Behavioural measures and training interventions for food-related cognition, motivation and affect

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PhD Thesis

by

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Abstract

The rise in overweight and obesity rates over the past decades can primarily be attributed to the over-consumption of unhealthy energy-dense foods. Understanding the determinants of eating behaviours is therefore paramount for helping individuals reduce their intake of unhealthy foods and make healthier choices. According to a dual-process framework of behaviour, individuals with lower inhibitory control may be more vulnerable to implicit influences on their actions, such as strong approach bias and automatic affective reactions towards cues in the environment. Automatic and controlled processes within this framework can be assessed using direct and indirect measures and there have been recent advancements in the development of behaviour change interventions, such as inhibitory control training (ICT). Chapter 1 of this thesis reviews the theory and methods surrounding cognitive control of eating behaviours. Chapter 2 reports an experiment on the effect of ICT on food evaluations, impulsive choices and automatic action tendencies. Although training had the expected effect on food choices, it did not reduce participants' approach bias towards unhealthy foods. Chapter 3 describes a study which provided evidence for the feasibility and potential effectiveness of a novel ICT paradigm for reducing unhealthy food evaluations and cravings. The study presented in Chapter 4 investigates the methodological validity of the affective priming paradigm (APP) as an indirect measure of food liking in the context of healthy and unhealthy foods. The APP was found to be robust in two cohorts of participants (direct replication), but its predictive utility for food choice behaviour requires further investigation. Chapter 5 shows that ICT can reduce individuals' food evaluations at both an explicit and implicit level (via the APP). In Chapter 6, these research findings are discussed in relation to theory and methods, together with general limitations and directions for future empirical and applied research.

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Acknowledgements

Collaboration is a key element of scientific progress. I whole-heartedly share my appreciation and gratitude for the supervision I have received throughout my PhD by Chris Chambers. He has taught me how important open science practices are for the psychological science and although at times research design, study preregistration and data collection proved to be very challenging, I have learned more than I could have hoped for during these four years. The design of the research studies conducted as part of this thesis has been reviewed by internal and external collaborators that should be acknowledged. The multi-site study presented in Chapter 2 was designed in collaboration with Rachel C. Adams, Natalia S. Lawrence and Katherine S. Button for the GW4 Undergraduate Psychology Consortium 2017/2018. It goes without saying that the study would not be completed without the data collection undertaken by the undergraduate students at Cardiff University, the University of Bath and the University of Exeter. The novel training paradigm introduced in Chapter 3 has been developed in collaboration with Frederick Verbruggen, whom I thank for his excellent input on the stop-signal and stop-change paradigms. The Stage 1 Registered Report that was included in Chapter 4 was reviewed by Leah Maizey and Andrew D. Lawrence who provided important recommendations for theory-related issues and contributed to manuscript revisions. During the review process, I received invaluable input from Andrew Jones, Harm Veling and Marcel van Assen, who helped me achieve a very high standard of reproducibility. For the study described in Chapter 5, I would like to extend my gratitude to the Second Year undergraduate students that collected a proportion of the data for their practical assignments. For their continued support throughout this PhD, I would like to personally thank the members of our lab, Leah Maizey, Jemma Sedgmond, and Rachel C. Adams and my fellow PhD student and friend Maciek Szul with whom I shared my daily struggles during the write-up months for this thesis. On a final note, pursuing an academic career away from home can be emotionally difficult and I am eternally grateful to my mother Mary, the strongest single mum I know, who was always there to support me when I needed her.

Dedication

In loving memory of my godfather Loukas, without whom I would not have the privilege to pursue my academic studies.

Publications in the Thesis

All the chapters in this thesis that describe conducted research studies involve preprint publications on the Open Science Framework (OSF). Specifically, the proposed study protocols from Chapters 2, 3 and 5, including the hypotheses, methods and analyses sections, were preregistered on the OSF, as outlined below. The research study presented in Chapter 5 was accepted in principle as a Registered Report for publication by the journal *Psychonomic Bulletin & Review*.

- **Chapter 2**: Tzavella, L., Adams, R. C., Chambers, C. D., Lawrence, N., & Button, K. S. (2017). The effect of inhibition training on approach-avoidance tendencies for unhealthy foods. Preregistered study protocol, date of registration: 15/10/2017. https://osf.io/wav8p
- **Chapter 3**: Tzavella, L., Chambers, C. D., & Verbruggen, F. (2017). Testing the efficacy of a novel inhibitory control training protocol for altering food preferences. Preregistered study protocol, date of registration: 30/08/2017. https://osf.io/5f9b2
- **Chapter 4**: Tzavella, L., Maizey, L., Lawrence, A. D., & Chambers, C. D. (2019). The affective priming paradigm as an implicit measure of food attitudes and related choice behaviour. *Psychonomic Bulletin & Review*, Stage 1 Registered Report, date of in-principle acceptance: 20/02/2019. https://osf.io/y2tus
- **Chapter 5**: Tzavella, L., & Chambers, C. D. (2019). Go/no-go training & food priming effects. Preregistered study protocol, date of registration: 29/03/2019. https://osf.io/c6z53

In line with the policies on the submission and presentation of research degree theses, preregistered study protocols have been adapted to the purposes of this thesis, with added detailed descriptions of experimental procedures and materials. Contribution notes are included in the main text of the thesis where appropriate.

Chapter 1

Literature Review

One of the most pressing health problems of our time is the rise in overweight and obesity in developed countries. The psychology of eating behaviours that can contribute to this health issue, such as over-consumption of energy-dense foods, can be classified into distinct, but interacting, themes: food-related affect, motivation, and cognition. Theoretical frameworks have attempted to explain unhealthy eating behaviours through automatic, or implicit and controlled, or explicit, processes that determine individuals' actions under different circumstances. These frameworks have informed the development of behavioural measures and interventions. In the context of eating behaviours, energy-dense foods can induce strong affective reactions (*affect*) and approach bias (*motivation*) that can lead to unhealthy food choices and subsequent consumption. This impulsive drive behind food consumption can be circumvented if and when inhibitory control is exerted successfully (*cognition*). Behavioural measures can capture both explicit and implicit affect and motivation for appetitive cues and behaviour change interventions, such as inhibitory control training, can be employed to strengthen inhibitory control in the presence of impulsive precursors, such as an approach tendency towards a food or its cue. In the literature review presented in Chapter 1, I provide a general description of all important concepts within this line of research and critically review both behavioural measures and interventions applied in the food domain.

1.1 Overweight, obesity & eating behaviours

1.1.1 Prevalence & impact

The global prevalence of obesity has almost tripled between 1975 and 2016, with more than 1.9 billion adults (39%) being overweight and over 650 million adults (13%) classifying as obese (World Health Organization, 2018). According to the World Health Organization (2018), overweight and obesity in adult populations are defined as body-mass indices greater than or equal to 25 and 30 respectively. The body-mass index (BMI) refers to the body weight divided by the squared height (i.e., kg/m^2). It has been reported that being overweight or obese can lead to an increased risk for non-communicable diseases, such as cardiovascular diseases with high mortality rates, diabetes, and different types of cancer (Burke et al., 2008; National Cancer Institute, 2017; World Health Organization, 2018). Individuals with a BMI in the obese category compared to those with a BMI in the normal- or healthy- weight category can also face mental health issues as they are at increased risk for lower quality of life, clinical depression and anxiety (Centers for Disease Control and Prevention, 2017; Kasen, Cohen, Chen, & Must, 2008; Luppino et al., 2010). Overweight and/or obese individuals can also be stigmatised when discriminatory behaviours occur in healthcare and workplace settings, which also affects their physical and mental well-being (Carr & Friedman, 2005; Sutin, Robinson, Daly, & Terracciano, 2016). Pharmacological and surgical treatment interventions for obesity are associated with an increased cost for healthcare systems (e.g., see Avenell et al., 2004). The economic burden on healthcare resources is even greater when considering health problems associated with overweight and obesity. Across the United Kingdom, National Health Service (NHS) costs related to overweight and obesity have been estimated to reach £9.7 billion per year by 2050 (Public Health England, 2017).

1.1.2 An obesogenic environment

Obesity is a multifaceted health problem with a complex aetiology and many contributing factors (e.g., genetic and biological traits; see Ghosh & Bouchard, 2017 for review). According to the World Health Organization (2018), the primary cause of overweight and obesity is an imbalance between consumed calories and expended calories which can arise from the combination of increased intake of energy-dense foods that are high in fat, sugar and salt content and reduced physical activity. In developed countries, the environment is characterised by an abundance of energy-dense foods,

such as high calorie snacks, which are constantly promoted via food advertising and marketing (e.g., television, supermarkets, vending machines) causing an omnipresent availability of unhealthy food choices (Havermans, 2013; Stice, Figlewicz, Gosnell, Levine, & Pratt, 2013). Over-consumption of unhealthy foods is a behavioural cause of overweight and obesity that is therefore reinforced by an 'obesogenic' environment that not only includes physical surroundings, but incorporates "costs, laws, policies, social and cultural attitudes, and values" (Swinburn & Egger, 2002, p. 292). In addition to the affordability and accessibility of foods that are high in caloric and fat content, local food environments now include bigger portion sizes and highly processed foods that are often hyper-palatable due to 'cosmetic additives', such as sweeteners and flavour enhancers (Monteiro et al., 2019; Wright & Aronne, 2012).

1.1.3 Incentive-sensitisation theory

How does the accessibility and availability of energy-dense foods in an obesogenic environment contribute to unhealthy eating behaviours? This question does not have a simple answer as an individual's reactions to foods and their cues (e.g., sight, smell) in the environment could in theory be regulated via self-control processes. However, there are individual differences in how people respond to such cues that have complex psychological and neurobiological underpinnings. Irrespective of the 'obesogenicity' of our current environment, there is apparent variability in how individuals develop and maintain unhealthy eating behaviours and subsequent weight gain (A. Jones et al., 2018). Energy-dense foods are intrinsically rewarding (e.g., fat and/or sugar content) and can produce strong cue-induced cravings when associative links are formed between their cues and subsequent food consumption (Veling et al., 2017) via Pavlovian conditioning mechanisms that have been substantiated in both animals and humans (see Berridge, 2009; Havermans, 2013). For example, the sight or smell of chocolate (i.e., cue) can trigger pleasure or enjoyment and elicit a strong desire for chocolate consumption. According to the incentive-sensitisation theory of addiction (IST; Berridge & Robinson, 2016; Robinson & Berridge, 1993), the rewarding value of energy-dense foods can be increased via over-consumption, which is known as incentive salience attribution. When the incentive value of a food is increased, reward-related cues can elicit a strong urge or desire to eat the food independent of homeostatic needs (i.e., hunger, energy repletion). This desire can also be dissociated from how much an individual likes the taste of the food. The IST postulates that "wanting"[1] for specific

[1]Quotation marks for the terms "wanting" and "liking" indicate that I refer to the constructs from the IST and not the intuitively understood concepts of explicit wanting and liking (also see

foods reflects a conditioned motivational process that can operate independently from "liking", so that repeated exposure to certain foods can be accompanied by reduced hedonic reactions and increased reward anticipation. This cyclical process results in an individual subjectively experiencing less pleasure ("liking"), but more desire ("wanting") for these foods (Berridge, 2009; Berridge et al., 2010). "Liking" and "wanting" are pre-conscious process (Robinson & Berridge, 1993) that have received considerable attention in experimental and neuroimaging studies in the food domain. The operationalisation of "liking" and "wanting" (see Pool, Sennwald, Delplanque, Brosch, & Sander, 2016; Tibboel, De Houwer, & Van Bockstaele, 2015 for reviews) goes beyond the scope of this thesis, but these are two constructs that undoubtedly contributed to important potential explanations of unhealthy eating behaviours, such as overeating.

A potential risk and contributing factor to overeating is this increased reward sensitivity to food cues, as described above, and this can be translated into a hyper-sensitivity to reward in the brain. Neuroimaging research has shown that overweight and obese individuals demonstrate increased activity in brain regions associated with reward, motivation and emotional processing, such as the orbitofrontal cortex (OFC), nucleus accumbens and amygdala, in response to a variety of energy-dense foods compared to healthy-weight individuals (see Pursey et al., 2014 for meta-analysis). In addition to heightened reward sensitivity, evidence suggests that overweight and obese individuals can have increased activity in motor-related regions implicated in approach tendencies and reduced activity in brain regions responsible for inhibitory control, such as the ventromedial and dorsolateral prefrontal cortices (vmPFC, dlPFC), relative to healthy-weight controls, when presented with high-calorie foods (see Stice, Lawrence, Kemps, & Veling, 2016; Pursey et al., 2014). A recent neuroimaging study has shown positive associations between activity in the nucleus accumbens associated and food intake in the laboratory that was independent of subjective cravings (Lawrence, Hinton, Parkinson, & Lawrence, 2012). A positive relationship between activity in the nucleus accumbens and BMI was only found for individuals with poorer self-control. Stoeckel et al. (2009) examined the connections between the regions of the brain's reward network in response to high- and low-calorie food stimuli in a sample of obese and normal-weight individuals using functional magnetic resonance imaging (fMRI). Exposure to food cues not only induced increased activity in the reward system for obese compared to normal-weight individuals, but there was evidence for significant group differences in connectivity. Reduced connectivity from

Berridge, Ho, Richard, & DiFeliceantonio, 2010).

the amygdala to the OFC could explain the inefficient regulation of affective responses to the reward value of a food cue, while increased connectivity from the OFC to the nucleus accumbens may be associated with the urge or desire for food consumption. Thus, even though there is no homeostatic need for food intake, increased reward sensitivity to food and their cues and an ineffective regulation of affective, or emotional responses (e.g., foods are not devalued after food intake) can lead to hyperphagia, or overeating (also see Stice, Spoor, Ng, & Zald, 2009 for anticipated food intake). These findings are consistent with the IST, but there is another crucial framework that predicts that eating behaviours (e.g., overeating) can be explained by strong affective and motivational responses to foods. It also accounts for the role of cognitive control processes, such as inhibitory control, in the (un)successful regulation of these behaviours. This framework is described in detail in section 1.2.

1.1.4 Food addiction

A critical question that has been receiving increasing attention over the past decade is why some individuals develop compulsive and addictive attitudes towards food, leading to the concept of 'food addiction' (Adams, Sedgmond, Maizey, Chambers, & Lawrence, 2019; C. Davis, 2017b; Gearhardt et al., 2011). Moore, Sabino, Koob, & Cottone (2017) suggest three key elements that can define compulsive eating behaviour: habitual overeating, overeating to relieve a negative emotional state and overeating despite adverse consequences (p. 1378). Although food addiction is not recognised in the fifth version of the Diagnostic and Statistical Manual (American Psychiatric Association, 2013), research studies have identified crucial similarities between substance use disorders (SUDs) and eating-related problems, such as binge eating disorder (BED), which involves an increase in cravings, impulsivity, reward sensitivity and impaired impulse control (C. Davis, 2017a; Smith & Robbins, 2013) and there are high rates of overweight and obesity in individuals diagnosed with BED (Kessler et al., 2013). Although the lifetime prevalence of BED is low (1.9 %; Kessler et al., 2013), the fact that overeating can turn from a passive state of liberal 'snacking' that can occur without awareness to compulsive and frequent episodes has implications for 'food addiction' research and interventions (Moore, Panciera, Sabino, & Cottone, 2018). Theoretical and empirical explorations of eating behaviours from an addiction perspective have yielded important insights, as for example the IST theory and related neuroimaging findings (section 1.1.3). However, the diagnostic and potential clinical utility of the 'food addiction' perspective is currently in development

(e.g., Gearhardt, Corbin, & Brownell, 2016, 2009; Ruddock, Christiansen, Halford, & Hardman, 2017). The food addiction debate (e.g., see Finlayson, 2017; Fletcher & Kenny, 2018; Hebebranda et al., 2014; Ruddock et al., 2016; Schulte, Potenza, & Gearhardt, 2017) goes beyond the scope of this thesis and is not discussed in more detail. The stance adopted here is that there are useful theoretical and neurobiological underpinnings of eating behaviours from an addiction perspective that can guide the development of behavioural measures and interventions in the food domain, but the clinical implications and applications of 'food addiction' should be explored further, as for example the impact of a food addiction 'diagnosis' on eating behaviours (see Ruddock et al., 2016).

1.2 A dual-process framework of behaviour

The negative consequences of over-consumption of energy-dense foods that are high in fat, sugar and/or salt on physical and mental health have long been acknowledged. However, many individuals who are aware of these consequences and are committed to long-term health and weight-management goals can have a difficulty in regulating their behaviour and exercise self-control because eating can largely be driven by automatic processes that occur without intention or awareness (Cohen & Farley, 2007). Recent dual-process models (Hofmann, Friese, & Wiers, 2008; Smith & DeCoster, 2000; Strack & Deutsch, 2004) have provided a comprehensive, predictive framework of behaviour across various domains. A prominent dual-process account of social behaviours that has been successfully applied in food research studies and extended to account for health behaviour (see Hofmann et al., 2009b, 2008) is the reflective-impulsive model (RIM; Strack & Deutsch, 2004). In a dual-process framework, the basic assumption is that there are two distinct information processing systems which act in parallel to determine behaviour: the reflective and the impulsive system. The reflective system refers to controlled processing, that is often explicit, such as dieting goals or beliefs about the consequences of food consumption. Information processing is slow, effortful and depends on the availability of cognitive resources/capacity. Conversely, the impulsive system involves automatic, or implicit, processing that can occur outside of conscious awareness, and is fast and effortless.

1.2.1 The reflective-impulsive model

The RIM postulates that there are associative clusters in long-term memory that can be automatically activated upon the perception of a relevant stimulus (e.g., unhealthy food). The impulsive system is therefore an associative network in which an element can be activated via spreading activation and associative clusters can be formed or strengthened via temporal or spatial co-activation of environmental, affective, cognitive and behavioural reactions to external stimuli. Associative clusters can be connected to behavioural schemata that can guide behaviour in the impulsive system. Drawing on an example from health behaviour (Hofmann et al., 2008), an individual who repeatedly eats crisps as a snack will have an associative cluster that links the potato crisps as a stimulus/concept with positive affect (hedonic) and the behavioural schema that underlies the positive affect, that is actually eating the crisps. If this behavioural schema exceeds the necessary activation threshold and/or is compatible with behavioural schemata in the reflective system, the overt behaviour will be food consumption. The reflective system involves higher-order mental operations such as executive functions that serve goal-directed behaviours. In the reflective system, behaviour is assumed to result from *reasoning* that creates a noetic decision about how positive the behavioural outcome will be and how feasible the execution of the desired action is. This decision is translated into behavioural schemata through the process of *intending*. Strack & Deutsch (2004) state that "the temporal gap between a behavioral decision and the execution of an instrumental behavior is bridged by a process that automatically reactivates the behavioral decision and thus activates behavioral schemata that are appropriate in the situation" (p. 230).

There are many assumptions in the RIM which can be complicated to understand in terms of behavioural predictions without specific examples. For this reason, the key RIM assumptions and respective predictions are further discussed in relation to eating behaviours, as shown in the schematic in Figure 1.1. Although the reflective system involves deliberate thoughts and decisions about goal-directed actions that can be flexibly formed and altered, it also requires cognitive, or control, resources, such as working memory capacity (Hofmann et al., 2008; Strack & Deutsch, 2004). The impulsive and reflective systems can both activate behavioural schemata, but when these are incompatible this can trigger a conflict and their activation becomes antagonistic. For example, an appetitive food cue (e.g., sight, smell) can activate behavioural schemata that are oriented towards impulsive consumption, but if an individual is trying to lose weight and follow a healthier diet this causes a conflict with the reflective system if that appetitive food is explicitly recognised as unhealthy (e.g.,

high in fat or sugar) and not suitable for a healthier diet. The outcome of the conflict resolution will largely depend on the relative strength between the incompatible behavioural schemata. If cognitive (control) resources are low, behavioural schemata in the reflective system will not exceed the threshold for activation and the reflective system will not be successful in implementing an inhibiting ("Put it away") or overriding tendency ("Eat something healthier") schema as an overt behavioural outcome (Hofmann et al., 2009b). The incompatibility between strong impulses and long-term goals or beliefs (e.g., "Reducing intake of unhealthy foods is good for my health") can create a sense of internal conflict and temptation (Hofmann et al., 2009b). One of the key predictions of the dual-process framework would be that eating behaviours are determined by the interaction between the impulsive (automatic) and reflective (controlled) processing systems. Specifically, unhealthy eating behaviours would be characterised by a strong impulsive system and a weak reflective system (Kakoschke et al., 2015).

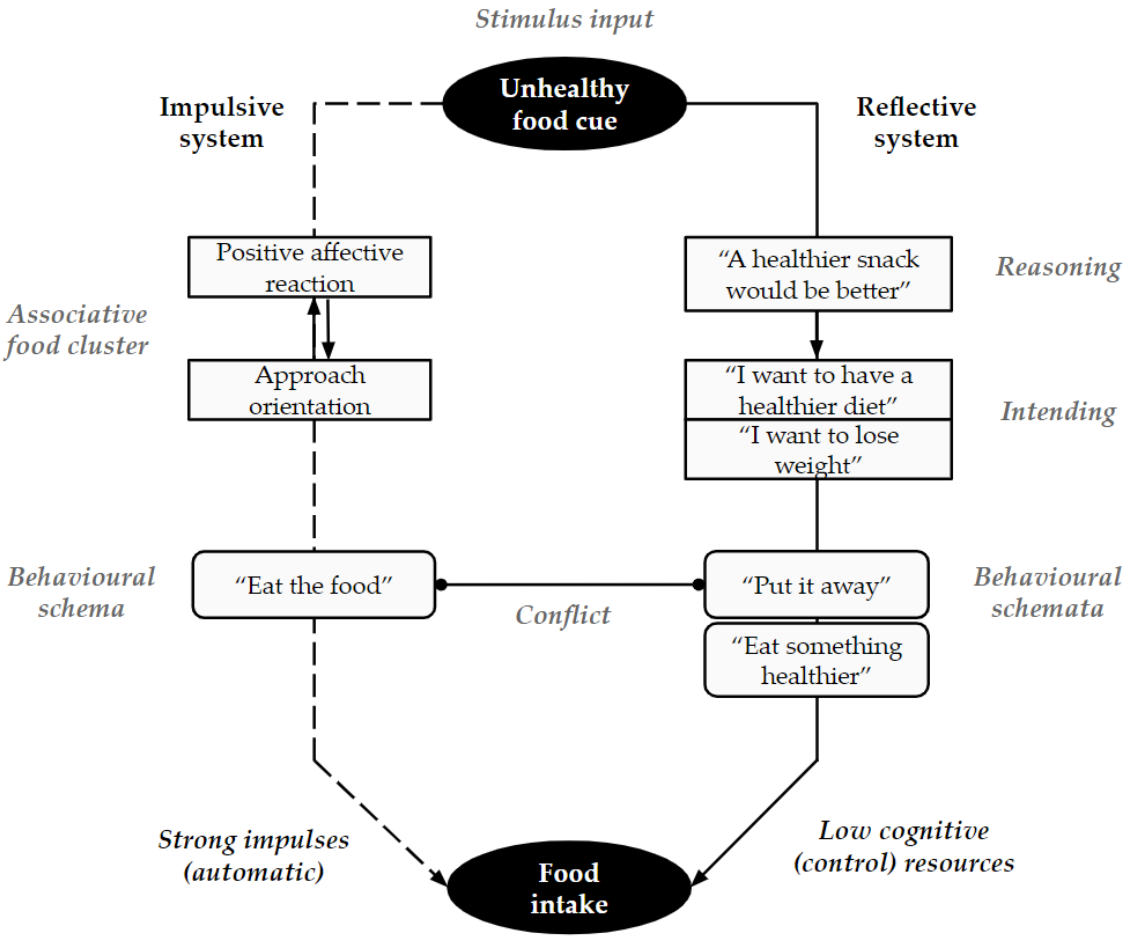


Figure 1.1: Schematic of the reflective-impulsive model for eating behaviours.

