distance from this boundary reflects the degree to which the neural

pattern supports one classification outcome over another. If these trial-wise distances predict behavioural outcomes (e.g., RT, decision confidence, or judgement strength), this would suggest that the decoded information is used to inform behaviour. In the object recognition literature, this logic has been used to show that the geometry of early visual representations predicts perceptual judgement performance across individuals and stimuli (Ritchie & Carlson, 2016). Users of the FOODEEG dataset may take a similar approach to examine the link between decoded food attribute representations and how quickly or consistently a participant makes attribute judgements. By linking the geometry of neural representations to behavioural decision boundaries, it may be possible to assess whether specific attribute representations are used to inform choice.

6.3.2 Ecological Validity of Lab-Based Food Choice

Another limitation is that there were no real food choices at stake in the experimental tasks for the current thesis. During the food categorisation task, EEG was recorded while participants made evaluative judgements about food images with no consequence for actual eating. As outlined in Chapter 2, the use of food images rather than real foods was necessitated by practical and methodological constraints, including replicability, control over visual properties, and ease of rapid presentation during EEG recording. Nevertheless, this raises the question of whether the neural time-courses (Chapter 4) and decision dynamics (Chapter 5) we observed would hold under more naturalistic conditions. This is particularly relevant for the finding that healthiness was represented earlier than tastiness during food appraisal (Chapter 4). Previous mouse-tracking work showing the

opposite pattern (i.e., earlier processing of tastiness) had participants consume a chosen food at the end of the experiment, a manipulation that is common in studies examining dietary self-control and is intended to increase the ecological validity of the choices during the task (N. Sullivan et al., 2015). It is worth noting, however, that RSA and mouse-tracking tap into different aspects of cognition, the latter involving motor execution dynamics, and so these findings are not directly comparable. It is possible that making tastiness immediately relevant, as it is when real eating is imminent, shifts the temporal dynamics of attribute processing in a way that aligns with traditional distinctions between attributes that our paradigm could not capture. Furthermore, the lack of real eating consequences may also have influenced the weaker associations between neural measures and attribute ratings in Chapter 5. Without real eating consequences at stake during the food rating task, participants' evaluations of the foods on a fine-grained scale may have been more susceptible to noise or biases. For example, willingness-to-eat ratings may have been influenced by social desirability bias, with participants indicating a greater willingness to eat for more socially acceptable food options than their true preferences. This would have introduced noise into the ratings that is unrelated to the underlying neural decision process, leading to an attenuation in the associations between CPP dynamics and the ratings. Importantly, however, such associations were still observed, suggesting that the neural signals captured meaningful aspects of the decision process even in the absence of real consequences. Future work may nonetheless address this limitation by increasing the ecological validity of the dietary decisions in similar paradigms. For instance, a

subset of the food items chosen during willingness-to-eat trials or rated highly on the tastiness scale could be presented to the participant for consumption at the end of the session. This may allow us to carefully examine how the prospect of real eating modulates both attribute representations and choice dynamics.

Real-world food choices are now routinely made through online food delivery platforms, digital menus at restaurants, and food-related content on social media (S. Bates et al., 2023; Farah et al., 2022), relying solely on visual food cues. Despite the paradigms used in the current thesis involving visual food images, the lab-based tasks do not fully capture the conditions of these real-world choice environments. In particular, they do not replicate simultaneous presentation of multiple food options, presence of extraneous but potentially influential information (e.g., health claims, nutritional labels, and price tags), or the customisable interfaces that allow users to sort and filter options according to their own preferences that characterise typical online food choice settings. It remains an open question whether the decision processes characterised in the current thesis generalise to these more complex, real-world visual contexts. Future work could address this by developing more ecologically valid paradigms. For example, web-based and virtual reality environments can be used to construct more naturalistic and immersive food choice contexts while maintaining experimental control (Fuchs et al., 2022; Ledoux et al., 2013; van Herpen et al., 2016; Waterlander et al., 2014). These may include paradigms that simulate grocery stores, food delivery app interfaces, or ordering at restaurants. Portable EEG systems may allow neural data to be collected in naturalistic settings such as

a real grocery store or a restaurant, or be used in conjunction with virtual reality technology (Folwarczny et al., 2019; Zulkarnain & Gere, 2026). Such paradigms would allow researchers to examine how the neural dynamics of food appraisal and choice processes are modulated by contextual features that more closely resemble real food choices. It should be noted that such naturalistic settings make it considerably more difficult to achieve the precise levels of experimental control necessary to isolate specific cognitive and neural processes, and the presence of uncontrolled contextual variables risks introducing confounds that complicate interpretation. Any move towards more ecologically valid paradigms should therefore be undertaken carefully, with deliberate attention to maintaining sufficient experimental rigour.