When applied to eating behaviours, automatic processing in the impulsive system commonly refers to (food) affect and motivation. In line with the RIM assumptions (Strack & Deutsch, 2004), there is a bidirectional relationship between automatic affective reactions towards appetitive stimuli and the execution of approach or avoidance behaviours (see Figure 1.1). The impulsive system has a motivational orientation (i.e., towards approach or avoidance) that can be activated when a stimulus induces positive or negative affect and when approach or avoidance behaviours are perceived or executed. Approach orientation refers to the tendency to reduce the distance between one's self and a stimulus, situation or person in the environment, whereas avoid orientation reflects an increase in distance such as by moving away (flight) or removing the relevant target from the environment (fight). Information processing based on valence and experience of affect will depend on the impulsive system's motivational orientation so that processing positive information and experiencing positive affect will be facilitated when an approach orientation exists and the same effect for negative information and negative affect will be observed when there is an avoid orientation. The bidirectionality stems from the reverse effects where the valence of the processed information and experienced affect can drive the corresponding motivational orientation (e.g., positive affect can induce an approach orientation).

1.2.2 The explicit-implicit distinction

In a dual-process framework, behaviour is guided by automatic, or implicit, processes and regulated via higher-order controlled processes when cognitive resources are available. This framework can successfully be applied to eating behaviours, but how can these automatic and controlled processes underlying these behaviours be measured? In the RIM, the distinction between an impulsive and reflective system does not rely on whether related processes require conscious awareness. The authors argue that the behavioural components of attitudes can be reflective when derived from an evaluation and impulsive when automatic action tendencies are associated with evaluative features of an attitude object (Strack & Deutsch, 2004). The broader concept of (implicit) attitudes, which refers to object-evaluation associations that can be automatically retrieved from memory (Klauer & Musch, 2003), has informed ample research in psychology, including individuals' attitudes towards appetitive cues.

Although there are key differences between the RIM and theoretical models of attitudes, such as the prominent 'motivation and opportunity as determinants' model (MODE model; Fazio, 1990), the measurement of impulsive precursors of behaviour

including approach bias and automatic affective reactions requires the use of indirect, or implicit, measures (also see Strack & Deutsch, 2004). Implicit measures do not require subjective assessments of evaluations or introspection, and researchers often draw conclusions based on participants' performance on speeded categorisation tasks (see Roefs et al., 2011 for review of implicit measures). Evaluation may simply refer to distinguishing good from bad, but it is a core aspect of attitudes and affect that can contribute to many behaviours, such as food choices (Herring et al., 2013). Attitudes can be defined as "evaluative summaries of information about an object" (Herring et al., 2013, p. 2). These attitudes can be explicitly, or directly, measured by asking individuals to report how they evaluate an object or concept, but there are important limitations with self-report measures (e.g., questionnaires), including but not limited to social desirability and strategic response bias (see Podsakoff, MacKenzie, Lee, & Podsakoff, 2003 for review).

This may be especially critical for the measurement of attitudes for appetitive stimuli because they could be affected by social desirability (e.g., reporting a high desire to eat an unhealthy food when an individual is on a diet) and automatic processes that can guide behaviour without the respondents' awareness (e.g,. "wanting"). The duality assumed between explicit and implicit attitudes is not entirely valid, however, as individuals can often be consciously aware of their attitudes and the implicit-explicit distinction should be used in the description of behavioural measures[2], rather than the psychological constructs (Fazio & Olson, 2003). The relationship between implicit and explicit measures is not clear and it may depend on the context and attitude object/concept of interest (see Fazio & Olson, 2003). In the food domain, the relationship between implicit and explicit attitudes in choice behaviour has not yet been elucidated and remains controversial (Ellis, Kiviniemi, & Cook-Cottone, 2014).

1.2.3 Criticisms and alternative models

Although dual-process theories of behaviour such as the RIM provide an informative descriptive framework for food-related research, there are alternative models that argue against the duality between automatic and controlled processing systems (Berkman, Hutcherson, Livingston, Kahn, & Inzlicht, 2017; Hommel & Wiers, 2017; also see Verbruggen et al., 2014b). Criticisms of the dual-process models of behaviour have recently been elaborated by Hommel & Wiers (2017) who highlighted the lack of

[2]For this reason, the terms direct and indirect measures should be preferred. However, the terms 'explicit' and 'implicit' are used in the majority of research studies outlined in this thesis even though a lack of awareness is not formally tested.

empirical evidence for clear-cut criteria that can distinguish between goal- and stimulus-driven behaviour. They argue that actions are often defined as automatic, or habitual, as opposed to goal-oriented, when they are considered independent from intentions, insensitive to external reward, and irrational (i.e., incompatible with long-term goals and/or anticipated consequences). However, this inferred distinction is primarily based on highly-controlled laboratory research and does not take into account individual differences, short-term goals and intentions that are not directly manipulated or measured.

Berkman et al. (2017) put forward a unitary model of action control that considers both short-term and long-term goals as determinants of the decision-making process (i.e., response selection criteria). Depending on the specific condition or context, these goals can facilitate overlearned actions that are simple and fast. For example, considering current cognitive resources and/or motivation (e.g., lower inhibitory control), choosing to eat an easily accessible palatable food could be a fast and efficient action compared to choosing a healthier alternative, especially if this action has been overlearned through previous experience. Choosing a healthy food in this scenario could be a more complex action that is slow and potentially novel. Although this model is conceptually more complicated (see Berkman et al., 2017 for details), this unitary approach to action control would predict that unhealthy eating behaviours, such as overeating, can be explained by both stimulus-driven and value-driven actions that often interact and are goal-oriented (also see Oomen, Grol, Spronk, Booth, & Fox, 2018).

The dual-process models of behaviour have further been criticised for placing an emphasis on "effortful inhibition" for overcoming impulses that are not compatible with goals (e.g., choosing to eat a salad instead of a burger when dieting) when there are other strategies that can influence outcomes (e.g., focusing on more appetitive salad ingredients; Berkman et al., 2017). In their proposed model, Berkman et al. (2017) suggest that self-control can more broadly be defined as value-based decision making. Each response, or choice, option is considered as the weighted sum of different value inputs for the option attributes. For example, when the two response options are eating a burger or a salad, the subjective values of these options are influenced by tangible (e.g., effort costs), social (e.g., acceptance) and self-related (e.g,. coherence) attributes. Through a stochastic accumulation process, the response option that has the greatest value will reach the activation threshold first and the respective action will occur (e.g., eat the burger). The attention placed on certain attributes can in turn influence this accumulation process and lead to certain response options reaching

the threshold faster. In the context of dietary self-control, this could have important implications as health-related food attributes may be 'under-weighted' during this value-based decision making process and increasing attention to these attributes (e.g., see Hare, Malmaud, & Rangel, 2011) can lead to behaviour change.

1.3 Affective evaluations & attitudes

As discussed in section 1.1.2, an important determinant of unhealthy eating behaviours that drive the rise in overweight and obesity rates, such as the over-consumption of energy-dense foods, may be the 'obesogenicity' of local environments. Foods in the environment and their cues (i.e., sight, smell) have been shown to induce positive affective reactions (Blechert, Meule, Busch, & Ohla, 2014; Lawrence et al., 2012; Sato, Sawada, Kubota, Toichi, & Fushiki, 2016) which can be linked to increased activity in the brain's reward system (Berridge et al., 2010). These cue-evoked positive affective reactions can have an impact on behaviour even when individuals are not aware and do not self-report a change in their emotions (Berridge & Winkielman, 2003; Hofmann & Dillen, 2012). Berridge & Winkielman (2003) argue that unconscious affective processes can be defined as positively or negatively valenced reactions that occur in the absence of conscious awareness and these core 'liking' reactions to sensory pleasures may have specialised neural substrates. In addition to "liking" as an unconscious hedonic reaction to the sensory properties of an appetitive stimulus (e.g., food) defined within the IST (see section 1.1.3), affective evaluations are a key element of the RIM's impulsive system, as they can automatically trigger behavioural schemata oriented towards food consumption (Hofmann et al., 2008; Strack & Deutsch, 2004). Food liking in general (implicit or explicit), is an important determinant of eating behaviours, not only in terms of food choices, or preferences, but potentially portion sizes, meal duration and overall nutrition health (Eertmans, Baeyens, & Van den Bergh, 2001). It is not surprising that both explicit and implicit evaluations of foods have been extensively examined in the food domain (Pool et al., 2016; Tibboel et al., 2015).

1.3.1 Implicit measures of affective evaluations

The most common implicit, or indirect, measure of affective evaluations and attitudes is the implicit association test (Greenwald, McGhee, & Schwartz, 1998) and there

are several task variants, such as the single category IAT[3] (SC-IAT; Karpinski & Steinman, 2006) and the recoding-free IAT (IAT-RF; Rothermund, Teige-Mocigemba, Gast, & Wentura, 2009). The IAT measures the strength of association between target stimuli (e.g., insects) and chosen attribute dimensions (e.g., pleasant or unpleasant). Participants are required to categorise pictorial and/or word stimuli as quickly as possible according to the concept and attribute dimensions, as for example categorising the word 'rose' as a flower and the word 'happy' as pleasant. The design of the IAT has a very specific block structure and concept/attribute pairings are not varied across trials, but across blocks. For example, in the first two blocks participants practice the target-concept discrimination (flowers vs insects) and the evaluative attribute discrimination (pleasant vs unpleasant). In the critical blocks the category labels pair the concepts with the evaluative attributes, such as 'flowers + pleasant' and 'insects + unpleasant'. An initial combined task is performed in the third block and a reversed combined task in the fifth block where the concept-attribute labels involve the opposite pairings, that is 'flowers + unpleasant' and 'insects + pleasant'. In the fourth block the target-concept discrimination is reversed. The procedural details may vary across studies, such as number of blocks, counterbalancing of label positions (left, right) and whether the evaluatively compatible labels are presented first (e.g., see more recent seven-block design in Greenwald, Nosek, & Banaji, 2003).

The basic logic of the IAT is that performance will depend on the strength of the association between the concept categories and the evaluative attributes, so that compatible categorisations (e.g., flower + pleasant, insects + unpleasant) are faster to process. The difference in average reaction times between the compatible and incompatible block can be used to indicate the strength of the implicit attitudes towards the object/concept of interest, such as foods. The difference in average reaction times can be divided by the standard deviation of the reaction times from both blocks to provide a standardised measure, referred to as D (see Greenwald et al., 2003 for different D scoring algorithms). The IAT has received considerable attention in social cognition research and even in the media, as it can presumably capture unconscious racial bias and stereotypes (e.g., see critical post by Singal, 2017). Responses in the IAT are assumed to reflect automatic processes because participants are asked to respond as fast as possible, liming the time for controlled processing to occur (Hermans, De Houwer, & Eelen, 2001). However, while it has been argued that time constraints limit conscious processing, the explicit categorisation of stimuli that

[3]The SC-IAT assesses the strength of evaluative associations for only one attitude object/concept, such as chocolate.

the IAT requires may alert participants to the aim of the task, and hence strategic responding to evaluative concepts may ensue (Fazio & Olson, 2003). Thus a major criticism of the IAT is that responses may not be a result of stimulus evaluation as much as an outcome of the evaluation of category labels (De Houwer, 2001).

Another indirect measure of automatic affective evaluations that has a number of advantages over the IAT is the affective priming paradigm (APP; Fazio, Sanbonmatsu, Powell, & Kardes, 1986; Fazio & Olson, 2003; Hermans et al., 2001; Klauer & Musch, 2003). In contrast to the IAT, the evaluative categorisation task variant of the APP involves participants responding to a set of targets that are not semantically relevant to the attitudes under investigation, thus reducing the likelihood of strategic responding. The *implicit* element of the APP can be evidenced in studies which have demonstrated that an affective priming effect can be obtained even when the primes are presented subliminally; that is, below the threshold for conscious detection (for a review see De Houwer, Teige-Mocigemba, Spruyt, & Moors, 2009). In contrast, participants in the IAT are aware of the concept-attribute labels and the assumption that the IAT can capture automatic affective evaluations (i.e., lack of awareness) has not received strong support (see De Houwer et al., 2009). The stimulus-onset asynchrony (SOA) between the prime and target is below 300ms, which is assumed to prevent controlled processing of the primes, and participants are instructed not to pay attention to the content of the primes. The APP follows a sequential response priming procedure (not semantic priming) and participants are asked to categorise target words according to their valence, that is positive or negative, when these are preceded by primes that represent the attitude object/concept that is being investigated (Wentura & Degner, 2010).

Affective congruence is manipulated across trials (not blocks as in the IAT), so that when positive primes and negative primes are paired with positive and negative targets respectively the trials are considered congruent. When positive primes and negative targets, or negative primes and positive targets are paired the trial is considered incongruent. When the prime-target pair is affectively congruent, performance is facilitated in terms of reaction times and/or error rates, so if a (food) prime automatically activates a positive evaluation it will be easier to categorise a positive target compared to a negative target and vice versa. The difference in performance between congruent and incongruent trials (incongruent - congruent for correct RTs and/or error rates) is defined as the *priming effect*. In semantic priming procedures, priming effects can be explained by a spreading activation account (Fazio, 2001; Fazio et al., 1986), which postulates that object-evaluation associations are

retrieved from memory upon the perception of the prime and this activation can spread from the prime to the evaluation, thus facilitating performance for evaluatively congruent targets. Although priming effects in the evaluative categorisation task variant of the APP could be explained by this *encoding* perspective, the prime can activate a response (e.g., positive) that can be either congruent or incongruent compared to the response activated by the target (i.e., positive or negative). This means that priming effects in the APP could also be considered from a *response* perspective that assumes a response facilitation/interference mechanism (Herring et al., 2013; Klauer & Musch, 2003).

1.3.2 Affective evaluations of unhealthy foods

Food choices can be determined by both internal and external factors, such as the psychological (e.g., mood) or physiological (e.g., thirst) state of the individual and situational context (e.g., where, when) but they are primarily guided by liking (Eertmans et al., 2001; Mela, 2001). Following the dual-process framework described in this thesis, food choices can be considered 'unhealthy' when they are driven by impulsive precursors such as strong automatic affective reactions and the reflective system fails to regulate the associated behavioural tendencies (e.g., purchase the food for consumption), which suggests a distinction between impulsive and deliberate food choices (also see Veling, Chen, et al., 2017; Zoltak, Veling, Chen, & Holland, 2018). Automatic affective reactions to foods, or liking, could therefore have predictive utility in food choice research and contribute to our understanding of individual differences. For instance, it would be expected that overweight and/or obese individuals would have stronger affective reactions to energy-dense foods and that potential moderators, such as dietary restraint, could explain why some individuals are more prone, or find it harder to overcome, unhealthy eating behaviours (e.g,. overeating).

Although food attitudes measured via indirect measures are thought to reflect the automatic affective evaluation of foods or food categories (e.g., high-fat vs low-fat), research findings in the literature are telling a more complicated story. Roefs & Jansen (2002) employed an IAT to test whether implicit attitudes towards high-fat foods relative to low-fat foods would be stronger in a group of obese individuals compared to a group of normal-weight individuals. Participants had to categorise words from the concept category (high-fat or low-fat) and the attribute category (positive or negative). Obese participants were therefore expected to respond faster when the label category was high-fat + positive rather than low-fat + positive. Contrary to

predictions, both obese and normal-weight individuals showed a negative implicit attitude towards high-fat foods. Specifically, obese individuals were slower to respond to the high-fat + positive category compared to normal-weight individuals, which was consistent with their explicit evaluations where they indicated that they preferred low-fat foods. However, the IAT required participants to pay attention to the fat content of the foods, which could indicate that the obtained measure of implicit bias reflected participants' attitudes towards high-fat foods as 'forbidden' due to dieting goals even if they had a strong liking for them. This raises a methodological issue (Roefs et al., 2011) because the explicit categorisation based on fat content in the IAT may mean that the strength of associations between concepts and attributes can represent participants' automatic affective evaluations (automatic processing) and/or health-related concerns (controlled processing).

Roefs et al. (2005) hypothesised that restrained eaters (i.e., individuals who restrict their dietary intake as a means of weight regulation) would show stronger liking of high-fat foods compared to unrestrained eaters. They employed an APP variant where participants had to categorise target words as either positive or negative when these were preceded by either high-fat or low-fat food word primes (Experiment 1). The primes were selected based on a direct rank order task as either most liked ('palatable') or least liked ('unpalatable') for both the high-fat and low-fat category. Across participants, there was a significant priming effect in the predicted direction, that is, reaction times were on average faster on congruent (palatable food prime and positive target or unpalatable food prime and negative target) compared to incongruent trials (palatable food prime and negative target or unpalatable food prime and positive target). Authors reported no differences between restrained and unrestrained eaters[4], which could indicate that restrained eating is characterised by increased "wanting" for palatable foods, but not "liking", consistent with the incentive-sensitisation theory (also see Roefs et al., 2011 for related findings based on other indirect measures). Interestingly, the fat content of the food primes did not have an effect on participants' performance in the affective priming task, while participants' direct (explicit) ratings indicated that low-fat foods were liked more compared to high-fat foods.

These results may indicate that the APP is less prone to influences in performance due to controlled processing (e.g., health concerns) compared to the IAT, but evidence for this assumption is inconsistent in the literature. For example, Becker, Jostmann, Wiers, & Holland (2015) also reported no differences for the food prime contrasts

[4]It should be noted that the are various measures of dietary restraint which can often yield inconsistent findings (see Williamson et al., 2007).

(healthy, unhealthy, control) in their APP (Study 2), whereas Roefs, Stapert, et al. (2005) showed that both the group of obese individuals and unrestrained normal-weight controls (Experiment 2) preferred low-fat palatable foods over high-fat palatable foods, suggesting that health concerns can influence the affective priming effect. Eertmans et al. (2001) highlighted that liking (sensory-affective response) is not the sole determinant of eating behaviours and anticipated consequences (e.g., nutrition and health attitudes) should also be considered. The evaluation of foods might be influenced by their perceived healthiness due to health and weight-related goals or social norms (i.e., what one *should* like; Czyzewska & Graham, 2008). Unhealthy foods can also be perceived to be tastier than healthy foods and chosen for consumption more frequently, even if individuals are not consciously aware of this association between healthiness and tastiness (Ackermann & Palmer, 2014).

Trendel & Werle (2015) recently drew attention to the importance of distinguishing between affective (e.g., palatability, hedonic reactions) and cognitive components (e.g., perceived healthiness, calories, dieting effect) of implicit attitudes towards food as potential predictors of eating behaviours. Although deliberate thoughts about dieting goals and weight regulation are part of a controlled processing system, the authors argue that the healthiness value of the foods can be automatically retrieved from memory (also see Rangel, 2013). Indirect measures of food evaluations or attitudes should be investigated further in relation to both the affective and cognitive components as there is currently not enough evidence to suggest that food choice behaviour can be reliably predicted in laboratory settings, especially when other moderators such as cognitive control resources are not considered (see Roefs et al., 2011). The interplay between automatic and controlled processes in eating behaviours, including food choices, is further discussed in section 1.5.3. Affective food evaluations and their measurement are also of paramount importance for studies that investigate the mechanisms of behaviour change interventions, such as inhibitory control training (see section 1.6.3).

1.4 Approach bias

Action tendencies refer to approach and avoidance responses towards stimuli in the environment that are triggered automatically (Wiers, Rinck, Dictus, & Van Den Wildenberg, 2009), consistent with the concept of motivational orientation in the RIM's impulsive system (Strack & Deutsch, 2004). Approach bias refers to the automatic action tendency to approach rather than avoid an appetitive cue (C. E.

Wiers et al., 2013) and has received considerable attention in neurobiological accounts of cravings. In the context of eating behaviours, cravings can be defined as motivational states in which individuals show a strong desire or urge to consume a specific food (Kemps, Tiggemann, Martin, & Elliott, 2013; Weingarten & Elston, 1990). Cravings are strongly related to the concept of "wanting" in the IST and recent neurocognitive models of obesity which link food-related motivation to the brain's reward system (Berridge, 2009; Berridge et al., 2010). In relative terms, "wanting" can represent an approach bias towards craving-related cues, such as the sight or smell of an appetitive food, that have acquired 'incentive salience' due to classically conditioned (Pavlovian) associations between cues and rewarding food consumption (Berridge, 2009; Kemps et al., 2013). These automatically triggered appetitive response towards craving-related food cues can occur without conscious awareness. These concepts and related neurobiological substrates are discussed in section 1.1.3.

1.4.1 Implicit measures of automatic action tendencies

Automatic action tendencies, including approach bias towards food cues, can be captured by implicit behavioural measures. The two most commonly employed measures in the food domain are the stimulus-response compatibility (SRC) task (Bradley, Field, Mogg, & Houwer, 2004; Mogg, Bradley, Field, & Houwer, 2003) and the approach-avoidance task (AAT; Neumann & Strack, 2000; Rinck & Becker, 2007; Reinout W Wiers et al., 2013). The SRC task assumes an interaction between affect and motivation (see Elliot, Eder, & Harmon-Jones, 2013; Chen & Bargh, 1999) similar to the bidirectionality assumption of the RIM (see section 1.2), whereby a positive stimulus can activate an approach orientation and thus there is a compatibility between responses to a positive stimulus and behavioural tendencies to approach that stimulus, and incompatibility when there is a behavioural tendency to avoid that stimulus (De Houwer, Musch, & Klauer, 2003; as cited by Mogg et al., 2003). In the SRC task participants are required to move a manikin figure towards or away from a centrally presented picture that appears above or below the picture with equal probability. The manikin element has been adapted from the Affective Simon (manikin) task employed by De Houwer et al. (2001). The responses require participants to pay attention to the features of the stimuli, such as judging whether the depicted scene is related or unrelated to smoking (Mogg et al., 2003). In a food-related example, participants can be instructed to move the manikin towards the picture if it is food-related and away from the picture if it is nonfood-related in one block of trials (approach-food), while

this stimulus-response assignment is reversed in a second block of trials (approach-nonfood; Mogg et al., 2012). Reaction times are recorded from stimulus onset until a response is initiated (i.e., a key is pressed to start moving the manikin). The mean RTs from correct approach-food trials are subtracted from the mean RTs from approach-nonfood trials to indicate approach bias, whereby positive difference scores correspond to approach bias towards foods.

The AAT is employed as an indirect measure of automatic action tendencies and has several variants with important methodological parameters that should be taken into account. The AAT assumes that approach and avoidance behaviour can be associated with the motor movements of flexion and extension respectively. Specifically, participants are instructed to either pull (flexion) or push (extension) a joystick in response to specific stimuli. Evidence contradicting this assumption has been reported in several studies (see Phaf, Mohr, Rotteveel, & Wicherts, 2014) and intuitively there are cases in which arm flexion and extension can represent the reverse behavioural tendencies, as for example extending one's arm to reach for a food item (object-reference) or extending one's arm to push a food item away from the body/self (self-reference; Phaf et al., 2014). For this reason, a common variant of the AAT pairs motor actions with visual feedback; that is, when participants pull the joystick the picture increases in size (zoom-in effect) and when they push the joystick away it decreases (zoom-out effect). The 'zooming' feature of the AAT acts as an exteroceptive cue of approach-avoidance responses which together with the proprioceptive element of the task (arm flexion/extension) strengthens the association of motor movements and approach-avoidance motivation, whereby pulling the joystick towards, or pushing the joystick away from, one's body/self reflects approach or avoidance respectively (Neumann & Strack, 2000; Wiers et al., 2009). Another important parameter in the AAT is that participants respond to a task-irrelevant feature, such as the orientation of the picture (portrait or landscape; C. E. Wiers et al., 2013). This variant of the AAT thus involves participants receiving implicit instructions and the stimuli do not need to be explicitly evaluated on affective valence (Phaf et al., 2014). It should be noted that there is evidence to suggest that explicit instructions, such as instructing participants to pull the joystick towards them when the picture is positive and push it away when the picture is negative, can yield larger effect sizes (Phaf et al., 2014; also see Lender, Meule, Rinck, Brockmeyer, & Blechert, 2018). Approach-avoidance bias is defined as the average (mean or median) RT from correct pull trials subtracted from average RTs on push trials. Positive scores reflect approach bias and negative scores indicate avoidance bias. A relative bias index can also be examined for food

and non-food difference scores (food − non-food; e.g., see Lender et al., 2018).

1.4.2 Evidence for food approach bias

Approach bias for foods has been examined in a variety of populations. There is evidence for heightened approach bias in individuals who purposefully restrict their dietary intake (i.e., restrained eaters) and individuals who are sensitive to external cues such as sight or smell of appetitive foods (i.e., external eaters; Brignell, Griffiths, Bradley, & Mogg, 2009; Veenstra & de Jong, 2010). Mogg et al. (2012) employed an SRC manikin task with approach-food and approach-nonfood blocks in a sample of overweight and obese adults. They found that participants were faster to respond in the approach-food/avoid-nonfood block compared to the approach-nonfood/avoid-food block, indicating approach bias for foods. A noteworthy limitation of this study was that the food and non-food stimuli differed in hedonic value (foods vs affectively neutral stimuli, such as household items) and it is thus not clear whether observed effects are due to approach bias or hedonic bias (i.e., liking). Also, participants were asked to fast before the study (no food intake for 15 hours) and approach bias could reflect behavioural tendencies driven by homeostatic eating motives. Kemps & Tiggemann (2015) extended these findings in a large community sample of obese individuals and normal-weight individuals (control group) that were not required to fast before the study. Instead of an SRC task, they employed an approach-avoidance variant of the IAT where participants had to categorise word stimuli based on two concept categories (food and non-food) and two attribute categories (approach and avoid). Non-food stimuli included appealing animals (e.g., kitten) that were assumed to be matched with food stimuli on liking. Approach bias in this variant of the IAT was indicated by participants responding faster when the food concept and approach attribute categories were paired together (food-approach) relative to the opposite pairings (food-avoid). The authors reported that there was evidence for approach bias towards foods in obese participants, but not normal-weight participants, while approach bias was observed for both high- and low-calorie foods. However, it should be noted that this may simply be an issue with the IAT which requires explicit evaluative categorisation based on concept/attribute labels, as discussed in section 1.3.1.

These behavioural studies have primarily focused on foods in general, but the association between approach bias and craving-related food cues and/or subjective cravings has also been investigated in recent research. Kemps et al. (2013) examined a specific highly-craved food (i.e., chocolate) and found that participants had strong

chocolate-approach compared to chocolate-avoid associations in a variant of the IAT with pictorial food stimuli (Experiment 1). A positive correlation between participants' approach bias for chocolate and subjective chocolate cravings was also reported (r = 0.29; Kemps et al., 2013). The association between food cravings and approach bias was further examined by Brockmeyer et al. (2015a) who classified participants according to trait food craving levels (extremely high or extremely low) using a validated self-report measure; that is, the Food Cravings Questionnaire - Trait (Meule, Lutz, Vögele, & Kübler, 2012). The food AAT involved pull and push joystick movements in response to the format of the picture frames (i.e., task-irrelevant feature; round vs rectangular) and a 'zooming' element, as previously described. Food cue reactivity was examined via the Food Challenge Task (FCT; Van den Eynde et al., 2010) in which participants report their state food cravings using the Food Craving Questionnaire - State at baseline and after watching a short video of various highly appetitive foods that presumably induces food cravings (i.e., cue-elicited food cravings). Participants who had high levels of trait cravings had stronger approach bias towards foods in the AAT compared to participants with low trait food craving levels. There were no differences between the two groups of participants for approach bias towards non-food stimuli. The authors also report evidence for significant positive correlations between food approach bias and food cue reactivity (state food craving change from baseline; r = 0.35), cue-induced cravings (post-exposure; r = 0.37) as well as trait food cravings (r = 0.36).

Approach bias for foods has been further evidenced in studies that employed the AAT as a training intervention with manipulated stimulus-response contingencies (e.g., unhealthy foods consistently presented on push-avoid trials). Brockmeyer et al. (2015b) indirectly measured automatic action tendencies via an AAT with food and neutral non-food stimuli (50:50 response-format assignment) and examined both trait and state food cravings. AAT training involved foods always being paired with push (avoid) trials and was delivered twice a week for a total of 10 short sessions. AAT training led to significantly reduced approach bias towards food as well as trait and state (cue-elicited) food cravings. Although the study design only included pre- and post-training measurements and no control group, the training effect for approach bias was specific to food stimuli, as there were no changes in bias scores for non-food stimuli. Schumacher, Kemps, & Tiggemann (2016) used a similar AAT training protocol tailored to manipulate approach bias for chocolate-related foods and measured food intake in the laboratory. The food stimuli were chocolate and non-chocolate items that were matched as much as possible (e.g., chocolate cake vs vanilla cake) and

a 90:10 contingency was used to reduce participant's awareness of response-format assignments. In the approach-chocolate group participants were trained to approach chocolate stimuli on the majority of trials, whereas in the avoid-chocolate group the opposite pairings were implemented. In the taste test, participants had to taste and rate a chocolate muffin and a non-chocolate muffin and chocolate muffin consumption was measured. The increase in chocolate approach bias from pre-to-post training in the approach-chocolate group was not significant, but there was conclusive evidence for a reduction in approach bias in the avoid-chocolate condition, including a between-group difference on chocolate muffin consumption (i.e., less consumed in the avoid group). Other studies employing AAT training protocols have yielded null and inconsistent findings (see meta-analysis by Aulbach, Knittle, & Haukkala, 2019; Becker et al., 2015; Dickson, Kavanagh, & MacLeod, 2016).

Overall, there is sufficient evidence to suggest that individuals' approach bias towards food cues is an important impulsive precursor for eating behaviours, as it has been evidenced in target populations (e.g., obese individuals, restrained eaters) and it has been associated with key elements of food cravings (i.e., subjective, trait, cue-induced). The training literature has indicated that approach bias can be manipulated via behavioural paradigms (e.g,. AAT training) and a decrease in approach bias towards highly-craved foods may result in health behaviour change, including a reduction in food consumption.

1.5 Inhibitory control

An important component of controlled processing is inhibitory control which has been defined as "the ability to inhibit a behavioural impulse in order to attain higher-order goals, such as weight loss" (Houben, Nederkoorn, & Jansen, 2012, p. 550) and is a critical aspect of executive functioning that can help individuals to overcome temptation or urges that are not compatible with health-related goals (Bartholdy et al., 2016b; Lavagnino, Arnone, Cao, Soares, & Selvaraj, 2016). Inhibitory control has been operationalised as an individual's ability to stop or change an action that has been planned or already initiated (Logan, 1982; Logan, Cowan, & Davis, 1984; Logan, Schachar, & Tannock, 1997). The term has been broadly applied in the literature and often used interchangeably with the concept of self-control or impulsivity (A. Jones, Robinson, et al., 2018) and appropriate definitions are provided in this section to aid in the interpretation of findings. Inhibitory control can be considered an umbrella term for several cognitive processes and functions, such as response inhibition, which

refers to one's ability to inhibit a motor response, and reward-based or motivational inhibition, which reflects one's ability to delay rewards or gratification (Bartholdy et al., 2016b).

Most research related to eating behaviours concerns the element of response inhibition which can further be categorised into two types: proactive and reactive inhibition and characterised as controlled or automatic in its operationalisation (see section below). Proactive inhibition primarily refers to preparatory processes and strategic response speed adjustments (e.g., proactive slowing) in anticipation of stop responses or in the context of uncertainty (Bartholdy et al., 2016a; Elchlepp, Lavric, Chambers, & Verbruggen, 2016). Although proactive inhibition may be an important aspect of inhibitory control involved in eating disorders (see Bartholdy et al., 2016a), reactive inhibition has received considerably more attention. Reactive inhibition can be manifested as either an action cancellation or action restraint, that is individuals can either cancel a response that has already been initiated or withhold a planned response (Schachar et al., 2007).

1.5.1 Behavioural paradigms

The two most prominent behavioural paradigms that are employed to examine inhibitory control are the go/no-go paradigm (Donders, 1969; Newman & Kosson, 1986) and stop-signal paradigm (Lappin & Eriksen, 1966; Logan et al., 1984), which both involve participants inhibiting a motor response towards a stimulus[5]. In go/no-go (GNG) tasks participants are often instructed to withhold a response when a specific type of stimulus (no-go stimulus) is presented. Participants respond to a go stimulus (e.g,. press the response key when the letter 'K' appears) and refrain from responding to a no-go stimulus (e.g,. do not press the response key when the letter 'L' appears). In the stop-signal task (SST), participants make speeded choices, such as pressing the left response key when the letter 'K' appears and the right response key when the letter 'L' is shown (no-signal trials). On a minority of trials (signal trials), a signal is presented after stimulus onset to indicate that participants need to withhold their responses (Verbruggen & Logan, 2008a). A crucial difference between the two paradigms is that in the SST a signal appears after a variable delay (stop-signal delay, or SSD) which can either be fixed or dynamic (i.e., adjusted based on participants' performance) and thus increases the difficulty of response inhibition (Verbruggen &

[5]An important measure that has not received attention in the food domain is the stop-change paradigm (Logan, 1982), which requires participants to cancel an initiated response and instead execute an alternative action. This paradigm is further discussed in Chapter 3.

Logan, 2008b). Performance in both paradigms can be modelled as a race between a go and a stop process, whereby successful response inhibition is dependent on whether the stop process finishes before the go process (Logan, Van Zandt, Verbruggen, & Wagenmakers, 2014; Verbruggen & Logan, 2008a). While in the GNG task the stop process is initiated upon stimulus/cue onset together with the go process, in the SST the stop process depends on the SSD. Therefore, the GNG task involves 'action restraint', whereas the SST taps into 'action cancellation', which may require increased control demands (Eagle, Bari, & Robbins, 2008).

Indices of inhibitory control ability, or capacity, can be derived from both the go/no-go and stop-signal paradigms. The finishing time of the stop process is not overt (i.e., cannot be directly observed) and in the GNG task researchers examine the proportion of errors on no-go trials, where participants incorrectly respond to a no-go stimulus (i.e., commission errors or false alarms). Higher proportions of errors on no-go trials can indicate lower, or poorer, inhibitory control ability (Eagle et al., 2008). In the SST, the stop-signal reaction time (SSRT) can be estimated via mathematical models of the race between the go and stop process (see Logan et al., 2014 for review of seminal and contemporary models). Higher SSRTs in the stop-signal paradigm can reflect lower inhibitory control ability (Logan et al., 1997) and have been successfully employed as an index of inhibitory control deficits in a range of clinical populations (see Verbruggen & Logan, 2008b for review). In addition to the distinction of action restraint and action cancellation, experimental studies have shown that the go/no-go and stop-signal paradigms tap into automatic and controlled response inhibition, respectively (Verbruggen & Logan, 2008a). Automatic, or bottom up, response inhibition refers to the development of automaticity during GNG task blocks due to the consistent stimulus-response (S-R) mapping, as for example no-go stimuli always require that responses are inhibited (Verbruggen & Logan, 2008a). This means that go and stop goals can be automatically activated from memory, whereas in the SST inconsistent S-R mapping ensures that control resources are not reduced due to automaticity, which means that it taps into controlled, or top-down, inhibition.

Early neuroimaging studies employing the GNG task have identified a right-hemisphere network of brain regions, including the dorsolateral prefrontal cortex (dlPFC) and inferior frontal gyrus (IFG), whereas later research indicated the involvement of bilateral dlPFC and ventrolateral prefrontal cortex (vlPFC), the anterior cingulate cortex (ACC), pre-supplementary motor area (pre-SMA), inferior parietal cortex and basal ganglia (Swick, Ashley, & Turken, 2011). Response inhibition operationalised through the SST has also been associated with a right-lateralised brain

network, including the IFG, pre-SMA and subthalamic nucleus (Aron, Robbins, & Poldrack, 2014). Other studies have implicated subcortical structures such as the striatum (Vink et al., 2005). Nevertheless, there have only been a few studies exploring direct contrasts of going and stopping in the GNG task and SST (McNab et al., 2008; Rubia et al., 2001; Zheng, Oka, Bokura, & Yamaguchi, 2008). This inconsistency in neuroimaging findings can provide complementary evidence for the assumption that the GNG and SST paradigms tap into different elements of response inhibition (Bartholdy et al., 2016b; Swick et al., 2011), such as action restraint and action cancellation (Eagle et al., 2008; Schachar et al., 2007).

1.5.2 Evidence for the role of inhibitory control

Evidence regarding the role of inhibitory control in eating-related behaviours from studies employing the SST has overall been mixed (Bartholdy et al., 2016b). For example, studies that have employed food-specific variants of the SST in overweight and obese populations have found evidence for lower inhibitory control in later blocks of the task (Guerrieri, Nederkoorn, & Jansen, 2008; Nederkoorn, Smulders, Havermans, Roefs, & Jansen, 2006), which may indicate difficulties in the maintenance of inhibitory control rather than an overall deficit (Bartholdy et al., 2016b). Houben, Nederkoorn, & Jansen (2014) provided evidence for an association between BMI and food-specific response inhibition, but not general response inhibition ability. Participant subgroups were created based on one standard deviation (SD) from the mean BMI of 22.28 kg/m^2 (range 13.86 - 39.86), and comparisons were conducted for high (+ 1 SD) and low (- 1 SD) BMI participants. The authors reported that participants with a higher BMI had lower inhibitory control, as indicated by higher SSRTs relative to participants with a lower BMI, but only in the food-specific SST. In a meta-analysis by Lavagnino et al. (2016), there was evidence in a proportion of studies (60%) that examined the differences in inhibitory control between obese and normal-weight individual that obesity may be characterised by lower inhibitory control performance in behavioural paradigms. For example, Chamberlain, Derbyshire, Leppink, & Grant (2015) employed a general (not food-specific) SST in a sample of overweight (N = 110), obese (N = 55) and normal-weight individuals (N = 346) and showed that obese, but not overweight, individuals had significantly higher SSRTs compared to normal-weight individuals (control group). Mole et al. (2015) reported similar findings for obese participants without binge eating disorder compared to a group of healthy-weight participants that were matched on age and gender.

Moving beyond research that treats inhibitory control as a *trait* characteristic, it could be assumed that in an obesogenic environment, constant exposure to appetitive food cues may actually reduce individuals' *state* inhibitory control (A. Jones, Robinson, et al., 2018). A recent meta-analysis showed that overall exposure to food-related cues does not significantly impact inhibitory control in overweight, obese or normal-weight individuals when studies employing various behavioural paradigms of inhibitory control were examined (A. Jones, Robinson, et al., 2018). However, exposure to food-related cues was found to have more robust effects on inhibitory control when studies using the go/no-go shifting tasks were removed from the analysis (see A. Jones, Robinson, et al., 2018; Meule, 2017 for discussion) and individually, inhibitory control was shown to be impaired when measured with SST variants, but not GNG tasks. Variability in methodology may be very crucial for the interpretation of findings, as SST variants could capture top-down inhibitory control, whereas GNG tasks tap into automatic, or bottom-up, response inhibition.

Evidence for the association of inhibitory control and actual eating behaviours, such as food intake in the laboratory, is not adequate to draw any conclusions. Guerrieri et al. (2007) reported that impulsivity measured using the SST did not affect food intake, but the expected group differences (i.e., increase food intake when impulsivity is high compared to low) were only observed when participants were classified as either high- or low-impulsives via a self-report measure of impulsivity, that is, the Barratt Impulsiveness Scale (Patton, Stanford, & Barratt, 1995). However, the role of inhibitory control in the regulation of food consumption can better be elucidated in studies that have employed behavioural paradigms of inhibitory control as training interventions, which are presented in section 1.6.2. Complementary evidence for the importance of inhibitory control in overweight and obesity stems from research studies that investigate the interaction between automatic and controlled processes which are outlined in the following section (1.5.3).

1.5.3 Interplay between automatic and controlled processes

One of the key predictions of the dual-process models is that automatic and controlled processes interact to predict behaviour and there is considerable empirical evidence to support this claim. A prominent example of this interaction is that automatic affective reactions or implicit evaluations (attitudes) towards unhealthy foods predict food choices and consumption only when individuals have poor trait and/or state inhibitory control or other low cognitive resources (e.g., working memory capacity),

as measured or manipulated in laboratory settings. Hofmann et al. (2009a) measured inhibitory control via an adapted SST and automatic affective reactions towards a specific food item (peanut m&m's) using an SC-IAT. Food consumption was examined in a product test procedure, where participants are provided with 125g of candy and are asked to taste and rate them on several characteristics. The weight of consumed candy is calculated at the end as a measure of food consumption. The authors reported that automatic affective reactions towards candy had a stronger influence on subsequent consumption in individuals that showed low inhibitory control. Differences in controlled processing, such as inhibitory control capacity, may therefore explain individual differences in how strongly automatic processing affects behaviour. Nederkoorn, Houben, Hofmann, Roefs, & Jansen (2010) measured response inhibition via an SST (i.e., top-down inhibitory control) whereby higher SSRTs can reflect lower inhibitory control (Logan et al., 1997) and examined implicit attitudes ('preferences'[6]) towards snack food via an SC-IAT. Instead of food consumption in the laboratory, Nederkoorn et al. (2010) provided a longitudinal measurement of weight after a one-year period to examine whether response inhibition and implicit snack food attitudes predicted actual weight change. They found that response inhibition efficacy predicted weight change only in individuals with strong implicit attitudes. Specifically, participants who showed a greater 'preference' for snack foods in the SC-IAT and had less effective response inhibition gained more weight after one year compared to participants with more effective response inhibition. A limitation of this study, however, was that although dietary intake was assumed to drive the potential weight-gain after the one-year period, a measure of dietary intake was not employed.

Other studies have directly manipulated cognitive control resources in the reflective system, such as working memory capacity and other self-regulatory resources (Friese, Hofmann, & Wänke, 2008; Hofmann, Rauch, & Gawronski, 2007). Friese et al. (2008) employed a food choice task where participants had to choose five items from a variety of fruit and chocolate categories (e.g., tangerines, apples, Snickers bars, Twix bars) which were placed on the table (Study 1). Working memory capacity was manipulated by instructing participants to remember a number they saw in the beginning of the task, which they would need to recall upon task completion. In the low-capacity condition participants were given a one-digit number to remember, whereas in the high-capacity condition the number consisted of eight digits. The behavioural outcome reflected the

[6]I purposefully avoid the term *preferences* as it is currently being used in the literature because food preferences incorporate an element of choice behaviour and not only evaluations or affect (e.g., see Chen, Holland, Quandt, Dijksterhuis, & Veling, 2019).

number of chocolates that were chosen out of the presented food items. The authors found that explicitly measured food attitudes (Likert scale) predicted food choices in the high- but not low- capacity condition, while implicit food attitudes (IAT variant) predicted choice behaviour very well in the low- but not high- capacity condition (Friese et al., 2008). In Study 2 (Friese et al., 2008), self-regulatory resources (Muraven & Baumeister, 2000) were manipulated via an emotion suppression task and food consumption (potato crisps) was measured using the product test procedure. Explicit and implicit attitudes (SC-IAT) were also assessed, while the explicit attitude index was merged from two types of ratings that incorporated affective valence ('negative' vs 'positive') and taste ('not delicious at all' vs 'very delicious'). In the control condition where participants were instructed to watch the short movie while expressing freely any emotions they had (no depletion), a good predictor of food consumption was the explicit attitude measure. On the contrary, when participants were required to suppress their emotions while watching the movie (depletion), the implicit attitude measure was the significant predictor of food consumption. Authors also reported that the interaction between explicit and implicit measures was non-significant, which indicates that explicit food attitudes that are based on controlled processes within the reflective system may differ from automatic affective reactions, or implicit attitudes, in the impulsive system. Similar results have been reported by Hofmann et al. (2007) who found that positive implicit attitudes towards candy as measured via an IAT significantly predicted increased candy consumption in the depletion condition, but not in the control condition. Both studies make references to previous research and theory on self-regulation, such as ego depletion (Muraven & Baumeister, 2000; Vohs & Baumeister, 2017) and these concepts are not discussed further due to recent findings that raised concerns about the replicability and size of the ego-depletion effect (Hagger et al., 2016). All the studies mentioned thus far measured general inhibitory control and it remains to be seen whether the interactive effects of automatic and controlled process on eating behaviour can be supported in studies that measure food-specific inhibitory control.

The interplay between automatic and controlled processing in the context of eating behaviours has also been examined for approach bias and inhibitory control. Kakoschke et al. (2015) measured approach bias via an AAT with positive food and non-food stimuli. Food items were high in sugar, salt and/or fat and non-food pictures included animal categories (e.g., koala) and all stimuli were selected from a pilot study where ratings of pleasure and arousal were provided. Inhibitory control was not measured via an SST, but a food-specific go/no-go task where a higher proportion of commission

errors (i.e., not inhibiting a response on no-go trials) reflects lower, or poorer, inhibitory control. The authors report that cognitive bias[7] and inhibitory control did not predict the intake of unhealthy foods in the laboratory taste test when considered in isolation. However, there was an interactive effect of approach bias and inhibitory control on food intake, whereby participants with high approach bias towards unhealthy foods and lower inhibitory control showed increased consumption compared to participants with high approach bias and higher inhibitory control. This interaction was not found for participants who had low approach bias towards unhealthy foods. This study provides additional evidence for the interaction between automatic and controlled processing in predicting eating behaviours when food-specific inhibitory control is examined, which may be more important for unhealthy eating compared to general inhibitory control, as previously discussed in section 1.5.2.

1.6 Behavioural training interventions

In sections 1.3, 1.4 and 1.5 evidence for the role of automatic and controlled processes in eating behaviours has highlighted the potential explanation for ineffective regulation of cue-evoked responses to food and subsequent consumption. When an appetitive food cue is initially perceived it can be automatically evaluated as positive and unconscious affective reactions can activate an approach orientation towards the food item. This is translated as a behavioural tendency to approach the food, which in turn triggers the behavioural schemata for food consumption (e.g., bring the food closer to one's mouth) in the motor cortex. When cognitive control resources are low, such as state and/or trait inhibitory control, the behavioural schemata in the impulsive system will guide behavioural outcomes even if these are incompatible with higher-order goals of a healthier diet and/or weight loss. The RIM also predicts that these impulsive (e.g., affective reactions, approach bias), and possibly reflective (e.g., inhibitory control capacity), precursors of behaviour can be changed via behavioural interventions (Hofmann et al., 2009b). Indeed, there has been a rapid rise in the number of research studies that have investigated behavioural training interventions that target both automatic and controlled processes, such as generalised- and cue-specific- inhibitory control training, attentional bias modification, working memory training and approach-avoidance training (for a recent review see Jones et al., 2018). These interventions can be administered via mobile technologies (e.g., portable device, computer), are

[7] They refer to cognitive bias because they measured both attentional and approach bias towards foods.

cost-effective and can potentially replace or complement more traditional interventions (Jones et al., 2018).

1.6.1 Inhibitory control training paradigms

In this thesis, the focus is on food-specific inhibitory control training (ICT) protocols that can target an individuals' ability to inhibit their responses to foods. These ICT protocols are primarily adapted from the go/no-go and stop-signal paradigms (see section 1.5.1), which can be tailored to train action restraint and cancellation with respect to specific food categories (e.g., unhealthy snacks) or items (e.g., chocolate). Generalised ICT protocols aim to increase inhibitory control capacity, whereas food-specific ICT tasks can form specific associations between response inhibition and food cues (Jones et al., 2018), consistent with the dual-process framework where inhibitory control needs to be exerted when appetitive stimuli that induce positive affective reactions and approach bias are encountered. Go/no-go training involves participants performing a simple reaction time task where they are instructed to press a button either when a specific cue, or no cue, appears (go trials). On other trials, a cue indicates that participants do not have to press a button, that is, refrain from responding (no-go trials). In some designs, cues are only presented on no-go trials, consistent with the concept of a 'signal' in the SST, as for example the visual cue of a picture frame turning bold, and participants perform a categorisation task (e.g., press "c" when picture appears on the left and "m" when it is on the left side of the screen; Lawrence, O'Sullivan, et al., 2015). Alternatively, auditory cues are presented on both go and no-go trials, as for example low- and high-Hz tones, and participants are instructed to press a button only when the go cue is identified (Chen, Veling, Dijksterhuis, & Holland, 2016). The essential design parameters in GNG training protocols include the high frequency of no-go trials (e.g., 50%), the consistent S-R mapping for food stimuli and no-go responses (e.g., 100%) and the very short, or zero, delay between cue and stimulus onset times, with appropriate time pressure that does not increase task difficulty (Veling et al., 2017). Go responses are paired with either other food stimuli or non-food stimuli. Control conditions and the type of stimuli presented on go trials vary across studies and are further described with respective protocols and findings in section 1.6.2 (also see Jones et al., 2018).