6.4 Future Directions

6.4.1 Dietary Decisions in Clinical Eating Disorders

A key advantage of establishing a general process model of dietary decision-making is that it provides a foundation for future work that can delve deeper into when and how food choice diverges in clinical populations. Rather than simply asking whether a clinical group makes different choices or evaluations regarding foods, future work can ask more targeted mechanistic questions. Does a given difference between the clinical population and healthy controls arise at the appraisal stage, where food attributes are encoded in the neural signals, or at the choice stage, where these representations are converted into an action outcome?

Future work may examine whether individuals with eating disorders exhibit differences in the neural time-courses of food attribute representations during

visual food cue processing. Existing behavioural work suggests that individuals with anorexia nervosa weight healthiness more heavily in food choices (Schröder et al., 2025; Steinglass et al., 2015) and are faster to categorise foods in terms of calorie content (Dondzilo et al., 2024) compared to healthy controls. However, it remains unclear whether these differences are present at the appraisal stage, through an earlier, stronger, or more prolonged neural representation of health- or calorie-related attributes, or emerge later, at the point where attribute representations are converted into an action outcome via differences in the speed of evidence accumulation or decision thresholds. Using RSA to characterise the neural time-courses of a broad set of food attributes in individuals with anorexia nervosa, and comparing these to the time-courses from a nonclinical control sample established in the present thesis (Chapter 4), could reveal whether the neural time-courses align with these behavioural findings, and investigate whether there are other differences in the processing of a wider array of attributes (e.g., food familiarity). Furthermore, using the CPP as a neural correlate of evidence accumulation in willingness-to-eat and attribute judgements (Chapter 5) to formally model dietary decisions in this population could reveal how these differences arise in terms of alterations in model parameters, such as in drift rates, indicating the representational strength of certain attributes, or in decision thresholds, reflecting greater caution in reaching a choice.

Neural measures of visual food cue processing may help distinguish between clinical populations that overlap in behavioural presentation but may differ in underlying mechanisms. Both anorexia nervosa and avoidant/restrictive

food intake disorder involve restriction in the amount or variety of foods consumed, but the underlying motivations differ (Cañas et al., 2021). In anorexia nervosa, restriction is driven by distress around body image and weight (Zipfel et al., 2015), while in avoidant/restrictive food intake disorder, restriction stems from disinterest in eating, sensory sensitivity, or fear of adverse consequences such as choking (Zimmerman & Fisher, 2017). It is plausible that these distinct motivational profiles produce different neural signatures at the appraisal stage (Chapter 4), such as an early or prolonged neural representation of calorie- and health-related attributes in anorexia nervosa and of sensory attributes (e.g., texture, familiarity) in avoidant/restrictive food intake disorder. Characterising these differences at the level of neural processing rather than behaviour alone could offer mechanistic insight into the distinct pathologies underlying these conditions, with implications for improving diagnostic tools with neural measures or the development of treatment targeting specific neural processes.

The current thesis excluded participants with a current or past history of eating disorders, meaning that these findings establish a process-level, mechanistic foundation in a nonclinical sample rather than having immediate clinical application. Establishing a process model is nonetheless an important prerequisite for future clinical work, as it provides a reference point against which clinical populations could be compared. Future studies recruiting clinical samples could apply the same paradigms and analyses used here to evaluate in which ways clinical samples diverge from this baseline in the decision process. The FOODEEG dataset (Chapter 3) also provides measures of food-related inhibitory control,

eating styles, and food motivations, which can support exploratory analyses of subclinical variation in these processes within nonclinical samples, providing a potential bridge toward future clinical work.

6.4.2 Individual Differences in Dietary Decisions

Beyond clinical populations, the process model established here provides a framework for examining how individual differences modulate the valuation and choice stages of dietary decision-making. Characterising the shared neural and computational mechanisms underlying food choice in a general sample allows for investigations beyond whether a given factor changes the choice outcome, to when in the decision process, and through changes in which decision parameters, that factor has an effect.

One population of theoretical and practical interest is individuals who have adopted plant-based or meat-reduced diets. From an environmental standpoint, reducing meat consumption is one of the most impactful dietary changes an individual can make (Poore & Nemecek, 2018; Xu et al., 2021), yet sustained adherence is a significant challenge, with many people who attempt to reduce their meat intake reverting to prior habits over time (Fehér et al., 2020; Rosenfeld, 2018). Understanding the dietary decision-making processes of long-term plant-based eaters, and how these differ from omnivores, could offer mechanistic insight into these individual differences. Previous event-related potential (ERP) work has found that although vegetarians report lower pleasantness, emotional arousal, and willingness to eat on meat-based dishes compared to omnivores, they may not differ in evoked neural responses (e.g., N2, late positive potential;