ICT protocols adopting the principles of the stop-signal paradigm involve speeded classification responses towards presented stimuli, such as correctly identifying the location of a stimulus on the screen (left or right), and on a proportion of the trials a

cue, or signal, appears to indicate that participants have to withhold their response (e.g., Lawrence et al., 2015). Two crucial elements of SST training protocols are the delay between the stimulus and signal onset times and the proportion of signal, or no-go, trials. The delay is often dynamically adjusted via a staircase procedure based on participants' performance on previous trials to maintain the difficulty of stopping (i.e., successful response inhibition in 50% to 75% of the trials) and the signal is presented only on a minority of the trials (e.g., 25%; Veling et al., 2017). In SST training, participants are required to respond to both non-food, or neutral, stimuli and target food stimuli (i.e., inconsistent S-R mapping). The consistent pairing of food stimuli with no-go trials in the GNG training tasks can lead to learned associations between a stop goal and the presented food items, thus leading to improved, possibly automatic, response inhibition (Spierer, Chavan, & Manuel, 2013; Verbruggen & Logan, 2008a). On the other hand, SST training protocols require more controlled, or top-down, response inhibition. The two different elements of response inhibition may be responsible for differential effects of training between the two paradigms.

In a meta-analysis by Allom, Mullan, & Hagger (2016) the GNG training paradigm was reported to have a medium effect size for the improvement of health behaviour (e.g., reduced food consumption), whereas the SST training protocols only yielded a small non-significant effect. This finding could primarily be attributed to the fact that the two paradigms tap into different elements of response inhibition and this has been corroborated in recent meta-analyses (Aulbach et al., 2019; Jones et al., 2016; Turton, Bruidegom, Cardi, Hirsch, & Treasure, 2016). Another potential explanation for this finding is that the SST is generally more demanding and increased task difficulty can reduce the overall success of response inhibition during training (Veling et al., 2017), which is a significant moderator of training effects on behaviour change in the laboratory (Jones et al., 2016) and may reduce the probability of food-inhibition associations being formed during training (Jones et al., 2018), as explained in section 1.6.3.

1.6.2 Inhibitory control training outcomes

Single-session studies

Recent meta-analyses have shown that food-specific ICT interventions have a small-to-medium effect on health-related outcomes in the laboratory, such as as food intake and choice behaviour (Allom et al., 2016; Jones et al., 2016; Turton et al., 2016). These effects have been primarily reported in studies that employed a single session of

food-specific ICT and recruited healthy-weight individuals (e.g., Houben & Jansen, 2015; Houben, 2011; Lawrence et al., 2015; Veling et al., 2013a, 2013b; Veling, van Koningsbruggen, Aarts, & Stroebe, 2014). There are a number of potential moderators of training outcomes which are often investigated, as for example training effects on food intake and choice behaviour may be greater for individuals who have high levels of dietary restraint or report existing dieting goals at the time of the study (Jones et al., 2016; also see study by Houben & Jansen, 2011).

Veling et al. (2013a) directly examined the role of appetite in ICT effects and assigned healthy-weight individuals into a low or high appetite condition depending on whether they participated in the study after or before lunch. They administered a GNG training task that required participants to respond according to a letter shown on the screen (A or L) in one of four quadrants of a picture. After 1500ms the stimulus was replaced by a blue question mark and participants had to either respond when a specific letter had appeared (counterbalanced) or refrain from responding when the other letter was presented. The letters represented the go and no-go cues and a consistent S-R mapping was used for the food stimuli. After training, participants provided explicit ratings of attractiveness for the foods and completed a food choice task in which they had to select three out of the seven foods (clicked on the foods). Participants were not explicitly instructed that their choice would not be consequential, that is, they would not receive any of the selected food items for actual consumption. Foods were also rated on palatability (tastiness) and consumption frequency. This study provided evidence for the effects of food-specific GNG training on reducing food evaluations and unhealthy food choices. Participants chose less no-go foods than go foods in the food choice task. These effects were only observed in the high appetite condition, which may be essential for studies that recruit healthy-weight participants who may otherwise not have strong impulsive reactions towards palatable foods (relative to overweight/obese individuals). A mediation analysis further showed that the effect of appetite on food choice was mediated by food evaluation.

A study that employed an SST training protocol has provided evidence for no effects of training on food consumption in the laboratory compared to double-response training, whereby a signal indicates that participants need to execute an additional response (i.e., pressing the spacebar after having to press ‘c’ or ‘m’ for left/right stimulus locations on the screen). Additionally, there was no evidence that participants’ implicit attitudes towards foods changed after training. An important finding that has also emerged from single-session laboratory studies is that training can influence people’s explicit evaluations of foods associated with response inhibition. A recent

meta-analysis did not find evidence for such effects in the ICT literature for food and alcohol stimuli, but five out of six studies had employed an IAT, which can add to the inconsistency of findings (Jones et al., 2016). Evidence and theory related to the devaluation of no-go foods after training is discussed in detail in section 1.6.3.

Multiple-session studies

Other research studies have provided evidence for the potential effectiveness of ICT interventions outside the laboratory by providing longitudinal measurements of participants' weight/BMI after multiple training sessions (e.g., Allom & Mullan, 2015; Lawrence, O'Sullivan, et al., 2015; Veling et al., 2014). Lawrence, O'Sullivan, et al. (2015) administered go/no-go training online and the majority of participants in both the active (32 out of 42) and control group (37 out of 42) completed four sessions. Participants were recruited from a community sample and consisted of healthy-weight (22%), overweight (42%) and obese (36%) individuals. GNG training involved participants responding to the location of a stimulus ('c' for left, 'm' for right) within a central rectangle on the screen. In the active group, energy-dense foods were always paired with a no-go cue (i.e., rectangle turning bold) and healthy foods were presented on go trials, whereas in the control group non-food stimuli (i.e., household objects) appeared on go and no-go trials. The task also included 'filler' stimuli (i.e., clothes) that appeared on go and no-go trials with equal probability to reduce participants' awareness of stimulus-response contingencies and promote more automatic, rather than rule-based, learning for stimulus- go and no-go- associations. Several measures for eating behaviours were examined, including but not limited to energy intake derived from 24h food diaries, weight and a laboratory taste test for chocolate and crisp food consumption. There was evidence for formed stimulus- go and no-go- associations in both groups in terms of lower error rates and faster reaction times for go and no-go stimuli compared to filler stimuli (50% go, 50% no-go) from baseline to the last training session. There was a significant reduction in weight from baseline to two weeks after training in the active group and a reduction in self-reported weight after six months[8]. There was a slight, non-significant, weight gain in the control group. The authors further report that a reduction in energy intake, averaged across no-go foods, was observed in the active group, but the groups did not differ on how much food they consumed in the taste test. The latter finding could be attributed to uncontrolled confounds such as hours since the last meal and hunger levels (see

[8]It should be noted that at the six-month follow-up participants were no longer blind to their training group assignment.

Lawrence, O'Sullivan, et al., 2015). In this study there was also evidence for a stimulus devaluation effect, that is, no-go foods were rated less positively on liking (taste) after training and the devaluation was greater in the active group relative to the control group.

Two studies published by Allom & Mullan (2015) have mixed findings regarding the effects of food-specific ICT on weight loss. In Study 1, the researchers employed an SST training protocol and participants were allocated one of three groups. Visual exposure to healthy and unhealthy foods was matched across groups (50% healthy, 50% unhealthy), but in the food-specific inhibition condition there was a consistent S-R mapping for unhealthy foods and stop-signal trials. In the general inhibition condition, a stop signal was paired with healthy or unhealthy foods with an equal probability and in the control (no inhibition) condition no stop-signals were presented. The protocol involved the administration of 10 online sessions and self-reported BMI was measured after training completion. Relative to baseline, subjective BMI was reduced in the training group (food-specific inhibition condition) compared to the other groups but there were no differences reported for saturated fat intake (see Allom & Mullan, 2015 for procedure). In Study 2 the researchers attempted to replicate these findings when BMI was objectively measured and not reported by the participants. Contrary to predictions, there was no evidence for differences in BMI from baseline compared to after training and one-week follow-up across groups.

1.6.3 Training mechanisms & related theory

Stimulus devaluation

An important explanation for the effectiveness of food-specific ICT on health-related outcomes, such as food choice behaviour and subsequent intake has been provided by the Behaviour Stimulus Interaction (BSI) theory (Chen et al., 2016; Veling, Holland, & van Knippenberg, 2008), which provides a theoretical framework for stimulus devaluation. There is evidence to suggest that training can reduce participants' explicit evaluations of food items that have been associated with response inhibition during training (e.g., Lawrence et al., 2015; Veling et al., 2013a, 2008). Jones et al. (2016) showed no evidence that cue-specific ICT (food, alcohol) can influence implicit evaluations when these were assessed via the IAT (also see null findings reported by Adams, Lawrence, Verbruggen, & Chambers, 2017). For this reason, in the following section the key findings from studies that have examined explicit evaluations are presented. The BSI theory is, to a great extent, consistent with the

RIM which assumes a bidirectional link between affect and motivation. Veling et al. (2008) propose that a potential mechanism of action behind training effects is that food stimuli that trigger positive affect can invoke an approach tendency that is incompatible with the situational constraints of response inhibition during the task that render the approach behaviour undesirable. This incompatibility causes a response conflict, similar to the internal conflict assumed in the RIM (see Figure 1.1). In order to prevent freezing or approach, this conflict between the behavioural tendency to approach the stimulus and the requirement of response inhibition needs to be resolved. A potential mechanism for conflict resolution is the attachment of negative affect to the appetitive stimulus that can reduce approach motivation. It is also possible that the conflict itself constitutes an aversive signal that can be associated with negative affect (see Chen et al., 2016 for the possible cognitive mechanisms of how response inhibition can cause devaluation). Two covert assumptions of the BSI theory state that there is an approach tendency towards the stimulus of interest and that the no-go cue (or stop-signal) triggers response inhibition. In a series of experiments, Veling et al. (2008) provided evidence for the BSI theory by showing that positive stimuli that were consistently paired with a no-go cue are devalued (attractiveness Likert scale) compared to stimuli associated with a go cue and novel stimuli that were not included in training. Importantly, the authors reported that devaluation effects were not observed when negative or neutral stimuli were consistently presented with a no-go cue.

In another series of preregistered experiments Chen et al. (2016) investigated alternative accounts of stimulus devaluation effects. The BSI theory supports a *response inhibition account*, but devaluation effects could also be attributed to an evaluative conditioning (EC) mechanism whereby the evaluation of a conditioned stimulus can become more negative when it is paired with a negative unconditioned stimulus, which could either be the no-go cue or not responding. Therefore, the authors tested whether devaluation effects could be explained by either a *no-go cue EC account* or a *nonresponse EC account*. In Experiment 1, the go/no-go training involved a simple reaction time task where randomly assigned go and no-go cues (400Hz or 1000Hz tone) appeared 100ms after stimulus onset to indicate whether participants had to press a button or not. The GNG task included no-cue trials where although no cue was presented participants were again instructed not to respond. Highly appetitive stimuli were selected based on participants' explicit evaluations at baseline and were randomly assigned as food stimuli for go, no-go and no-cue trials. Another set of appetitive foods was used for post-training evaluations and was not

included in training (i.e., untrained items). A robust devaluation effect for no-go foods was observed relative to two baselines, that is compared to go food items and untrained items. They also provided evidence for a no-cue devaluation effect, which indicates that the presence of a no-go cue is not necessary for devaluation to occur. In Experiment 2, the delay between the cue and the stimuli was dynamically adjusted to exclude an implicit no-go cue hypothesis, whereby the absence of a cue that was predictable (e.g., always presented 100ms after stimulus onset) can be considered an 'implicit' no-go cue. The devaluation effect was replicated in Experiment 2 and Experiment 3 where a no-go cue was not presented at all during training, providing more conclusive evidence against the *no-go cue EC account*. In order to test the *nonresponse EC account* which predicts that devaluation would be observed irrespective of the proportion of no-go trials, researchers employed GNG tasks with 25% no-go trials (Experiment 4a) and 75% no-go trials (Experiment 4b). According to the *response inhibition account*, the devaluation effect would be weaker or absent when the proportion of no-go trials was high. In line with their prediction, no devaluation effect was observed in Experiment 4b. In Experiment 5 they examined the differences between not responding at all (i.e., passive viewing) and engaging in response inhibition, which consistent with the *response inhibition account*, did not lead to stimulus devaluation. Further support for the BSI theory was obtained in Experiment 6 where low-rated stimuli were not devalued after training. A pure response inhibition account would predict that neutral or even negative stimuli could be devalued because it does not assume a response conflict triggered by an approach tendency. However, Chen et al. (2018) found that no-go food items were devalued after GNG training compared to both go and untrained food items when these were both high-rated and low-rated in two experiments. These findings do not support the assumption of the BSI theory that only highly appetitive (food) stimuli can be devalued via response inhibition training. There is also an indication of a go valuation effect, whereby the evaluations of go foods are increased after training compared to no-go and/or untrained foods, which could be attributed to the link between action and affective valence (e.g., see Chen et al., 2016; Chen, Veling, et al., 2018).

Overall, there is evidence to suggest that food-specific ICT, but primarily GNG training, can lead to robust devaluation of no-go foods compared to go and/or untrained foods. There are a number of unanswered questions regarding the exact underlying mechanisms behind this no-go devaluation effect that need to be investigated further (see Chen et al., 2018, 2016; Veling et al., 2017), one of which is addressed in Chapter 5.

Stimulus-stop associations

An important theoretical account of ICT mechanisms assumes that stimulus-stop associations for stimuli that are consistently paired with no-go cues, or signals, during training can be formed via associative learning and that these associations can later be retrieved automatically from memory, consistent with the concept of automatic inhibition outlined in section 1.5.1 (Best, Lawrence, Logan, McLaren, & Verbruggen, 2016; Verbruggen et al., 2014a; Verbruggen & Logan, 2008a). When these stimuli are encountered again on go, or no-signal, trials, the acquired associations interfere with responding, which can result in slowing of (go) reaction times (Best, McLaren, & Verbruggen, 2019; Verbruggen et al., 2014a). Specifically, on no-go, or stop-signal, trials stimuli are associated with a 'stop' representation that can later be activated via associative retrieval and when that stimulus (e.g., apple) or category (e.g., fruit) is presented on go, or no-signal, trials the retrieved information is not consistent with the required response/goal and this results in impaired performance (Verbruggen et al., 2014a). The go and stop responses, or goals, are mutually inhibitory (Boucher, Palmeri, Logan, & Schall, 2007), consistent with the Pavlovian appetitive and aversive centres (Dickinson & Boakes, 2014), which Verbruggen et al. (2014a) consider the "instrumental equivalents" of the go and stop systems (p. 271).

Verbruggen & Logan (2008a) provided evidence for the automatically retrieved stimulus-stop associations when a consistent S-R mapping was used in a go/no-go training task where participants had to respond according to a stimulus category (e.g., go: living objects vs no-go: non-living objects). The S-R mappings were reversed in a test phase (e.g., no-go: living objects vs go: non-living objects) and participants had to respond to specific stimuli that were previously presented on no-go trials. The authors reported evidence for slowing of RTs in the test phase for stop-associated stimuli compared to untrained (new) stimuli. Evidence for the 'automatic inhibition' account has been obtained for food-specific ICT protocols in previous studies (e.g., Veling, Aarts, & Papies, 2011), but stimulus-stop associations are also assumed when the error rates (e.g., commission errors in GNG training) for stimuli that are consistently presented on no-go trials are reduced over the course of training (e.g., Lawrence et al., 2015). Veling et al. (2017) have clarified that there is an important difference between these two approaches. Performance improvements in terms of accuracy can be attributed to both strengthened top-down inhibitory control and automatic, bottom-up, inhibition. For this reason, slowing of RTs due to stimulus-stop associations should be examined by presenting no-go (stop) stimuli on 'catch' go trials or post-training test trials where participants are explicitly instructed that they would not have to

withhold their responses (i.e., inhibitory control no longer required).

A crucial element of the proposed *associative stop system* (Verbruggen et al., 2014a) is the assumed hard-wired, and mutually facilitatory, connections between a go system and the appetitive system, and between the stop system and the aversive system. It is therefore possible for a stop-associated stimulus to be devalued via the interaction between the stop system and the aversive system, while the value of a stimulus would be increased if it is consistently paired with a go response/goal via the interaction between the go system and the appetitive centre. These findings could explain both the no-go devaluation effect and the go valuation effect, as discussed in section 1.6.3.

1.7 Reproducibility & open science

1.7.1 Reproducibility in psychological science

The reliability and transparency of studies in food-related research is paramount for both theoretical implications of findings and the development of clinical applications. It has recently been acknowledged that there is a reproducibility, or replication, 'crisis' in psychological science[9] that needs to be addressed (e.g., see Open Science Collaboration, 2015; Munafò et al., 2017). In 2012, multiple researchers joined their efforts to start a systematic large-scale attempt to estimate the reproducibility of psychological science by conducting high-quality replications of published findings from prominent journals. The aggregated results from the reproducibility project were published in 2015 and from 100 replications only 36% had significant results (95% of original studies) and only 39% of effects were subjectively evaluated as successfully replicated assuming no bias in the original results (Open Science Collaboration, 2012, 2015). During the past decade, meta-scientific research has also shown that researcher degrees of freedom can easily turn into naive, or purposeful, questionable research practices that can severely affect the reproducibility of research, such as selective reporting of independent or dependent variables and/or results ("cherry-picking"), hypothesising after the results are known (HARKing) and *p*-hacking[10] (Banks, Rogelberg, Woznyj, Landis, & Rupp, 2016; John, Loewenstein, & Prelec, 2012; Munafò et al., 2017; Simmons, Nelson, & Simonsohn, 2011). Lack of replicability in psychology and neuroscience can further be attributed to 'under-powered' research designs which do not have the adequate

[9] In this thesis I focus on psychological science and related fields, but this does not suggest that other scientific disciplines are not affected by a lack of reproducibility in published research.

[10] Statistical decisions or manipulations after data and results have been observed that are conducted until the *p*-value reaches the desired alpha threshold for significance (e.g., 0.05).

sample size for observing a true effect (especially if the true effect is expected to be small) and have higher rates of false positive findings (Button et al., 2013) which even with reproducible methods and analyses would not be replicated.

1.7.2 Reproducibility in food-related research

Concerns about reproducibility in psychology have recently received empirical attention in food-related research. As indicated by the literature review presented in this Chapter and recent meta-analyses of behavioural interventions in the food domain (e.g., Aulbach et al., 2019; Jones et al., 2016, 2018), there is considerable variability in published study protocols that can often lead to inconsistent findings. Even though this variability exists, scientific progress in this research area can further be hindered by a lack of transparency and reproducibility in reported methodologies and results, including but not limited to the blinding of participants to study aims and experimental manipulations (e.g., training group allocation), statistical effect sizes for food intake analyses, detailed eligibility criteria and sample characteristics, and how the sample size was determined (Robinson, Bevelander, Field, & Jones, 2018).

The food-related ICT literature has also been examined for selective reporting using a *p*-curve analysis (Simonsohn et al., 2014b, 2014a) and authors reported that while selective reporting is not prevalent, overall evidence was mixed and it is possible that a true effect of ICT outcomes on food intake would be small (also see adjusted ICT effect size in Jones et al., 2016) when the majority of studies have inadequate statistical power to detect it (Carbine & Larson, 2019). In a follow-up analysis, Veling, Chen, Liu, Quandt, & Holland (2019) included recent preregistered ICT studies to assess whether the evidential value of the ICT literature would increase. The authors indeed provide evidence for evidential value over selective reporting, suggesting that ICT does have an effect on eating behaviours (e.g., food choice). In addition to study preregistration and appropriate sampling plans (e.g., based on power analysis), Veling et al. (2019) highlight the need for more robust methods that can help reduce variation across published studies, such as tailoring the food-specific ICT protocols to participants' evaluations of the target food stimuli.

1.7.3 Open science practices

A variety of open science practices can aid in tackling the reproducibility 'crisis' in psychology, such as making the data and analyses scripts available for other researchers, employing positive controls and/or manipulation checks for observed effects where

appropriate and preregistering the proposed study protocols on platforms such as the Open Science Framework (OSF; see https://cos.io/prereg/) to ensure that all confirmatory, *a priori*, hypotheses and analyses are clearly outlined before data collection is initiated (Munafò et al., 2017). Proposed study protocols can also be submitted to eligible journals as *Registered Reports* (RRs) to reduce publication bias, as the journal guarantees to publish the study irrespective of the results (e.g., null findings), and promote reproducibility in the relevant fields (see https://cos.io/rr/). The RR format can increase methodological rigour as proposed study protocols are peer-reviewed and any potential issues with the study design (e.g., lack of appropriate controls) or statistical analyses can be corrected prior to data collection (C. Chambers, 2019; Chambers, 2019; Grand, Rogelberg, Banks, Landis, & Tonidandel, 2018).

1.7.4 Bayesian inference

One practice that does not fall under the open science approach but can aid in the interpretation of null findings is conducting Bayesian statistical analyses to allow inferences based on the data instead of the true effect size assumed to exist in the general population as with null-hypothesis significance testing (NHST). In this thesis Bayesian tests are reported with a Bayes factor that indicates the *relative* evidence for the alternative hypothesis, which is in essence a model fitted to the data, and the null hypothesis (Lee & Wagenmakers, 2013). The BF for the alternative hypothesis compared to the null hypothesis can be expressed as a ratio, as shown below. *H1* and *H0* denote the alternative and null hypotheses respectively[11].

$$BF_{10} = \frac{p(Data|H1)}{p(Data|H0)}$$

The Bayes factor can therefore be interpreted as an odds ratio, as for example when $BF_{10} = 10$, the data are 10 times more likely to have occurred under H1 than under H0. BF_{01} represents the *relative* evidence for H0 compared to H1 (1 / BF_{10}). Although opinions regarding the classification of BFs into discrete categories vary (see Morey, 2015), in this thesis I interpret the evidential strength of the BFs according to the guidelines presented in Lee & Wagenmakers (2013) (Table 7.1, p. 105) to aid in the interpretation of the results. The evidence categories for BF_{10} can be found in Appendix A. The calculation of BFs in statistical tests also depends on *prior odds*, which reflect the prior expectations of the researcher about the *relative* evidence for

[11] In the Bayesian framework *H1* and *H0* are defined as models *M1* and *M2* (Lee & Wagenmakers, 2013), but I have adapted the equation to aid in the interpretation of the Bayes factor.

H1. Priors can be justified based on previous research findings or other subjective criteria which may often be advocated (Aczel et al., 2018; Johnson, Tomlinson, Hawker, Granton, & Feldman, 2010), but for the research studies included in this thesis I have used the 'default' priors for respective statistical tests[12].

1.7.5 Open science statement

All research studies in this thesis (Chapters 2, 3, 4, and 5) involve reproducible methods and analyses with openly shared materials, data, and code. Data collection for all studies was initiated only after preregistering the confirmatory hypotheses and analyses on OSF, with the exception of the feasibility (pilot) experiments conducted as part of the protocol development for a Registered Report, which can be found in Appendix D. Specifically, the study presented in Chapter 4 received in-principle acceptance (IPA) by an eligible journal prior to data collection and was extensively reviewed to achieve maximal transparency and reproducibility. The study described in Chapter 2 was conducted as part of the GW4 Undergraduate Psychology Consortium 2017/2018, which is an important initiative for promoting and teaching reproducible science at an undergraduate level (Button, Chambers, S.Lawrence, & Munafò, 2019).

1.8 Thesis objectives

In this Chapter I have reviewed the literature that supports the dual-process framework of eating behaviours and provided evidence for the role of affect, motivation and cognition, as well as their interactive effects in predicting behaviour in laboratory settings. The literature review has yielded a number of research questions that prompt further investigation and these are empirically addressed in this thesis and are briefly described below.

Does food-specific ICT have an effect on automatic action tendencies?

The bidirectional relationship between affect and motivation is not only included in the dual-process framework for eating behaviours, but also the theoretical accounts for potential mechanisms of ICT protocols, such as the associative stop system described in section 1.6.3. The study presented in Chapter 2 investigated whether go/no-go training that included unhealthy foods would influence automatic action tendencies measured via an AAT. In a within-subject design, approach and

[12]More details are provided in the statistical analyses sections of Chapters 2-5.

avoidance bias was measured before and after training, and several outcomes from the existing ICT literature were also examined (i.e., food choices, explicit food evaluations).