Giraldo et al., 2019). However, as discussed in Chapter 2, multivariate methods such as RSA or MVPA may be more sensitive to subtle differences in the distributed patterns of neural activity that are missed by univariate ERP analyses. Using the RSA approach (Chapter 4), future work may examine on a more fine-grained level whether plant-based eaters differ in their appraisal of meat-containing foods. For example, attributes such as edibility, valence, arousal, or emotional properties (e.g., disgust or craving) may be represented more strongly or earlier for meat-containing foods in this group compared to omnivores, and this difference may be modulated by the time spent adhering to plant-based diets (Ruehlman & Karoly, 2022). Comparing committed plant-based eaters, people who are actively attempting to reduce their meat intake, and omnivores could help identify which aspects of the decision process differ between those who have successfully shifted their dietary patterns and those who have not, informing interventions designed to support long-term dietary change.

Individual differences in food motivation and eating style represent another promising avenue for future investigation. People vary substantially in the degree to which they eat in response to external food cues, emotional states, or internal hunger signals (Chapter 3), but the neural and computational mechanisms through which these traits influence dietary decisions remain poorly understood. Future work could examine whether differences in dietary restraint (Stunkard & Messick, 1985; van Strien et al., 1986) are linked to specific parameters of the DDM. For example, by regressing per-participant decision threshold and starting point estimates against the restraint scores, researchers could uncover whether

higher dietary restraint is associated with an increased decision threshold indicating heightened response caution or a starting point bias that increases the likelihood of choosing not to eat. Future work can also investigate whether self-reported food motivations (Renner et al., 2012; Steptoe et al., 1995) are reflected in differences in the appraisal or choice dynamics, by linking these trait scores to the onset and strength of specific attribute representations as revealed by the neural time-courses using RSA. For instance, individuals who report that they are more driven by weight control or health motivations in their food choices may exhibit earlier or more prolonged representations of health- and calorie-related attributes. Broader motivational tendencies measured by the Behavioural Inhibition and Behavioural Activation System Scales (Carver & White, 1994) may also be reflected in the decision process, and could similarly be tested by regressing parameters from the DDM against the subscale scores. For example, researchers may test whether higher trait approach motivation (e.g., reward responsiveness or drive) is potentially associated with stronger drift rates for appetising foods, and higher trait behavioural inhibition is potentially linked to higher decision thresholds, indicating response caution.

The FOODEEG dataset (Chapter 3) is a useful resource to support future research into individual differences. Alongside the neural and behavioural data collected during food cognition tasks and normative ratings across 22 food attributes, the dataset includes a battery of individual difference measures spanning dietary styles, food motivations, general motivational tendencies, and hedonism, providing a rich resource for examining how motivational variation

relates to the neural and computational processes characterised here. The dataset establishes a baseline from a sample with no dietary restrictions who are not dieting, against which data from more targeted populations (e.g., plant-based eaters, dieters, or individuals with distinct motivational profiles) can be compared. Researchers can leverage this reference dataset to identify divergences from typical food choice processing, situating individual and group differences within the broader process model developed across this thesis.

6.4.3 Understanding Goal-Directed Decision-Making

A broader contribution of food cognition research may lie in what it can offer the science of goal-directed decision-making more generally. Dietary decision-making involves goal-directed control, with influences from competing motivations, internal states, personal values, and contextual demands (Rangel, 2013). Unlike other types of goal-directed decisions, such as financial or consumer choices, eating is a biological imperative that must be undertaken every day. At the same time, food decisions are characterised by the striking heterogeneity in the goals that drive them (Renner et al., 2012; Steptoe et al., 1995). The same decision may be governed by health considerations in one individual, sustainability or animal welfare in another, hedonic preference in a third, and by familiarity and cultural tradition in a fourth. The same individual may shift between goal structures across different contexts (e.g., social, physical, cultural) and time (e.g., time of day, across the lifespan). Studying food decisions provides an opportunity to study a goal-directed decision process that is ecologically meaningful and comparable across individuals and populations, with

the potential to inform the development of a general process model for goal-directed decisions beyond food choices. The approaches developed in this thesis can provide ways to study food decisions within this broader conceptual framework.

6.5 Conclusion

The current thesis advances our understanding of dietary decision-making by characterising the neural and computational mechanisms underlying two core stages of the decision process: the rapid, parallel appraisal of a rich diversity of food attributes during valuation, and the stochastic accumulation of evidence that converts these representations into a food choice outcome. Together, these findings challenge longstanding assumptions embedded in traditional models of food choice and lay the foundation for more mechanistically grounded accounts of how people choose what they eat. The open-access FOODEEG dataset, containing neural and behavioural data from a large, nonclinical sample, provides a foundation on which future research can examine how these mechanisms are shaped by individual differences and clinical conditions. Taken together, the findings of this thesis bring us closer to a mechanistic understanding of the complex dietary choices people navigate every day.

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