Can a novel ICT protocol influence food cravings and evaluations?

The SST training protocols have not received strong support in the literature, as they often result in small, or non-significant, effects on behaviour change. In Chapter 3, I introduce a novel protocol that builds on the SST principles and requires the inhibition of initiated whole-arm movements with a computer mouse (i.e, stop training). The stimulus-response mapping in this protocol was consistent to increase the possibility of stimulus-stop associations being learned during training and extends previous work to manipulate action updating, or re-engagement, in addition to action cancellation (i.e., stop-change training). In a between-group design, the effects of stop and stop-change training on food cravings and evaluations are examined in comparison to a control group.

Can the APP indirectly measure food attitudes and predict food choice behaviour?

Considering the inconsistency in findings about the indirect measurement of food attitudes and the influence of affective and cognitive components, it was crucial to test whether the APP can reliably measure food liking and to what extent it is sensitive to the healthiness of the food primes. In Chapter 4, I present a laboratory experiment and direct online replication experiment that examine the utility of the APP in the food domain and also test whether priming effects are associated with impulsive food choices. This research project required extensive piloting and paradigm development, which is presented separately in the Appendix.

Does food-specific ICT have an effect on implicit food evaluations?

After obtaining preliminary evidence that the APP can reliably capture food evaluations, I aimed to investigate an outstanding question from the ICT literature. In the study described in Chapter 5, I employed an adapted go/no-go training paradigm that has been shown to change food evaluations at an *explicit* level (see section 1.6.3) in order to test whether the no-go devaluation effect can also be observed at an *implicit* level, which would have important theoretical implications for future research into ICT mechanisms of action.

Chapter 2

Does inhibitory control training have an effect on automatic action tendencies for unhealthy foods?

2.1 Introduction

The recent rise in overweight and obesity rates can primarily be attributed to the over-consumption of energy-dense foods that are high in fat, sugar and salt content (World Health Organization, 2018). Individuals are constantly exposed to visual cues of such foods in the environment (e.g., through advertisements) and this often leads to increased cravings and subsequent food intake (Havermans, 2013). A theoretical explanation for overeating has been provided by dual-process models which argue that behaviour is determined by the interaction of impulsive (*automatic*) and reflective (*controlled*) processes (Kakoschke et al., 2015; Strack & Deutsch, 2004). For example, over-consumption of unhealthy foods can be ascribed to a heightened approach bias towards food cues in the environment, which can result in increased food intake if these automatic action tendencies are not regulated via controlled processes, such as inhibitory control (Kakoschke et al., 2017b). Such theoretical frameworks have led to the development of behaviour change interventions for unhealthy eating behaviours that target either automatic or controlled processing, such as approach bias modification and inhibitory control training respectively (see Kakoschke et al., 2017a; Jones et al., 2018 for recent reviews). The primary aim of the present study was to investigate the interaction between automatic and controlled processing in the context of inhibitory control training (ICT). Specifically, we tested whether food-specific ICT could influence

individuals' automatic action tendencies towards unhealthy foods.

In the dual-process framework (see section 1.2), unhealthy eating behaviours may be explained by a weak reflective system and/or a strong impulsive system (e.g., Lawrence et al., 2012; Nederkoorn, Coelho, Guerrieri, Houben, & Jansen, 2012). These systems are often in conflict; for example, when an individual has to decide whether or not to consume an unhealthy food, automatic attentional (e.g., attending to the cue) and motivational (e.g., approaching the food) processes would antagonize the controlled process of considering long-term goals such as losing weight when an individual has to decide on an action, that is to eat or not eat the food (Kakoschke et al., 2015). This study focuses on an automatic process known as approach bias, which is the automatic action tendency to approach an appetitive (food) cue in the environment, rather than avoid it (C. E. Wiers et al., 2013). An approach bias has been demonstrated for a variety of energy-dense foods in both obese and healthy-weight individuals (Brignell et al., 2009; Kemps & Tiggemann, 2015; Kemps et al., 2013; Veenstra & de Jong, 2010). Interestingly, Kakoschke et al. (2015) found that approach bias alone did not predict increased intake of unhealthy foods, but it was the interaction between approach bias and inhibitory control that was the significant determinant of subsequent behaviour. The authors report that approach bias had the expected effect on food intake only for participants with low inhibitory control. As discussed in Chapter 1 (see section 1.5), an important component of controlled processing is inhibitory control, which refers to the ability to inhibit behaviours and impulses that are incompatible with higher-order goals, such as wanting to lose weight (Houben et al., 2012), and encompasses several elements, such as response inhibition and cognitive flexibility (see Bartholdy et al., 2016b). Inhibitory control capacity is often measured via response inhibition paradigms, such as the go/no-go task (Donders, 1969; Newman & Kosson, 1986) and stop-signal task (Lappin & Eriksen, 1966; Logan et al., 1984), and has been associated with unhealthy eating behaviours (e.g., Jasinska et al., 2012; Guerrieri, Nederkoorn, et al., 2007; Hall, 2012). For example, Nederkoorn et al. (2010) showed that strong implicit preferences for snacks paired with low 'inhibitory control capacity' predicted weight gain over one year. Overall, there is evidence to suggest that both inhibitory control and motivational processes are important determinants of eating-related behaviour.

Complementary evidence for the role of automatic and controlled processes in the regulation of eating behaviours stems from the line of research dedicated to the development of health behaviour change interventions. Approach bias modification training is commonly delivered via an approach-avoidance task (AAT; Neumann &

Strack, 2000; Rinck & Becker, 2007; Wiers et al., 2013) and has been found to be effective in re-training approach bias for foods (Brockmeyer et al., 2015b) and even reduce food intake in the laboratory (Schumacher et al., 2016; see Kakoschke et al., 2017a for review). The AAT is assumed to capture automatic action tendencies when participants are instructed to respond to a task-irrelevant feature such as the orientation (portrait or landscape) of the presented picture, by pulling or pushing a joystick (C. E. Wiers et al., 2013). The AAT can also pair actions with visual feedback, so that the picture gets bigger when participant pull the joystick towards them (zoom-in) and gets smaller when they push it away (zoom-out). Arm extension could indicate an approach response towards an appetitive food (object-reference) or an avoidance response when the food is pushed away from the body/self (Phaf et al., 2014) and thus visual feedback provides the self-reference attribute to the responses (e.g., object comes closer to one's body). The 'zooming' feature disambiguates the mapping of responses to approach and avoidance actions, whereby pulling the joystick represents approach and pushing it reflects avoidance (Neumann & Strack, 2000). In AAT training, contingencies between actions and stimuli are manipulated so that appetitive cues are associated with push actions (avoidance) and neutral items are paired with pull actions (approach).

In the context of controlled processes, ICT interventions involve cue-specific go/no-go or stop-signal tasks whereby participants are instructed to make a speeded choice response to appetitive stimuli such as foods or alcohol, but to withhold that response when a visual, or auditory, signal is presented. In go/no-go training, signal-stimulus mappings are manipulated so that appetitive cues (e.g., unhealthy foods) are consistently paired with a stop signal. Stopping to unhealthy foods has been shown to reduce food consumption (Adams et al., 2017; Houben & Jansen, 2011, 2015; Lawrence et al., 2015; Veling et al., 2011; also see Allom et al., 2016 for meta-analysis) and promote healthy food choices in the laboratory (Veling et al., 2013a; Veling, Chen, et al., 2017). ICT protocols have even been associated with increased weight loss (Lawrence, O'Sullivan, et al., 2015; Veling et al., 2014). A potential mechanism of action behind ICT effects on food consumption is stimulus devaluation (Veling et al., 2017), whereby the evaluations of appetitive foods are reduced during training to facilitate performance when response inhibition is required (e.g., Chen et al., 2016). A possible explanation for this devaluation effect is provided by the Behaviour Stimulus Interaction (BSI) theory which posits that food stimuli are devalued when negative affect is induced to resolve the ongoing conflict between triggered approach reactions to appetitive foods and the need to inhibit responses towards those stimuli (Chen

et al., 2016; Veling et al., 2008, 2017). When a food is devalued, the approach bias towards that cue is reduced and inhibition can successfully take place. It is possible that this reduction in approach bias can be observed after go/no-go training[1].

Theoretically, the effects of ICT could also be explained by hard-wired connections between Pavlovian appetitive/ aversive centres (Dickinson & Boakes, 2014) and go/no-go responses (McLaren & Verbruggen, 2016; Verbruggen et al., 2014a). Verbruggen et al. (2014a) suggest that conditioned inhibitory control in ICT paradigms, such as go/no-go training, can have an influence not only on the evaluations of stimuli, but also their motivational value via links to the appetitive/aversive centres. For example, a stimulus consistently paired with stopping on signal trials would be devalued and the approach motivation for that stimulus could also be reduced via a hard-wired excitatory connection between the 'stop' system and the aversive centre (also see Dickinson & Boakes, 2014; McLaren & Verbruggen, 2016). Similarly, approach bias for foods consistently paired with go responses on no-signal trials could be increased via the link between the 'go' system and the appetitive centre.

This study attempts to answer this question by employing a go/no-go training paradigm with unhealthy food stimuli and measuring automatic action tendencies via an AAT before and after training. We tested whether individuals would show reduced approach bias for the foods associated with response inhibition and/or increased approach bias for the foods paired with go responses after training. Consistent with previous ICT literature, the study also examined impulsive food choice and food liking as secondary training outcomes. The research study was conducted as part of the GW4 Undergraduate Psychology Consortium 2017/2018 and data were collected across Cardiff University, University of Exeter and University of Bath campuses.

2.2 Hypotheses

All hypotheses described in this section are confirmatory and have been preregistered[2] on the Open Science Framework (https://osf.io/wav8p/). Effects of ICT (go/no-go training; see section 2.3.4) on automatic action tendencies (see section 2.3.5) and liking (see section 2.3.6) for unhealthy foods were investigated using change scores

[1]It should be noted that a link between affect and motivation is also included in the dual-process framework of (eating) behaviour, as discussed in Chapter 1 (see section 1.2.1).

[2]Exact hypotheses from the preregistered protocol have been re-ordered according to outcomes for clarity. There were no deviations from the protocol for the hypotheses and corresponding statistical tests, with the exception of minor alterations regarding the supplementary frequentist statitics (see section 2.4.3).

from pre-to post-training for both outcomes (H1, H3). The training condition was also expected to have an effect on food choice behaviour (H2; see section 2.3.7). The study assessed contingency learning mechanisms for the training paradigm, as a manipulation check (H4).

2.2.1 Training effects on automatic action tendencies

The primary outcome measure in the study was the change in automatic action tendencies from pre-to post- ICT training for the foods associated with different conditions (go, no-go and control - see Figure 2.1). Action tendencies were indirectly measured via the AAT and approach-avoidance bias scores were obtained by subtracting the median completion response times (RTs; for details see section 2.4.1) in avoid trials (push action) from the RTs in approach trials (pull action) at the participant level (correct responses only), for each training condition and then calculating the change from pre-to post-training. It was hypothesised that ICT training would lead to a reduction in approach bias for no-go foods and potential increase in approach bias for go foods compared to the control foods.

H1. There would be evidence for an effect of training condition (go, no-go, control) on the change in approach-avoid bias scores from pre-to post-training.

H1a. Participants would show a reduction in approach bias for no-go foods compared to the control foods, from pre-to post- training.

H1b. Participants would have increased approach bias towards go foods relative to the control foods, from pre-to post- training.

2.2.2 Training effects on impulsive food choices

As a secondary outcome, the effects of ICT on impulsive food choices for unhealthy foods were tested by comparing the probabilities of choosing a food from each training condition.

H2. It was expected that after ICT participants would show reduced impulsive choices for no-go foods and increased choices for go foods relative to control foods.

H2a. The probability of choosing a no-go food would be lower than the probability of choosing a control food.

H2b. The probability of choosing a go food would be higher than the probability of choosing a control food.

2.2.3 Training effects on food evaluations

The mean change in food liking ratings from pre-to post-training was examined in order to test whether go/no-go (GNG) training led to the devaluation of no-go foods compared to control foods (H3a). It should be noted that this was not a positive control for training effectiveness, as the findings for stimulus devaluation outcomes remain controversial (see Jones et al., 2016 for meta-analysis). Nonetheless, stimulus devaluation in this study was treated both as a manipulation check for the employed training paradigm and a secondary outcome measure. The possibility that positive evaluations for go foods would be increased after training compared to the control foods was also considered and tested in a separate hypothesis (H3b).

H3. There would be evidence for an effect of training condition (go, no-go, control) on the change in food liking from pre-to post-training.

H3a. Participants would show reduced liking for no-go foods relative to the control foods, from pre-to post- training.

H3b. Participants would show increased liking for go foods relative to the control foods, from pre-to post- training.[3]

2.2.4 Contingency learning during training

Contingency learning was a more fundamental manipulation check for GNG training. ICT paradigms, such as the go/no-go training task, might lead to stimulus-response associations and learning can be observed in both reaction times and error rates (e.g., Lawrence, O'Sullivan, et al., 2015; see Best et al., 2019). The proportion of correct responses on signal trials (i.e., successful stops) and the mean reaction times from no-signal (go) trials were compared for specific training conditions, as stated in the hypotheses below.

H4. Go/no-go training would result in contingency learning in terms of reaction times on no-signal trials and the percentage of successful inhibitions on signal trials.

H4a. The proportion of correct responses on signal trials would be greater for no-go foods compared to the control foods associated with a signal ($\text{control}_{\text{nogo}}$).

H4b. Go reaction times would be faster for go foods compared to the control foods presented on no-signal trials ($\text{control}_{\text{go}}$).

[3]This was only a hypothesis for secondary outcomes, as stimulus devaluation is exclusively defined as a reduction in positive evaluations for foods associated with no-go responses during training.

2.3 Methods

2.3.1 Participants

A total of 255 participants were recruited in total from the University campuses of Cardiff, Bath and Exeter[4] via research participation schemes (e.g., Experimental Management system; EMS) and advertisements (see Figure B.1 for recruitment details). Participants recruited through participation schemes received course credits, whereas other individuals were offered entry into a prize draw for one of three £20 shopping vouchers. Participants were informed about the study eligibility criteria, completed a screening survey in the beginning of the study and provided their consent. They were asked to refrain from eating for 3 hours before the study. Participants had to be at least 18 years of age, be fluent in spoken and written English and have normal or corrected-to-normal vision, including normal colour vision. Participants were excluded if they were dieting at the time of the study, with a weight goal and time-frame in mind, if they had a current and/or past diagnosis of any eating disorder(s) or they had a body-mass-index (BMI) lower than 18.5 kg/m^2 (i.e., underweight category). All screening questions can be found in Appendix G. The study was approved by the Ethics Committees of Cardiff University, University of Bath and the University of Exeter.

2.3.2 Sampling plan

The required sample size was estimated based on a frequentist power analysis conducted for the primary outcome measure (i.e., change in approach-avoidance bias, from pre-to post-training, between go and no-go foods; H1a and H1b) and the stimulus devaluation manipulation check (i.e., change in food liking, from pre-to-post training, between go and no-go foods; H3). Both of these effect sizes were in the medium range and therefore calculations were based on the primary outcome measure. For an expected effect size, other studies that have measured approach bias pre-and post-approach-avoidance training (Becker et al., 2015; Schumacher et al., 2016) were considered. Both studies reported an effect size of ${\eta_p}^2 = 0.07$ which corresponds to a 'medium' effect size ($dz = 0.50$). Becker et al. (2015) also reported two non-significant results, although

[4]**Contribution note.** The data were collected by undergraduate students in line with the GW4 Undergraduate Psychology Consortium 2017/2018 guidelines. In laboratory data collection, all experimental tasks and relevant forms (e.g., consent, debrief) were programmed by me as a single fully automated script in order to minimise the need for the involvement of the researcher(s) during testing sessions. Students only run selected frequentist statistical tests on preregistered hypotheses and exploratory analyses for moderators (see section 2.3.8), which are not reported in this thesis.

effect sizes were not provided. Note, however, that Becker et al. (2015) compared an active group with 90:10 mapping (i.e., avoidance of 90% for unhealthy trials and 10% healthy trials) to a control group with 50:50 mapping whereas Schumacher et al. (2016) compared a 90:10 active group with a 10:90 control group. A conservative approach was followed for the sample size calculation. Firstly, the effect size was reduced by 33% (i.e., $dz = 0.34$) to account for publication bias (Button et al., 2013) and secondly an alpha of 0.005 was used, which has recently been recommended for any research that cannot be considered a direct replication and can increase the reliability of new discoveries (Benjamin et al., 2017). Based on a priori power calculations using G*Power (Faul, Erdfelder, Buchner, & Lang, 2009) it was estimated that a total sample of 149 participants[5] was necessary for 90% power.

The sampling method and power analysis of the study adopted a conservative frequentist approach, but the preregistered analyses were based on a Bayesian framework (see section 2.4.3). Frequentist analyses were also reported in a supplementary fashion ($\alpha = 0.005$). Bayes factors (BFs) informed the interpretations of the results and the guidelines by Lee & Wagenmakers (2013) were followed to indicate the evidential strenth of the BFs. A threshold of $BF_{10} > 6$ (and $BF_{10} < 10$) was used to indicate *moderate* evidence for the alternative hypothesis relative to the null, and $BF_{10} < 1/6$ (and $BF_{10} > 1/10$) reflected *moderate* evidence for the null relative to the respective alternative hypothesis. Bayes factor analyses were favoured for drawing conclusions from the study, as they would allow us to interpret null outcomes as evidence of absence when traditional analyses would not make such inferences feasible.

[5]Due to the large number of participant exclusions based on mean error rates in the AAT (see Figure A1) and the group testing laboratory setting at Cardiff University, final recruitment led to the expected sample size including 14 more participants (N=163).

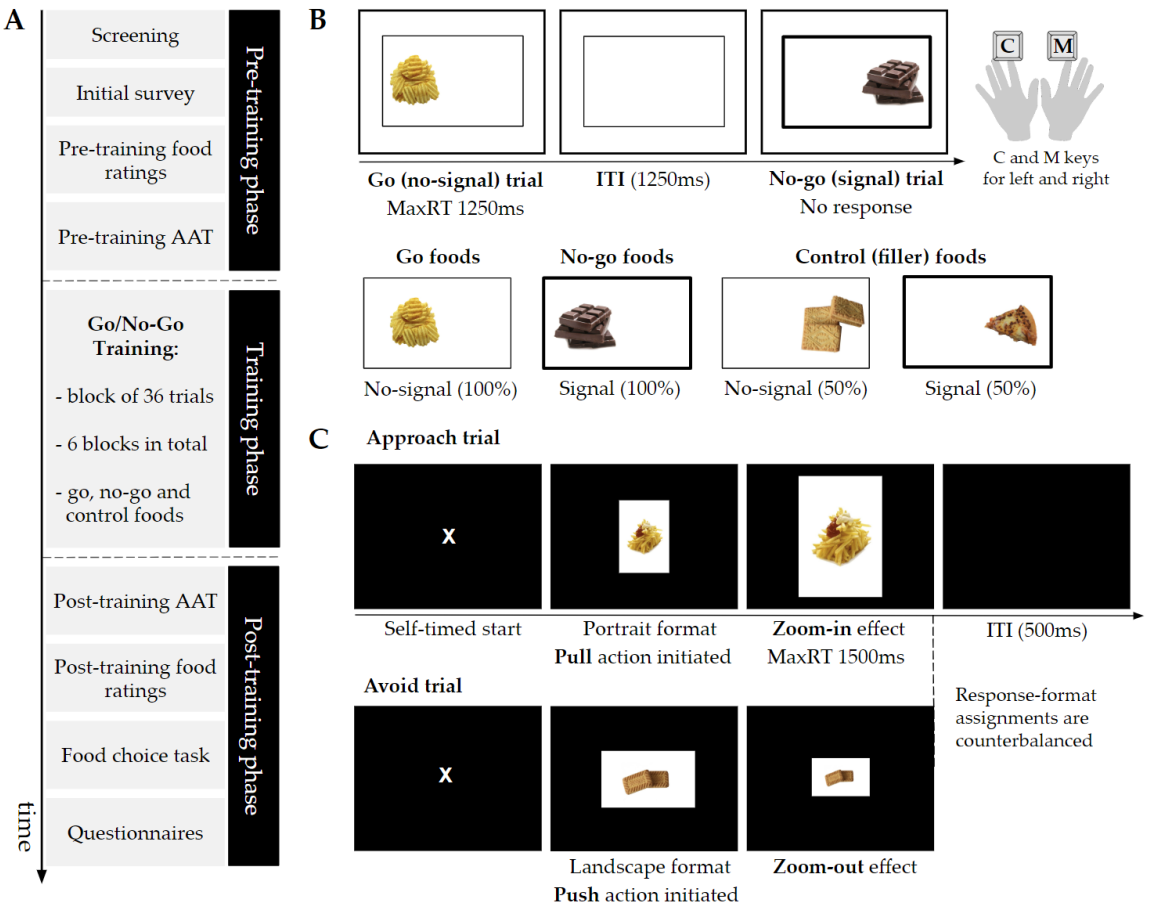


Figure 2.1: Schematic diagram of the study procedure, go/no-go training and approach-avoidance tasks. A. After completing the screening and initial survey, participants rated all food stimuli (liking) and proceeded to perform the pre-training approach-avoidance task (AAT) blocks. In the training phase, participants completed six blocks of go/no-go training. The post-training AAT blocks were then presented and followed by food liking ratings. At the end of the study, participants completed a short food choice task and several questionnaires, in random order. **B.** The go/no-go training paradigm involved go (no-signal) and no-go (signal) trials that occurred with equal probability. On go trials, participants had to respond within 1250ms by pressing the "C" and "M" keys to indicate the picture location (left or right, respectively). On no-go trials, participants were instructed not to respond at all. The inter-trial interval (ITI) was 1250ms. Food categories were randomly assigned to three conditions. Go foods were only paired with no-signal trials and no-go foods were always associated with signal trials. Control, or filler, foods were presented in both signal and no-signal trials (50:50). **C.** In the AAT, participants were asked to respond according to the format of the presented picture (portrait or landscape). Response-format assignments were approximately counterbalanced across participants. As an example, on approach trials a participant would have to pull the mouse towards them when the picture was in portrait format (approach trial) and push it away from them when the picture was in landscape format. Push and pull actions were paired with visual feedback, that is, zoom-out and zoom-in effects respectively. The maximum reaction time (maxRT) was 1500ms and the ITI was set to 500ms. Participants clicked on a central "X" to begin a trial (self-timed start).

2.3.3 Procedure

An overview of the study procedure can be seen in Figure 2.1 (panel A). After screening, eligible participants were provided with a short survey (see section 2.3.8) and proceeded to rate all food categories on how much they like the taste (see section 2.3.6). Three blocks of the approach-avoidance task (see section 2.3.5) were completed before the go/no-go training paradigm was performed (see section 2.3.4). Rated food categories were randomly assigned to three conditions for training: go, no-go and control, as shown in Figure 2.1 (panel B). Post-training, participants were presented with another three blocks of the AAT, provided ratings for all food stimuli again and finally completed a short food choice task (see section 2.3.7). At the end of the study, several questionnaires were presented in random order and participants were debriefed about the aims of the study. All study components were programmed using Inquisit Lab (Millisecond Software, 2017) and run online across data collection sites via Inquisit Web.

2.3.4 Go/No-go training

The Go/No-Go (GNG) training paradigm involved go and no-go responses to six pre-selected energy-dense food categories. Food categories differed in terms of taste, so that three foods were savoury (i.e., pizza, crisps, chips) and three foods were sweet (i.e., biscuits, chocolate, cake)[6]. Two food categories were randomly assigned to each training condition (go, no-go, control foods) in the beginning of the experiment and food taste was counterbalanced so that each condition had one sweet and one savoury food. There were three training conditions according to the mapping of foods to signal (no-go) and no-signal (go) trials in the GNG. All go foods appeared in go (no-signal) trials and all no-go foods were presented in no-go (signal) trials (see Figure 2.1, panel B). Control, or filler, foods appeared on both go and no-go trials with equal probability (50:50). Each food category had three exemplars which appeared twice in each block.

All foods were presented on either the left or right side of the screen within a rectangle for 1250ms, which was the maximum reaction time (maxRT), as shown in Figure 2.1, panel B. Participants were asked to respond to the location of the food as quickly and as accurately as possible by pressing the “C” and “M” buttons on the keyboard with their left and right index fingers, respectively. The central rectangle remained on the screen throughout the training, including the inter-trial-interval (ITI), which was 1250ms. On signal trials, the rectangle turned bold, indicating that

[6]All study materials are openly available at https://osf.io/wcf4r/.

participants should withhold their response. In line with the GNG training paradigm, this signal appeared on stimulus onset (i.e., no delay between stimulus and signal) and stayed on the screen until the end of the trial. A correct response on no-signal trials was registered when participants responded accurately to the location of the food within the maxRT window and a successful stop (i.e., correct signal trial) was considered when participants did not respond at all. Incorrect responses in no-signal trials refer to either to a wrong location judgement or a missed response. Left and right responses were counterbalanced across all manipulated variables for each type of trial. Training was split into 6 blocks of 36 trials (216 trials in total) and lasted approximately 10 minutes with inter-block breaks (15s). Task practice included 12 trials of go and no-go responses (50% - 50%) and participants responded to the location of grey squares, instead of food pictures. For the practice trials, accuracy feedback was provided during the ITI.

2.3.5 Approach avoidance task

The approach-avoidance task was adapted from an existent paradigm (Rinck & Becker, 2007; Wiers et al., 2009), which involves 'pull' (i.e., towards self) and 'push' (i.e, away from self) movements of a joystick. Each type of motor response is paired with visual feedback so that when the joystick is pulled, the image gets bigger (zoom-in) and when it is pushed, the image gets smaller (zoom-out). As previously explained, this 'zooming' feature acts as an exteroceptive cue of either an approach or avoidance response (Neumann & Strack, 2000) and complements the proprioceptive properties of the task, where responses requiring arm flexion and extension correspond to approach and avoidance trials, respectively (Wiers et al., 2009). The evaluation-irrelevant feature of the paradigm was also incorporated and participants responded according to the format of the picture (portrait or landscape; e.g., Wiers, Rinck, Kordts, Houben, & Strack, 2010).

AAT responses involved 'push' and 'pull' movements of the computer mouse (adaptation of the joystick version). Food stimuli were presented in the centre of the screen and participants were instructed to pull the mouse towards them or push the mouse away from them according to whether the image was in portrait or landscape format (see Figure 2.1, panel C). Response-format assignments were approximately counterbalanced across participants (45.4% portrait-approach, 54.6% landscape-approach). Instructions highlighted moving the mouse cursor until it reaches the end of the screen (top or bottom edge) for a correct response to be registered and

making smooth whole-arm movements. Participants had 1500ms to respond after the stimulus appeared. Each trial started with a central 'X' on the screen and participants had to click on it to begin (self-timed start). The ITI was 500ms and there was no delay between the 'X' click response and the stimulus onset. In order to account for the natural movement of the mouse, pixel tolerance was added to every mouse movement (± 1.25% of display height), including movement initiation in the beginning of the trial. A response in the AAT was registered as correct only when participants completed the correct action (e.g., pull or push) within the maxRT window and also initiated a movement towards the correct direction. Even if the final response was correct, participants could have changed their movement after making an initial error (e.g., pull instead of push the mouse in an 'avoid' trial) and therefore the direction of their initial movement was also taken into account. The complete RT for an AAT trial was defined as the time from the stimulus onset to the successful completion of a response (i.e., completion time) and was used for the bias score calculations (see section 2.4.1).

Each AAT block consisted of 72 trials and go, no-go and control foods appeared with equal probability for both 'pull' (approach) and 'push' (avoid) responses. There were 12 approach and 12 avoid trials for each training condition (e.g., no-go) and within those trials, there were six savoury and six sweet foods presented (i.e., three exemplars repeated twice). Three AAT blocks were performed before training (AAT_{pre}) and three after training (AAT_{post}). Two constraints were placed on the quasi-random order of the trials within an AAT block (cf. Wiers et al., 2009). There were no more than three images of the same food category being presented consecutively and no more than three trials with the same picture format in sequence. AAT practice consisted of 10 trials with grey rectangles instead of food stimuli and accuracy feedback. The screen background for the AAT was black and the task lasted approximately 15 minutes, including the inter-block 15s breaks, where participants received a reminder of the main instructions.

2.3.6 Food liking ratings

Participants provided food liking ratings before and after training using a visual analogue scale (VAS). They rated all foods included in the GNG paradigm according to how much they liked the taste ("How much do you like the taste of this food?"), ranging from 0 (not at all) to 100 (very much). Task instructions encouraged participants to imagine they were tasting the food in their mouth and then rate how much they liked

the taste. The cursor position was initially set to 50 for each food. The order of the presented foods was randomised and each block consisted of 18 trials.

2.3.7 Food choice task

Impulsive food choices were assessed using a food choice task adapted from Veling et al. (2013a), which included all food categories from the GNG paradigm (two exemplars per category). The twelve foods were presented on a grid layout, in a random order, and participants had ten seconds to select three foods that they would like to consume the most at that specific time, by clicking on them with the computer mouse. Participants were asked to click on a 'start' button to begin the trial and when a response was registered the selected food stimulus disappeared from the screen. This task element was introduced to prevent participants from deliberating on their choices and changing their initial responses, which would mean that *impulsive* food choices were no longer measured. Task instructions did not mention whether the nature of their choices would be consequential or hypothetical (i.e., whether they would get a food item at the end of the study or not).

2.3.8 Survey & Questionnaires

Eligible participants were presented with an initial survey to record demographics and other variables for exploratory analyses. The survey consisted of height and weight measurements to calculate participant's body-mass-index (BMI; kg/m^2), the number of hours since their last meal ('less than 3 hours ago', '3-5 hours ago', '5-10 hours ago', 'more than 10 hours ago') and hunger state at the the time of the study (VAS: 1="Not at all" to 9="Very"). Gender was also recorded with the options of male, female, transgender male, transgender female, gender variant/non-conforming, and an open-ended text response for 'other'.

Several questionnaires were completed by the participants at the end of the study for exploratory analyses, as part of the undergraduate student projects of the GW4 Undergraduate Psychology Consortium 2017/2018. The Barratt Impulsivity Scale (BIS-15; Spinella, 2007) was introduced as a measure of impulsivity and the Stop Control Scale (SCS; De Boer, van Hooft, & Bakker, 2011) was used to examine a distinctive element of general trait self-control, referred to as stop control. Other administered questionnaires included the Food Cravings Questionnaire - Trait - reduced (FCQ-T-r; Meule, Hermann, & Kübler, 2014), Perceived Stress Scale (PSS; Cohen, Kamarck, & Mermelstein, 1983) and the 'food' and 'money' subscales from the Delaying

Gratification Inventory (DGI; Hoerger, Quirk, & Weed, 2011). A correlation matrix of main questionnaire measures and sample characteristics can be found in Appendix B.1.

2.4 Analyses

2.4.1 Measures & indices

The mean error rates in no-signal and signal trials as well as mean reaction time in no-signal trials (GoRT) from the GNG informed participant exclusions (see section 2.4.2). For the contingency learning manipulation check (H4), measures included the proportion of successful stops from signal trials for no-go and control foods which were paired with a signal (control-nogo) and the mean GoRTs for each participant from correct go and control-go trials.

Performance in the AAT_{pre} and AAT_{post} blocks was considered only for correct responses. Median RTs for 'push' and 'pull' responses from all training condition levels were calculated for each participant[7]. Medians were used instead of means as they are less sensitive to outliers in RT distributions (also see Wiers et al., 2009, 2010). The approach-avoidance bias score for each condition was calculated as the difference between the median completion RTs for 'push' and' pull' responses ($MedianRT_{push}$-$MedianRT_{pull}$). Bias scores were computed for both AAT_{pre} and AAT_{post} blocks. Positive scores indicate an approach bias towards the foods of interest and negative scores reflect avoidance for those foods. Change scores for approach-avoid biases from pre-to post-training (ΔAAT) were calculated for preregistered analyses (H1). The proportion of correct responses for each AAT design cell informed participant exclusions and exploratory analyses (see section 2.5.3).

Participants were required to choose three foods out of twelve in the food choice task and selections could vary in their number for each training condition (go, no-go, control). Food choices were therefore normalised according to the total number of responses per participant (i.e., proportion). These calculated proportions, which were calculated for each participant were then compared across training conditions. For example, if a participant had chosen two go foods and one control food, the

[7]RTs were recorded continuously from movement initiation to response completion with samples every 33ms (two display refresh rates) to allow dynamic zoom-in/zoom-out effects based on participants' mouse movements. However, a bug was encountered with the version of the software and the temporal resolution at which coordinates and times were recorded was reduced. For this reason, linear interpolation was applied to increase the samples for every trial and obtain more precise RT measures. All details regarding this procedure can be found in the analyses scripts.

probability (i.e., calculated proportion) of choosing a go food would be 0.667, the probability of choosing a control food would be 0.333 and the probability of choosing a no-go food would be 0. Food rating VAS scores were averaged (mean) across the two foods per training condition (i.e., sweet and savoury foods for go, no-go and control conditions) and the three exemplars of each food. Changes in food liking from pre-to-post training (ΔLiking) were compared for preregistered analyses. Pre-training scores were subtracted from post-training scores and negative values represent a reduction in liking ratings.

2.4.2 Data exclusions

Participant-level data exclusions were conducted based on GNG training and AAT performance and participants who met any of the following criteria were excluded from all respective analyses. Participants who had a mean GoRT greater than three standard deviations from the group mean and percentage of correct responses in no-signal trials less than 85% were excluded. Participants were also excluded if their percentage of errors in signal trials was greater than three standard deviations from the group mean. For the AAT, participants were excluded if the percentage of errors in either pre- or post- AAT blocks greater than 25%. Additionally, participants who submitted a food rating of 50 (i.e., neutral) for 24 or more trials (~67%) either pre-or post-training would not be included as multiple such responses could indicate that participants skipped the rating trials by using the default setting of the VAS.

2.4.3 Preregistered analyses

Data pre-processing and analyses were conducted in R (R Core Team, 2017) via RStudio (RStudio Team, 2016) and JASP (JASP Team, 2018). Preregistered analyses are described under their pre-specified hypotheses, as previously presented (see section 2.2). For all Bayesian paired samples t-tests mentioned hereinafter, a prior with the $\sqrt{2}/2$ scale parameter for the half-Cauchy distribution was used. All data are available at https://osf.io/eu6xj/ and R scripts can be found at https://osf.io/hz2nb/.

H1. The effect of training condition on the change in approach-avoid bias scores from pre-to post-training was examined using Bayesian paired samples t-tests[8], as shown

[8]I have deviated from the preregistered analysis plan which specified a Repeated Measures ANOVA, because it was not needed for only one main effect that would be examined via directional comparisons irrespective of the results. The same deviation applies to H3.

below.
H1a. $\Delta AAT_{nogo} < \Delta AAT_{control}$
H1b. $\Delta AAT_{go} > \Delta AAT_{control}$

H2. Two Bayesian paired samples t-tests were conducted for the mean proportions of selected foods in the go and no-go training condition compared to the control.
H2a. p(no-go) < p(control)
H2b. p(go) > p(control)

H3. The effect of training condition on the change in food liking from pre-to post-training was examined using the directional Bayesian paired samples t-tests outlined below.
H3a. $\Delta Liking_{nogo} < \Delta Liking_{control}$
H3b. $\Delta Liking_{go} > \Delta Liking_{control}$

H4. Contingency learning during go/no-go training was examined using Bayesian paired-samples t-tests for the percentage of successful inhibition trials and go RTs.
H4a. $PCsignal_{nogo} > PCsignal_{control\text{-}nogo}$
H4b. $GoRT_{go} < GoRT_{control\text{-}go}$

The evidential value of confirmatory findings was solely determined by the Bayesian tests outlined in this section, as previously explained (see section 2.3.2). Frequentist tests were conducted in order to further the reproducibility of findings (e.g., potential use in meta-analyses). Paired samples t-tests were two-tailed, in line with the reported power analysis[9]. Contingency plans were not considered in case the normality assumption was violated for paired t-tests (Shapiro Wilk test: $p \leq .005$), but appropriate exploratory analyses were conducted and reported in the 2.5.3 section[10].

[9] Although Bonferroni corrections were preregistered for paired sample t-tests following Bayesian Repeated Measures ANOVAs, there were only two planned contrasts for each ANOVA and reflected distinct hypotheses about the data. Therefore, such corrections were not applied for the reported p-values. Also, the ANOVAs were not conducted as previously noted.

[10] For other analyses reported in section 2.5.3, p-values from Wilcoxon signed-rank tests are reported as p_W in a supplementary manner.

2.5 Results

2.5.1 Sample characteristics

After exclusions (see Figure B.1), the final sample consisted of 163 participants (80.98% female). Participants had on average a healthy BMI (M = 22.88, SD = 2.98, range = 18.54 - 32.36) and their mean age was 22.39 (SD = 9.04, range = 18 - 59). 108 participants (66.26%) reported that they had their last meal 3-5 hours before the study, while 24 participants (14.72%) did not adhere to the instruction not to eat 3 hours before. Hunger levels were not particularly high (M = 5.70, SD = 2.22).

2.5.2 Findings from confirmatory analyses

Primary training outcomes

All results for paired comparisons are shown in Table 2.1. There was *moderate* evidence that the change in bias scores for no-go foods (ΔAAT_{nogo}; M = -3.31, SD = 62.91) was not reduced compared to the change for control foods ($\Delta AAT_{control}$; M = -1.81, SD = 59.55). Similar to H1a, there was *strong* evidence for the null compared to the alternative for H1b. The change in bias scores for go foods (ΔAAT_{go}; M = -10.47, SD = 59.57) was not greater than the change for control foods. Approach-avoidance bias scores pre- and post-training across conditions have been visualised using rainclouds (Allen, Poggiali, Whitaker, Marshall, & Kievit, 2019, 2018) in Figure 2.2.

Table 2.1: Results for all preregistered hypotheses and respective statistical tests

						95% CI for d		
	BF_{10}	t	df	p	d	Lower	Upper	Evidence interpretation
H1a	0.11	-0.25	162	0.805	-0.02	-0.17	0.13	*Moderate* evidence for H0
H1b	0.04	-1.35	162	0.179	-0.11	-0.26	0.05	*Strong* evidence for H0
H2a	247.78	-3.93	161	< .001	-0.31	-0.47	-0.15	*Extreme* evidence for H1
H2b	0.85	1.82	161	0.070	0.14	-0.01	0.30	*Anecdotal* evidence for H0
H3a	2.65	-2.38	162	0.019	-0.19	-0.34	-0.03	*Anecdotal* evidence for H1
H3b	0.07	-0.37	162	0.715	-0.03	-0.18	0.13	*Strong* evidence for H0
H4a	140.25	3.77	162	< .001	0.30	0.14	0.45	*Extreme* evidence for H1
H4b	3973.21	-4.66	162	< .001	-0.37	-0.52	-0.21	*Extreme* evidence for H1

Note. Evidence is interpreted for the alternative hypothesis (H1) compared to the null (H0) and vice versa. All Bayesian paired samples t-tests were directional, as indicated in the 2.4.3 section and frequentist equivalents were non-directional (two-tailed). The effect size is represented by Cohen's *d*.

Secondary training outcomes

The effect of training on impulsive food choices was examined for no-go and go foods compared to control, as stated in H2a and H2b respectively. One participant did not complete the food choice task. There was *extreme* evidence that the probability of choosing a no-go food ($M = 0.21$, $SD = 0.27$) was lower than the probability of choosing a control food ($M = 0.36$, $SD = 0.31$) after training (see Table 2.1). There was only *anecdotal* evidence that probability of choosing a go food ($M = 0.44$, $SD = 0.33$) was not higher than the probability of choosing a control food. Differences in food choice probabilities can be seen in Figure 2.3.

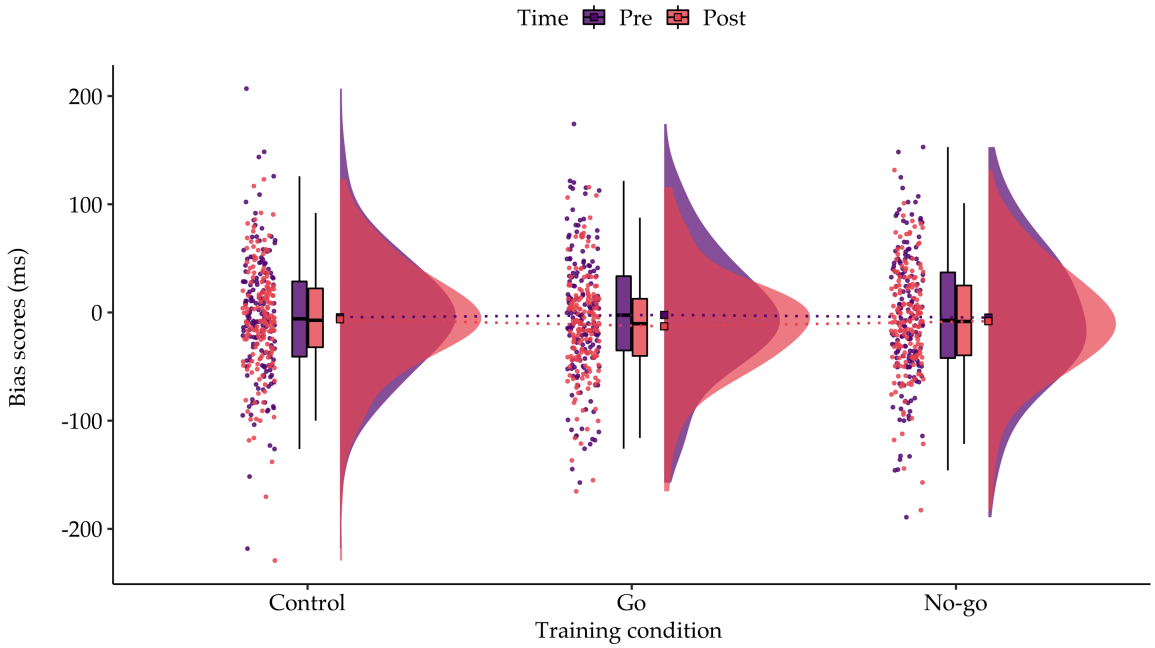


Figure 2.2: Raincloud plot of the approach-avoidance bias scores pre- and post- training across training conditions. There were no differences between the sample mean changes in approach-avoidance bias scores for no-go and go foods compared to control (filler) foods, as shown by the dashed lines. At a closer inspection, individual bias scores do not seem to be clustered around the positive end of the distribution as it would be expected for appetitive unhealthy foods, but actually show less dispersion around zero. Exploratory analyses confirmed that baseline bias scores for go, no-go and control foods did not statistically deviate from zero (see section 2.5.3). *Note.* The 'split-half violin' elements in the plot show smoothed distributions and boxplot vertical lines represent the range, excluding outliers based on the Interquartile Range. Square boxes have been added to depict the sample means, connected with dashed lines across training conditions.

As a first manipulation check and secondary training outcome, it was investigated whether GNG changed the evaluations of foods associated with stopping (signal trials) during training compared to the evaluations of control foods which were paired with both go and stop responses with equal probability (50% signal, 50% no-signal). The

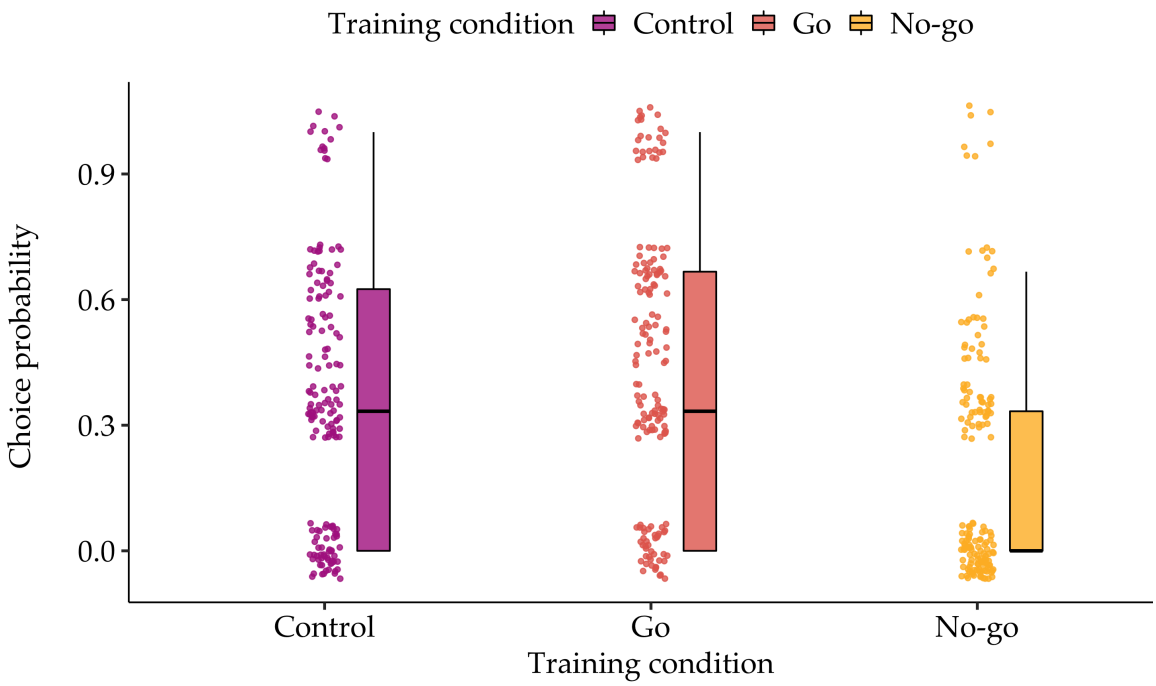


Figure 2.3: Boxplots showing the food choice probabilities across training conditions. The boxplots with corresponding jittered individual data points clearly show that the probability of choosing a no-go food after training was lower than the probability of choosing control food (H2a). Contrary to initial predictions, the average choice probability was not higher for go foods relative to the control (H2b). *Note.* The 'split-half violin' elements in the plot show smoothed distributions and boxplot vertical lines represent the range, excluding outliers based on the Interquartile Range.

change in liking scores from pre-to post-training for nogo foods ($\Delta\text{Liking}_{\text{nogo}}$; M = -4.16; SD = 9.51) was only slightly reduced compared to change in liking for control foods ($\Delta\text{Liking}_{\text{control}}$; M = -2.61, SD = 8.77), and there was only *anecdotal* evidence for this effect (H3a; see Table 2.1). The change in liking scores from pre-to post-training for go foods ($\Delta\text{Liking}_{\text{go}}$; M = -2.87, SD = 10.15), however, was not greater than the change for control foods as originally expected. Instead, there was *strong* evidence for the null hypothesis compared to the alternative (H3b).

Contingency learning

In order to validate whether the implemented go/no-go training paradigm led to stimulus-response associations (i.e., contingency learning manipulation check), we tested whether the percentage of correct responses for no-go foods (i.e., successful inhibitions) would be greater compared to the percentage of correct responses for control foods associated with signal trials (H4a). There was *extreme* evidence that participants had on average a higher proportion of successful inhibitions for no-go foods ($\text{PCsignal}_{\text{nogo}}$; M = 0.97, SD = 0.03) than control foods ($\text{PCsignal}_{\text{control-nogo}}$;

M = 0.96, SD = 0.04). Results are graphically presented in Figure 2.4. For H4b, it was examined whether mean reaction times would be reduced for go foods ($GoRT_{go}$; M = 507.00, SD = 70.48) compared to control foods associated with no-signal trials ($GoRT_{control\text{-}go}$; M = 515.00, SD = 75.51) and there was *extreme* evidence for such an effect. Therefore, contingency learning was observed in the employed GNG paradigm for both reaction time and accuracy outcomes.

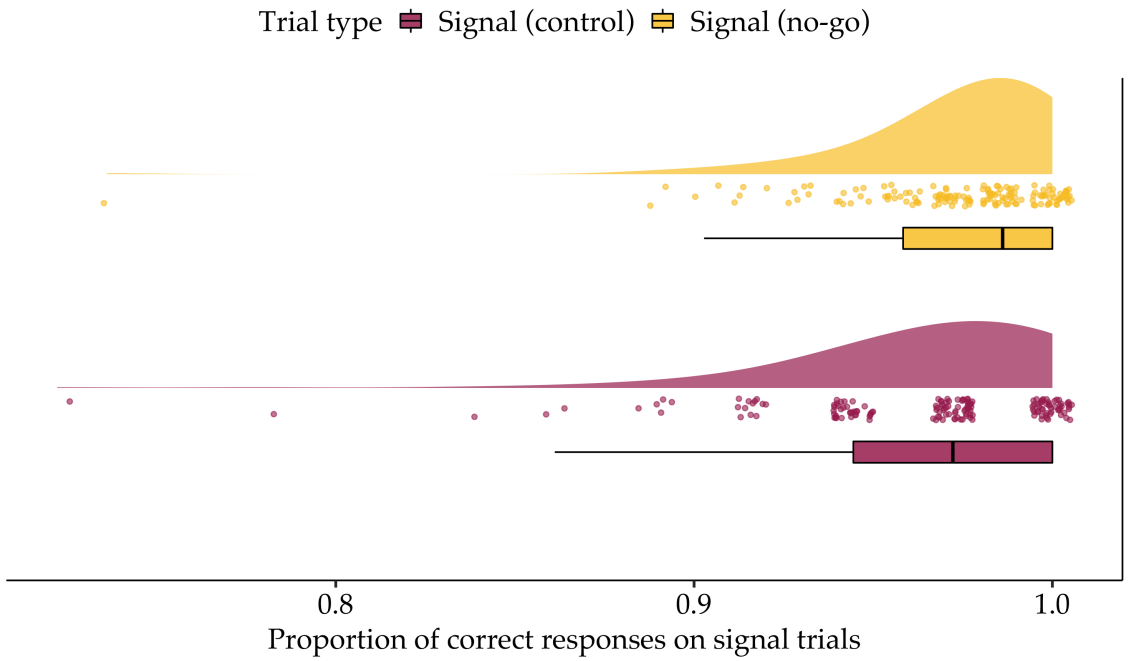


Figure 2.4: Raincloud plot of the proportion of correct responses on signal trials. The proportion of correct responses on signal trials (PC_{signal}) was relatively greater for no-go foods compared to control foods. The PC_{signal} distribution for control foods was heavily skewed and this observation warranted a robustness check for effect estimates, as presented in the 2.5.3 section. *Note.* The 'split-half violin' elements in the plot show smoothed distributions. Individual data points have been jittered to some degree due to overfitting, as it can be seen for the cluster of data points for very high proportions of correct responses. For example, when the proportion of correct responses on signal trials was 1.0 the individual data points were extended on the x-axis to enable their visualisation.

2.5.3 Findings from exploratory analyses

Baseline approach bias scores

Performance in the AAT was inspected further to check if approach bias for foods was present in the final sample and whether error rates differed across conditions. Although the sample means for AAT_{pre} bias scores were negative for go foods (M = -2.32, SD = 58.14), no-go foods (M = -4.75, SD = 60.58) and control foods (M =

-4.48, $SD = 52.25$), individual data points (see Figure 2.2) show less dispersion close to zero, suggesting that, on average, neither approach or avoidance bias was captured by the AAT. In line with previous literature (see Table 1 in Becker et al., 2015), this hypothesis was directly tested by examining whether baseline bias scores statistically deviated from zero using Bayesian one sample t-tests with the default prior settings for the two-sided alternative hypothesis that the population mean was not equal to the test value ($\neq 0$). Equivalent frequentist tests were also conducted. Overall, conclusive evidence for the absence of baseline bias was obtained (see Table 2.2).

Table 2.2: Results of Bayesian and frequentist one sample t-tests for baseline approach-avoidance bias scores

					95% CI for d	
	BF_{01}	$t(162)$	p	d	Lower	Upper
Completion time: AAT_{pre}-go	10.08	-0.51	0.611	-0.04	-0.19	0.11
Completion time: AAT_{pre}-no-go	7.01	-1.00	0.318	-0.08	-0.23	0.08
Completion time: AAT_{pre}-control	7.02	-1.00	0.319	-0.08	-0.23	0.08
Initiation time: AAT_{pre}-go	10.73	-0.36	0.718	-0.03	-0.18	0.13
Initiation time: AAT_{pre}-no-go	10.18	-0.49	0.626	-0.04	-0.19	0.12
Initiation time: AAT_{pre}-control	10.46	-0.43	0.669	-0.03	-0.19	0.12

Note. AAT_{pre}: Pre-training approach avoidance task bias scores (for go, no-go or control foods)

As baseline bias scores calculated from completion times may be 'contaminated' by motor demands in this version of the AAT that requires computer mouse movements and arm flexion/extension, the possibility that motor initiation times may be more sensitive to capturing automatic action tendencies was considered. Movement initiation was registered when participants had moved their mouse cursor since starting a trial (i.e., stimulus onset), including the pixel tolerance for natural movements of the mouse (see section 2.3.5). Therefore, tests were also conducted for baseline bias scores calculated using median initiation times, instead of median completion times. Consistent with the results presented above, there was strong evidence that baseline bias scores did not deviate from zero across training conditions (see Table 2.2).

Reliability of bias scores

The absence of baseline approach bias as measured by the AAT indicated that the internal reliability of the calculated bias scores may be questionable. A permutation-based split-half approach was used to estimate the internal consistency of the AAT bias scores ($MedianRT_{push} - MedianRT_{pull}$) at baseline (Parsons, 2019). Split half estimates were computed for 10000 random splits of the correct completion RTs

at baseline (raw data) and the Spearman-Brown corrected reliability estimate was 0.67, 95% CI [0.58, 0.75]. Although completion RTs were used for the preregistered analyses, this analysis was also conducted for AAT initiation times to test whether questionable internal consistency was associated with potential motor demands of completing whole-arm mouse movements, as discussed above (see *Baseline approach bias scores*). The Spearman-Brown corrected estimate for AAT bias scores at baseline based on initiation RTs was 0.69, 95% CI [0.61, 0.77].

The Spearman-Brown corrected estimates were in a similar range for both types of calculated bias scores. I purposefully refrain from adopting commonly used thresholds for 'adequate' or 'good' reliability (see Parsons et al., 2019), but acknowledge that the internal reliability of the AAT bias scores should be investigated further because the computed estimates were not very high (e.g., ≥ 0.8). Specifically, the internal reliability would need to be reported in future studies that use AAT bias scores to make inferences about training outcomes within specific conditions (e.g., no-go vs control foods).

Sub-group analysis

In an effort to show that the lack of a training effect on AAT outcomes was not due to the absence of baseline approach bias for unhealthy foods, a sub-group analysis for participants with positive baseline bias scores (N=72) was conducted. The findings from this exploratory analysis for food choice outcomes were consistent with the results reported in section 2.5.2. There was *strong* evidence that the probability of choosing a no-go food ($M = 0.20$, $SD = 0.27$) was lower than the probability of choosing a control food ($M = 0.37$, $SD = 0.33$) [$BF_{10} = 13.97$; $t(70)$] = -2.96, $p = 0.004$, $p_W = 0.004$, d = -0.35, 95% CI for d = -0.59, -0.11]. There was *moderate* evidence for the absence of a general effect of training condition on the change in liking scores from pre-to post-training [$BF_{01} = 8.91$; $F(2, 142) = 0.94$, $p = 0.392$][11]. With regards to the contingency learning manipulation check, there was *very strong* evidence for a greater proportion of correct responses in signal trials with no-go foods compared to control foods [$BF_{10} = 37.80$; $t(71) = 3.33$, $p = 0.001$,$p_W < .001$, $d = 0.39$, 95% CI for $d = 0.15, 0.63$]. However, there was only *anecdotal* evidence that GoRTs were faster for go foods compared to control foods [$BF_{10} = 3.52$; $t(71))$ = -2.38, $p = 0.020$, d = -0.28, 95% CI for d = -0.52, -0.04].

[11]This analysis was conducted via a Bayesian Repeated Measures ANOVA with the default prior settings (Rouder, Engelhardt, McCabe, & Morey, 2016; Rouder, Morey, Speckman, & Province, 2012).

Accuracy in the approach-avoidance task

Although reaction times are the primary measure of interest for studies that utilise the AAT, an exploratory examination of error rates is also reported. At baseline, average error rates were not increased for trials where participants were required to avoid an appetitive food and complete a push action ($M = 0.136$, $SD = 0.070$) relative to trials where an approach (pull) action was completed ($M = 0.143$, $SD = 0.066$) [$BF_{01} = 26.49$; $t(162) = 1.42$, $p = 0.159$, $d = 0.11$, 95% CI for d = -0.04, 0.26]. However, after training, participants had on average more errors in approach trials ($M = 0.124$, $SD = 0.074$) compared to avoid trials ($M = 0.105$, $SD = 0.062$) [$BF_{10} = 90.98$, $t(162) = 3.64$, $p < .001$, $p_W < .001$, $d = 0.29$, 95% CI for $d = 0.13, 0.44$]. It is possible that training had a 'hidden' effect on accuracy, as for example it was more difficult to approach no-go foods compared to go and/or control foods due to a learned association between response inhibition and these food stimuli. Difference scores were calculated from the mean error rates post-training (pull - push) to check whether this increase in error rates was general or specific to training conditions. There was *very strong* evidence for the absence of a general effect of training condition on differences in mean error rates between approach and avoid trials [H3; $BF_{01} = 37.16$; $F(2, 324) = 0.17$, $p = 0.844$]. RT differences between approach and avoid trials were also inspected and there was *strong* evidence for slower RTs on pull compared to push actions after training [$BF_{10} = 11.32$; $t(162) = 2.95$, $p = 0.004$, $p_W = 0.002$, $d = 0.23$, 95% CI for $d = 0.08, 0.39$]. Together these results may indicate fatigue effects associated with bio-mechanical costs (e.g., arm flexion muscle group activation).

Devaluation trends across training conditions

As explained in Figure 2.5, there was a general trend of devaluation in the data for all training conditions from pre- to post-training. These observed differences were tested directly and there was conclusive evidence that within each training condition cell, there was a negative change in mean liking ratings from pre- to post-training. The control (filler) foods should have been unaffected in terms of affective evaluation changes, but participants rated control foods more negatively after training ($M = 68.55$, $SD = 15.81$) relative to baseline ($M = 71.16$, $SD = 14.80$) [$BF_{10} = 156.54$, $t(162) = 3.80$, $p < .001$, $p_W = 0.001$, $d = 0.30$, 95% CI for $d = 0.14, 0.45$]. Contrary to predictions about the increase in positive evaluations for go foods (relative to control), within that condition cell the evaluations of go foods were less positive after training ($M = 67.42$, $SD = 16.85$) compared to before ($M = 70.29$, $SD = 16.80$) [$BF_{10} = 84.52$,

$t(162) = 3.62$, $p < .001$, $p_W < .001$, $d = 0.28$, 95% CI for $d = 0.13, 0.44$]. The effect was greater for no-go foods, but this is the only data trend that was theoretically consistent with effects of training. Participants provided less positive ratings for no-go foods after training ($M = 68.83$, $SD = 16.81$) compared to before ($M = 72.99$, $SD = 15.38$) [$BF_{10} = 211398.68$, $t(162) = 5.58$, $p < .001$, $p_W < .001$, $d = 0.44$, 95% CI for $d = 0.28, 0.60$].

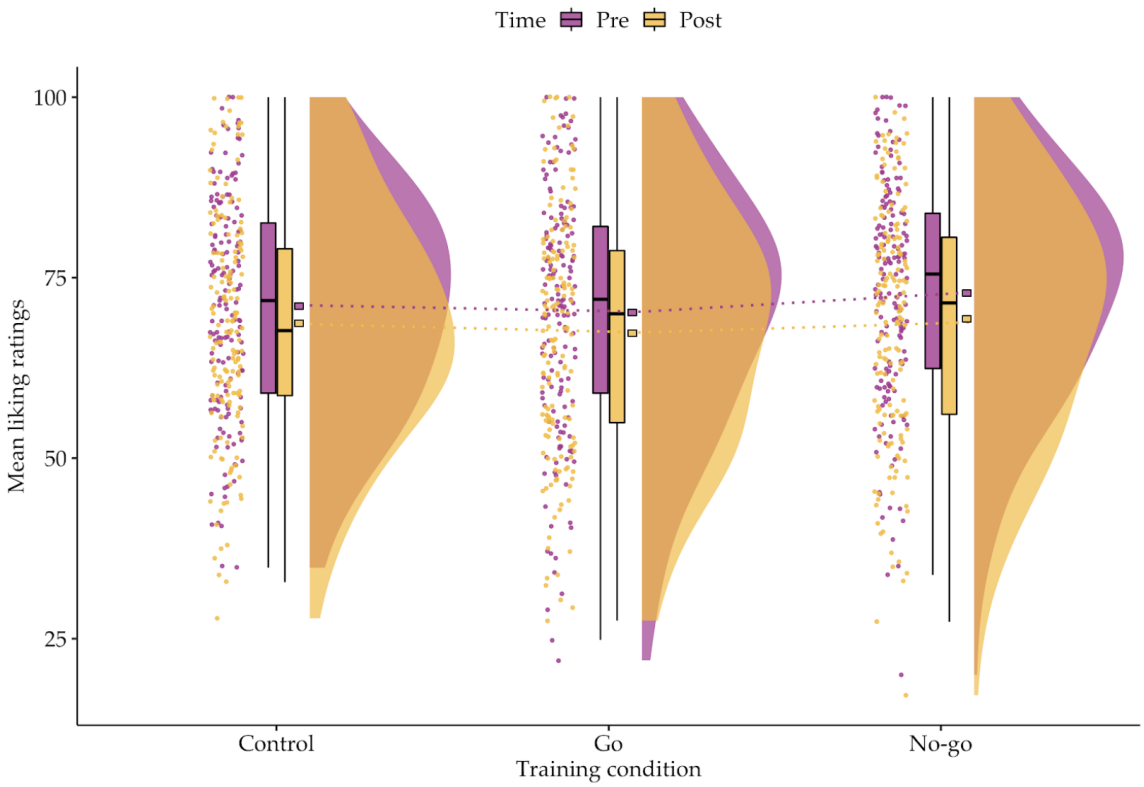


Figure 2.5: Raincloud plot of the mean liking ratings pre- and post- training across training conditions. This visualisation of the mean liking ratings from all participants revealed that the distributions are more skewed than expected, towards the least liked range of the visual analogue scale (VAS). Taste (liking) ratings were registered on a VAS ranging from 0 to 100 (i.e., 50=neutral). Although there appears to be a small difference between the change in liking for no-go foods compared to the control, the trends presented in this plot were inspected further to establish whether observed effects were robust (see section 2.5.3 - Robust statistics). Also, there appears to be a general trend of devaluation across training conditions and this was statistically supported (see section 2.5.3 - Devaluation trends across training conditions). *Note.* The 'split-half violin' elements in the plot show smoothed and trimmed distributions and boxplot vertical lines represent the range, excluding outliers based on the Interquartile Range. Square boxes have been added to depict the sample means, connected with dashed lines across training conditions.

General linear model of food choice data

As shown in Figure 4 and as expected for counts data, food choice probabilities were not normally distributed and the inferences based on paired t-tests would need to be validated further. Choice count data from the impulsive food choice task were modelled using a general linear model (GLM) in R. The error term of the model was specified with a Poisson distribution and the link function log-transformed the linear predictor within the model (i.e., logarithms of fitted means). The only predictor in this model was the training condition (i.e.., go, no-go, or control foods). Diagnostic plots showed mild violations of the assumptions of homoskedasticity and normality of residuals and

thus robust standard errors for the parameter estimates were computed (Cameron & Trivedi, 2009). An overdispersion test (Cameron & Trivedi, 2005; Kleiber & Zeileis, 2008) showed that true dispersion was not greater than 1 and the goodness-of-fit chi-squared test was not statistically significant, indicating that the model had a good fit (residual variance = 436.15, df = 486, $p = 0.949$). The GLM results are consistent with the preregistered statistical test results (see Table 2.1). The model showed that impulsive choice probability for no-go foods was 0.53 times the choice probability for control foods [Estimate (log) = -0.617, Robust SE = 0.119, $p < .001$, 95% CI = -0.851, -0.383)]. The probability of choosing a go food after training was 1.22 times the probability of choosing a control food [Estimate (log) = 0.197, Robust SE = 0.091, $p = 0.030$, 95% CI = 0.019, 0.374].

Robust statistics

For certain preregistered paired comparisons, where the difference scores were found to violate the normality assumption (Shapiro-Wilk test with $p \leq 0.005$), it was possible that effect size estimates were biased and therefore robust statistics are also reported (Lakens, 2015). H2a and H2b have been omitted as robust analyses have already been implemented above (see section 2.5.3).

Table 2.3: Yuen's tests of trimmed mean differences for paired comparisons that violated the normality assumption

				95% CI			Comparison to	Effect size
	$t(98)$	p	MD_t	Lower	Upper	ξ	confirmatory test	interpretation
H1a	-0.90	0.369	-5.12	-16.37	6.14	0.07	Consistent	None
H3a	-1.67	0.098	-1.03	-2.25	0.19	0.10	Consistent	Very small
H3b	-0.09	0.932	-0.06	-1.50	1.38	0.01	Consistent	None
H4a	-3.11	0.002	-0.01	-0.01	0.00	0.20	Consistent	Small

Note. The degrees of freedom for the robust t statistic are 98 because of trimming at 20% for both tails of the distribution (i.e., N = 99). 'Comparison to confirmatory test' refers to whether or not the results from Yuen's tests were consistent with the preregistered, confirmatory test results. MD_t: trimmed mean difference; ξ: explanatory measure of effect size

Yuen's method of comparing trimmed means was applied via the WRS2 package, with the recommended percentage of 20% trimming from both tails of the distribution (Mair & Wilcox, 2019; Wilcox & Tian, 2011; Yuen, 1974). The explanatory measure of effect size ξ is provided and can be conventionally interpreted as small, medium and large at 0.15, 0.35 and 0.50 (Mair & Wilcox, 2019). The null hypothesis in Yuen's test for paired sample comparisons is that there is no difference between the trimmed

means ($\mu_{t1} = \mu_{t2}$). The test results are shown in Table 2.3 and were consistent with findings from preregistered confirmatory analyses. The explanatory effect sizes did not deviate in their interpretation from Cohen's d values presented in Table 2.1 for frequentists paired-samples t-tests, as the observed effects were small for both H3a and H4a.

2.6 Discussion

The primary aim of the study was to investigate whether inhibitory control training (ICT) can have an effect on automatic action tendencies. This research question was based on previous theoretical ground for hard-wired mutually excitatory connections between appetitive/aversive centres and 'go'/'stop' systems that could lead to changes in the motivational value of stimuli included in training (McLaren & Verbruggen, 2016; Verbruggen et al., 2014a). The formulation of this research question was also based on the BSI theory of stimulus devaluation (Veling et al., 2008), which argues that the devaluation process that occurs during training may lead to reduced approach bias for foods associated with response inhibition. It was hypothesised that approach bias for unhealthy foods associated with a no-go response during go/no-go training (i.e., response inhibition) would be reduced compared to control foods that were paired with both go and no-go responses with an equal probability (control). Automatic action tendencies were indirectly measured using a variant of the approach-avoidance task (AAT) that includes a 'zooming' feature for push/pull actions (Neumann & Strack, 2000) of the computer mouse and requires participants to judge the orientation of the presented picture (C. E. Wiers et al., 2013).

2.6.1 No effects of training on automatic action tendencies

As a primary outcome measure, the change in bias scores from pre-to post-training was examined across training conditions. Approach-avoidance bias scores were calculated from AAT blocks before and after training by subtracting median RTs on approach trials (pull action) from median RTs on avoid trials (push action). Positive scores would indicate an approach bias towards unhealthy foods. The results from the preregistered analyses showed that ICT did not have an effect on automatic action tendencies, as there was *moderate* evidence that approach bias for no-go foods was not reduced relative to control foods after training (H1a) as well as *strong* evidence that approach bias for go foods was not increased compared to control foods after training

(H1b). Although such ICT effects may not have been previously investigated, there is empirical evidence to suggest that food stimuli included in AAT training protocols can be associated with increased avoidance behaviour (or reduced approach) after training (e.g., Dickson et al., 2016; Schumacher et al., 2016). A significant change in approach-avoidance bias scores was not observed in another series of experiments (Becker et al., 2015), but presence or absence of training effects may also depend on methodological parameters of training and employed controls (see Jones et al., 2018 for review), as discussed further below (see section 2.6.4).

2.6.2 Response inhibition & impulsive food choices

As a secondary outcome measure, impulsive food choices were assessed via an adapted food choice task (Veling et al., 2013a) after training. Participants had ten seconds to choose three food stimuli from all training conditions (go, no-go or control). preregistered analyses showed that the probability of choosing a no-go food was lower than the probability of choosing a control food (H2a). Meanwhile, there was no difference between the probability of choosing a go food relative to the probability of choosing a control food (H2b). The conclusion that ICT can have an effect on impulsive food choices is consistent with previous studies that have used both go/no-go and stop-signal task paradigms (Veling et al., 2013b, 2013a), but cannot be directly compared to experiments involving cue-approach training, which involves responding to go items in response to a cue or signal. These studies have found increased food choices for go food items (Schonberg et al., 2014; Veling, Chen, et al., 2017). Food choices can either be deliberate or impulsive (added time pressure in experimental settings) and hypothetical or consequential, whereby participants are aware that their choices will determine what food they are offered by the experimenter at the end of the study (e.g., see Chen et al., 2019). The present findings should therefore be replicated and extended with different experimental manipulations (e.g., speeded binary choice task).

2.6.3 Devaluation effects & design limitations

Another important training outcome which was also treated as manipulation check for the ICT paradigm was the change in food evaluations from pre-to post-training. According to the BSI theory of stimulus devaluation, as already introduced, successful inhibition of responses on signal trials is facilitated by an underlying devaluation process for appetitive foods, whereby approach bias for these foods is reduced (Veling

et al., 2008, 2017). Consistent with previous studies where go/no-go training led to robust food devaluation effects (see Chen et al., 2016 for a series of preregistered experiments), it was expected that the change in mean tastiness ratings (i.e., food liking) for no-go foods from pre-to post-training would be reduced compared to the change in ratings for control foods. Preregistered analyses showed only *anecdotal* evidence that no-go foods were rated less positively after training compared to control foods (H3a). Similarly, participants did not show increased liking for go foods relative to the control foods, from pre-to post-training (H3b). It should be noted that control foods which were associated with both go and no-go responses (50:50) are not an ideal control for devaluation effects, as Chen et al. (2016) correctly point out that effects should be observed for two baselines in order for proper inferences to be made. They compared changes in evaluation for no-go foods compared to changes for go foods as well as changes for untrained food stimuli, which were never included in training. In their design, food stimuli sets were matched in valence before training. However, participants in this study were only presented with a fixed set of unhealthy foods which were considered appetitive (e.g., pizza, cake, crisps) and this was a viable limitation with regards to the examination of devaluation effects. Indeed, there is evidence to suggest that devaluation is observed only when highly appetitive foods are associated with response inhibition (see Chen et al., 2016).

Exploratory analyses further showed that while on average no-go foods were rated less positively after training compared to before, there was a general devaluation trend for both go and control foods (see section 2.5.3). Although this observation could simply be attributed to regression to the mean (e.g., see Experiment 1 in Chen et al., 2016), it is possible that 'over-exposure' to specific food stimuli from all training conditions during the phases of the study (pre-training, training, and post-training) could have had a habituation effect on participants' affective evaluations at the end of the study. It is also unclear whether stimulus-response mappings in the AAT affected GNG manipulations, as for example a correct response on push trials may require response inhibition, whereby an initial approach tendency towards an appetitive food cue is inhibited. Following the theoretical framework of an *associative stop system*, go foods were also associated with an aversive centre through avoidance responses and no-go foods presented on approach trials were linked to an appetitive centre. This would mean that, at least to a certain extent, hard-wired connections between go/stop and appetitive/aversive centres (Verbruggen et al., 2014a) could have confounded expected effects on food evaluations. However, the absence of devaluation effects specific to no-go foods could not be attributed to ineffective training, as the second

manipulation check for contingency learning during the go/no-go task was positive. There was *extreme* evidence that GoRTs on correct no-signal trials were reduced for go foods compared to control foods and that the percentage of correct responses on signal trials were greater for no-go foods relative to control foods. Overall, ICT outcomes for devaluation contradicted prior expectations, while taking into account that limitations of the experimental design may have had a significant impact on observed effects.

2.6.4 Methodological considerations for the approach-avoidance task

There were several findings from exploratory analyses regarding the approach avoidance task that may explain the absence of ICT effects on automatic action tendencies and yielded methodological considerations for future studies. First, overall baseline bias scores did not statistically deviate from zero (see *Baseline approach bias scores*), which suggests that either participants did not have any approach bias for the selected foods (on average) or the employed variant of the AAT was not sensitive enough to capture both baseline bias and potential effects of training. Sub-group analyses showed that even when participants had positive bias scores for unhealthy foods, which reflect existing approach bias, there were still no effects of training on automatic action tendencies (see *Sub-group analysis*). Consequently, the internal reliability of the calculated bias scores at baseline was inspected (see *Reliability of bias scores*). The estimates for baseline bias scores based on both completion times and initation times were not very high, which may indicate 'questionable' internal reliability of these scores in this research context[12]. However, more research is needed to provide evidence for this claim (see Parsons et al., 2019) and internal reliability should be investigated further in future training studies.

It is also unclear whether any type of response latency measure derived from sensorimotor tasks, such as the AAT variant employed in this study, can be indicative of approach-avoidance bias, since the role of arm movements in these motivational processes has recently been questioned for the controversial replicability of findings and the importance of whole-body movements in real-world approach-avoidance behaviours (Rougier et al., 2018). An element of the AAT variant that could have affected the internal consistency of the bias scores was the use of a computer mouse instead of a joystick, as in the seminal version of this paradigm (Rinck & Becker, 2007; Wiers et

[12]Here I only refer to the calculated bias scores (*measurement*) and not the AAT as an indirect *measure* of automatic action tendencies.

al., 2009). However, it could be assumed that any motor demand differences between the joystick and computer mouse would not affect the initiation times, for which the computed reliability estimates were in a similar range.

The variability in methodology for the measurement of motivational bias should be taken into account, as different parameters might need to be examined further when the AAT is applied in the food domain (e.g., explicit vs implicit task instructions; see Phaf et al., 2014 for meta-analysis). In a recent study, Lender et al. (2018) found that the irrelevant-feature of the AAT did not lead to robust approach-bias, compared to relevant-feature variants which require participants to pay attention to the content of the stimuli. Setting aside the methodological utility of the AAT in this context, it is possible that go/no-go training with the specific parameters applied in this study, did not have an effect on automatic action tendencies, but this research question could be addressed in future empirical studies that utilise alternative measures of motivational bias, such as the relevant stimulus-response compatibility task (e.g., see Field, Caren, Fernie, & De Houwer, 2011) and tailor stimuli to participants' individual liking ratings.

2.6.5 Concluding remarks & future directions

A thorough search of the literature did not indicate that the AAT had previously been employed as an outcome measure in ICT studies using the go/no-go training paradigm. I believe that the null findings presented here can shed light into methodological and theoretical issues that need to be explored further. The BSI theory could predict ICT effects on automatic action tendencies if there was conclusive evidence for a no-go devaluation effect, which was not supported in this study. Alternatively, hard-wired mutually excitatory connections between appetitive/aversive centres and 'go'/'stop' systems could lead to changes in the motivational value of stimuli included in training. There are several methodological limitations regarding the application of the AAT as an indirect measure of motivational bias that need to be addressed before drawing any conclusions and these could be addressed in future studies. On a final note, it is worth mentioning that there are various methodological parameters and protocols that can be implemented for both inhibitory control training and measurement of approach-avoidance bias and this can pose an important replicability issue. It is recommended that novel findings, irrespective of statistical significance, are replicated and/or extended in a rigorous and reproducible manner, in an effort to reduce selective reporting and publication bias in this line of research (e.g., see Aulbach et al., 2019; Carbine & Larson, 2019).

Chapter 3

A novel inhibitory control training paradigm for changing food evaluations and cravings

3.1 Introduction

Inhibitory control training in the food domain has been primarily implemented using adapted variants of the go/no-go task and stop-signal task. Overall, there has been promising evidence regarding the utility of ICT paradigms as cost-effective behaviour change interventions for unhealthy eating behaviours, such as reducing food intake (Allom et al., 2016; Aulbach et al., 2019; Jones et al., 2016, 2018). However, there are several methodological differences and inconsistencies in reviewed findings from laboratory studies, which should be explored further. For instance, recent meta-analyses of ICT outcomes have shown that the food-specific go/no-go (GNG) training paradigm, as described in Chapter 2, may be more effective as an intervention for health behaviour change compared to the stop-signal task (SST) training protocols (Allom et al., 2016; Aulbach et al., 2019; Jones et al., 2016; Turton et al., 2016). This finding could be attributed to a number of conceptual and methodological differences between the two training paradigms. First, GNG training may involve automatic, or 'bottom-up', inhibition, whereas SST training influences behaviour via controlled, or 'top-down', response inhibition (Verbruggen & Logan, 2008a). The different cognitive control demands required by the two paradigms may be very important for food-specific ICT outcomes, as it has been found for the moderating role of the proportion of successful inhibitions during training (Jones et al., 2016). Second, ICT studies

employing variants of the SST often have inconsistent mappings between 'target' foods and signal trials, which are only presented on a minority of the trials (Veling et al., 2017). In the current study, a novel ICT paradigm that builds on previous SST training protocols and adopts the principles of the stop-change task (Logan, 1982) was developed. Unhealthy food stimuli were always the targets on signal trials and the training tasks required participants to initiate whole-arm movements towards the stimuli using the computer mouse. The study investigated whether the novel task variants would lead to changes in food evaluations and cravings for healthy and unhealthy foods.

In the SST, participants are required to respond to both neutral and 'target' stimuli, such as foods, as fast as possible and on a minority of the trials a signal appears to indicate that they have to inhibit their responses. In contrast to the GNG task, the signal appears after a delay, thus increasing the difficulty of successful response inhibition when an action has already been initiated. Specifically, the GNG task requires 'action restraint', while the SST involves 'action cancellation', which can be more demanding (Eagle et al., 2008). The stop-signal delay (SSD) is commonly adjusted via an adaptive staircase procedure and performance is modelled as a race between a 'go' and a 'stop' process (Verbruggen & Logan, 2008b). Response inhibition occurs when the stop process finishes before the go process and response inhibition latency can be estimated via the independent race model (Logan et al., 2014). The stop-signal reaction time (SSRT) has been successfully employed as a measure of inhibitory control deficits in clinical populations (see Verbruggen & Logan, 2008b for review). In SST training, participants can be trained to inhibit their responses towards unhealthy foods on a minority of trials when a signal is presented after a dynamically adjusted SSD (e.g., Lawrence et al., 2015). Previous studies have implemented the SST as a training intervention where target foods paired with a stop signal were expected to be associated with decreased food intake, reduced *implicit* food evaluations and even weight loss (e.g., Allom & Mullan, 2015; Adams et al., 2017; Forman et al., 2016; Houben, 2011; Lawrence et al., 2015). The evidence reported in these studies, however, has been mixed with positive findings that were often inconsistent across reported experiments (e.g., Allom & Mullan, 2015; Lawrence et al., 2015) as well as null findings (e.g., Forman et al., 2016; Study 1 in Adams et al., 2017). Recent meta-analyses have shown that effects of SST training are small-to-medium and weaker compared to the effects of GNG training (Allom et al., 2016; Aulbach et al., 2019; Jones et al., 2016; Turton et al., 2016).

Despite the acquired evidence regarding the efficacy of SST training in the food

domain, controlled, or top-down, inhibitory control could be involved more in real-world eating behaviours compared to automatic response inhibition trained via the GNG paradigm. For example, 'action cancellation' may be required in curbing binge eating episodes or controlling portion sizes, where the action of eating has already been initiated and an approach tendency for energy-dense foods has not been inhibited. More importantly, real-world eating behaviours do not solely require action cancellation or restraint, but the updating of action plans and re-engagement in new, or alternative, actions (Boecker, Gauggel, & Drueke, 2013). For example, following a healthier diet on a daily basis would involve the cancellation of action plans to consume an unhealthy appetitive food and instead choosing to eat a healthier alternative (e.g., "food-swaps" concept; NHS, 2018). This contradicts the view that total motor suppression (i.e., response inhibition) is the key process that should be targeted in ICT paradigms that aim to promote healthier eating behaviours. With this in mind, the stop-change paradigm (Logan, 1982) was considered a suitable candidate for an ICT intervention in the food domain.

Both the stop-signal and stop-change paradigms require participants to cancel an initiated response on signal onset, but when a stop-change signal is presented the cancelled response is replaced by a new, or alternative, action that needs to be executed (Verbruggen et al., 2008). The stop-signal and stop-change training tasks can be matched in all methodological parameters, such as SSD and stimulus-response contingencies and they both require the activity of a go process, and a stop process (Verbruggen et al., 2008), as previously explained. The stop-change task (SCT), however, also involves a response re-engagement process (Boecker et al., 2013). A search of the ICT literature did not yield any studies that have assessed the feasibility of the SCT as an ICT intervention for appetitive stimuli, such as foods or alcohol. There are several variants of the SCT which could be adapted to an ICT paradigm, such as pressing alternate keys on stop-change trials (e.g., Brown & Braver, 2005). The stop-change paradigm has also been developed as a continuous task with whole-arm movements of the computer mouse (Study 4 in Maizey, 2016). The continuous version of the SCT has many benefits, including but not limited to, the calculation of stop-signal and change-signal reaction times (SSRT, CSRT) without the need for estimation procedures (Logan et al., 1984) and direct observations of action initiation, cancellation as well as action updating processes. In this study, the continuous version of the stop-change task was also preferred as whole-arm movements were considered more ecologically valid relative to key presses.

The ICT paradigm employed in this study has peen primarily adapted from

previously used SST training protocols (e.g., Lawrence et al., 2015) and the continuous version of the SCT reported in Maizey (2016). The developed training tasks were randomly administered to different groups of participants (stop and stop-change) and the control group received go training. The training tasks did not involve inconsistent stimulus-response contingencies/associations, but instead unhealthy food targets were always paired with a signal. In line with previous literature which suggests that a prominent underlying mechanism of action behind ICT outcomes (i.e., reduced food intake) is the devaluation of no-go stimuli (Veling et al., 2008, 2017), the evaluations of unhealthy foods presented on signal trials was measured in all groups after training (i.e., tastiness ratings). In order to examine whether training can have an effect on state cravings for these foods, participants also rated how much they desired to eat the specific foods at that time. In an effort to assess the importance of tailoring food stimuli in ICT protocols to individual preferences, participants completed an initial food selection task which required them to select a number of healthy and unhealthy foods that they liked the most and rank them according to how much they would like to eat them. Both selected and non-selected foods were presented during training on signal and no-signal trials. The assumption that only highly appetitive foods would induce stimulus devaluation effects is supported by the Behaviour Stimulus Interaction (BSI) theory (Chen et al., 2016; Veling et al., 2008), which suggests that an aversive conflict signal is triggered when an initial approach tendency towards an appetitive food needs to be inhibited during training and thus successful response inhibition may be facilitated via stimulus devaluation. Extending the concept of alternative healthier food choices in real-world eating behaviours, the SCT included healthy foods as non-target stimuli to which participants had to respond to when a stop-change signal appeared. Specifically, once participants initiated a motor action towards the target, a signal appeared to indicate that they had to change direction and move their mouse towards the opposite stimulus on the screen (i.e., healthy non-target). Therefore, evaluations and cravings were also measured for healthy non-target stimuli from signal trials in all groups.

3.2 Hypotheses

The current study tested a number of confirmatory hypotheses related to primary and secondary outcomes of a novel ICT paradigm, which have been preregistered on the

Open Science Framework (https://osf.io/5f9b2)[1]. Effects of training were examined for two primary outcomes, which were food evaluations (i.e., 'tastiness' ratings) and cravings (i.e., 'desire to eat' ratings) as measured via an explicit evaluation task (EET; see section 3.3.7). These effects were defined as changes from the experimental groups (stop and stop-change training) relative to the control group (go training). Primary hypotheses related to expected training effects (H1-H4) were included in the preregistered sampling plan and stopping rule for data collection (see section 3.3.2). The study also included a manipulation check for the designed training paradigm (H5). All hypotheses have been aligned with the corresponding statistical tests for analyses, as shown below.

3.2.1 Primary hypotheses

H1. Food evaluations for unhealthy foods presented on signal trials during training would be examined as a function of a three-way interaction between training group, selection condition and stimulus novelty in a linear mixed-effects model. In a top-down model selection approach, evidence should be obtained for an interaction between training group and selection condition, but not stimulus novelty. The best fitting model for the tastiness ratings of unhealthy foods would include the main effects of training condition and selection condition as well as their interaction. The two-way interaction would be further examined with the specific hypotheses presented below.

H1a. Stop-change training would lead to a decrease in evaluations of selected unhealthy foods relative to the go group.

H1b. Stop-change training could lead to a decrease in evaluations of non-selected unhealthy foods relative to the go group.

H1c. Stop training would lead a decrease in evaluations of selected unhealthy foods relative to the go group.

H1d. Stop training could lead to a decrease in evaluations of non-selected unhealthy foods relative to the go group.

H2. In line with H1, food cravings for unhealthy foods presented on signal trials during training would be examined as a function of a three-way interaction between training group, selection condition and stimulus novelty. Main effects of training

[1]Minor changes from the preregistered study protocol are described throughout this chapter, where appropriate, and deviations regarding the hypotheses and corresponding analyses are outlined in section 3.4.4.

condition and selection condition and an interaction between these effects were expected to receive strong support, while stimulus novelty was not predicted to affect food cravings. Specific directional hypotheses about these effects are outlined below.

H2a. Stop-change training would lead to a decrease in cravings for selected unhealthy foods relative to the go group.

H2b. Stop-change training could lead to a decrease in cravings for non-selected unhealthy foods relative to the go group.

H2c. Stop training would lead to a decrease in cravings for selected unhealthy foods relative to the go group.

H2d. Stop training could lead to a decrease in cravings for non-selected unhealthy foods relative to the go group.

Expectations about observed effects for H1 and H2 were also preregistered. We hypothesized that the training effects for selected foods would be greater than the effects for non-selected foods. Theoretically, it could also be expected that no effects would be obtained for non-selected foods if participants disliked the food items, in line with the BSI theory of stimulus devaluation (Chen et al., 2016; Veling et al., 2008). The study design did not incorporate baseline ratings for selected and non-selected foods and therefore it may be possible that non-selected foods were not disliked per se. Also, other accounts of stimulus devaluation predict a reduction in evaluations regardless of whether the stimuli are appetitive or not (e.g., see Chen et al., 2018). For this reason, respective hypotheses state that an effect *could* be observed. The differences between any obtained training effects for food evaluations would be interpreted based on the effect sizes (see Figure 3.6).

H3. A two-way interaction between training condition and selection condition would also be examined for the evaluations of healthy foods and was further investigated via specific hypotheses. The healthy foods presented in the evaluation task were used as non-targets on signal trials and thus selection condition in this case refers to whether the healthy non-target stimuli were selected by the participants or not in the initial food selection task (see Figure 3.2).

H3a. Stop-change training would lead to an increase in evaluations of selected healthy foods relative to the go group.

H3b. Stop-change training would lead to an increase in evaluations of non-selected

healthy foods relative to the go group.

H3c. Stop training would not have an effect on evaluations of selected healthy foods relative to the go group.

H3d. Stop training would not have an effect on evaluations of non-selected healthy foods relative to the go group.

H4. Consistent with H3, a two-way interaction between training condition and selection condition would be investigated via model comparison and specific follow-up hypotheses for healthy food cravings.

H4a. Stop-change training would lead to an increase in cravings for selected healthy foods relative to the go group.

H4b. Stop-change training would lead to an increase in cravings for non-selected healthy foods relative to the go group.

H4c. Stop training would not have an effect on cravings for selected healthy foods relative to the go group.

H4d. Stop training would not have an effect on cravings for non-selected healthy foods relative to the go group.

A two-way interaction between training group and selection condition was examined for H3 and H4, but effects of stop-change training were equally expected for both selected and non-selected healthy foods. The reason for examining both selected and non-selected healthy foods is that although studies have shown that evaluations for 'go' foods can be increased relative to 'no-go' stimuli or stimuli not included in training ("untrained" foods; see Chen, Veling, et al., 2018), it is possible that if 'go' foods were already evaluated highly changes would not be observed due to a ceiling effect.

3.2.2 Secondary hypotheses

H5. Stimulus-stop associations could be formed for the foods associated with stop and stop-change responses on signal trials and these could manifest as longer RTs towards the unhealthy foods paired with response inhibition during training. Blocks of no-signal trials were administered before and after training and participants responded to unhealthy and healthy foods from signal trials with equal probability (i.e., 'go test'; see section 3.3.6). Difference scores from their go reaction times (GoRTs) on correct trials were calculated for pre-to post-training blocks. The difference scores were then compared between the experimental groups and the control group.

Stimulus-go associations could also be observed in terms of faster RTs towards healthy foods which were presented on signal trials for the stop-change group. This form of contingency learning was used as a manipulation check for training mechanisms, as training effects (e.g., changes in food evaluations) could be a result of learned associations between stimuli and responses (see Verbruggen et al., 2014a; Veling et al., 2017).

H5a. Participants in the stop-change group would be slower to respond correctly towards unhealthy foods in the go test after training compared to participants in the go group.

H5b. Participants in the stop group would be slower to respond correctly towards unhealthy foods in the go test after training compared to participants in the go group.

H5c. Participants in the stop-change group could be faster to respond correctly towards healthy foods in the go test after training compared to participants in the go group.

3.3 Methods

3.3.1 Participants

Participants were recruited via the experimental management system (EMS) at Cardiff University and Prolific (https://www.prolific.ac/). EMS participants received course credits when eligible (e.g., undergraduate students) and monetary compensation (£6) if not eligible for credits. Participants recruited via Prolific received monetary compensation (£5.25/hr), in line with the web platform's guidelines for participant payments at the time of data collection. EMS participants also had the option to enter a prize draw for a £20 Amazon voucher. In total, 206 participants were recruited online and 365 attended the laboratory testing sessions. Recruitment details and recorded number of drop-outs and exclusions based on ineligibility are presented in section 3.5.1.

Several inclusion and exclusion criteria were preregistered for recruitment. Eligible participants had to be at least 18 years of age and have normal or corrected-to-normal vision, including normal colour vision. Only individuals with a self-reported body-mass-index (BMI) of 18.5 kg/m^2 or above were included. Participants were excluded if they were not able to understand written and spoken English well, reported having a food allergy and/or intolerance to any of the major food allergens, and had a

self-reported past, or current, diagnosis of an eating disorder, with the exception of binge eating disorder.[2] For the recruitment via EMS, individuals were not allowed to participate if they had previously completed other food-related studies. Past participation in such studies could disclose the aims of the research and increase awareness and expectancies for training outcomes. The study was approved by the local Research Ethics Committee at the School of Psychology, Cardiff University.

3.3.2 Sampling plan

The study employed an open-ended Sequential Bayes Factor (SBF) design (Schönbrodt, Wagenmakers, Zehetleitner, & Perugini, 2017) with a minimum sample size of 30 participants per training group. Data collection was set to continue until either the preregistered primary hypotheses reached the desired evidential threshold, or the set deadline was reached (31 January 2019). *Strong* evidence for the alternative hypothesis compared to the null was defined as a threshold of $BF_{10} \geq 10$ and a threshold of $BF_{01} \geq 10$ would indicate *strong* evidence for the null compared to the alternative hypothesis (Lee & Wagenmakers, 2013). The stopping rule set according to BF thresholds was applied only to the Bayesian independent samples t-tests (see section 3.4.2) conducted for the primary hypotheses under H1, H2, H3 and H4 predictions. The data were inspected at random intervals with no pre-specified number of participants needed. Frequentist statistical tests were not conducted until data collection had stopped.

3.3.3 Procedure

An overview of the study procedure can be found in Figure 3.1. Recruited participants first completed a screening survey to confirm their eligibility and were presented with a consent page and a short survey on demographics and trait/state variables (see section 3.3.8). Participants were randomly assigned to a training group at the beginning of the study. The first task to be completed was the food selection task for the stimulus selection procedure (see section 3.3.4). Participants then proceeded to practice their assigned training task and if they did not meet the performance criteria for successful practice after three blocks, they were instructed to quit the experiment (see section 3.3.5). For the manipulation check, a short block of 'go' trials was performed before training, referred to as the pre-training go test (see section 3.3.6). In the training

[2]We preregistered that individuals who self-report a past and/or current diagnosis of binge eating disorder would be considered a subgroup for exploratory analyses, but only one participant met this criterion and they were excluded from analyses.

phase, participants completed four blocks of the ICT task (see section 3.3.5), with short breaks in between. In the test phase, the timed explicit evaluation task (EET; see section 3.3.7) consisted of tastiness and desire to eat rating blocks, performed in the specified order. Participants completed the post-training go test and were debriefed about the aims of the study. The total study duration varied between 40 and 55 minutes due to the self-paced start element of all task trials.

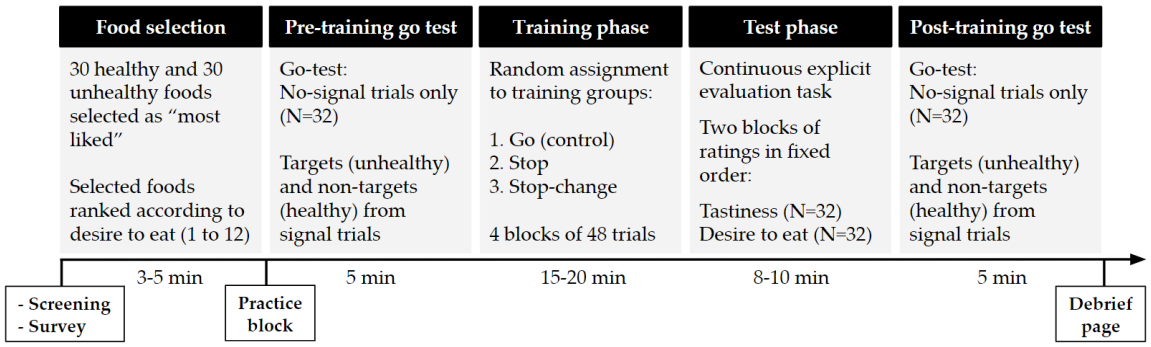


Figure 3.1: Schematic of the study procedure. The study procedure is described in section 3.3.3.

3.3.4 Food & stimulus selection

The food selection task[3] involved participants choosing a number of healthy and unhealthy foods from a fixed set of pictures (see Appendix C.2 for details). The task consisted of two main selection pages for healthy and unhealthy foods which were presented in random order. Participants were required to select 12 food items from 30 categories on each page. The pictures were shown in random positions on a grid for each participant, as shown in Figure C.1 in the Appendix. Participants were instructed to choose the foods they liked the most and were able to change their selections by clicking again on a chosen food item. After each selection page, participants were required to rank their chosen foods according to how much they would like to eat them. The ranks ranged from 1 = "Very much" to 12 = "Not much". This sorting page was used for the assignment of food stimuli to the ICT task. More details about the visual setup of the food selection task can be found in Appendix C.1.

The chosen foods informed the assignments of stimuli according to the selection

[3]The food selection task was referred to as the 'virtual supermarket' task in the preregistered study protocol, but this term has been discarded completely due to the potential confusion between the task employed here and methodologies which more closely reflect a virtual supermarket (e.g., see Nederkoorn, Guerrieri, Havermans, Roefs, & Jansen, 2009; Waterlander, Scarpa, Lentz, & Steenhuis, 2011).

condition (selected vs non-selected foods). The first four ranked unhealthy foods were assigned as the categories to be used as targets on signal trials of the ICT task (selected foods). Similarly, the first four ranked healthy foods were used as selected non-targets on signal trials. By tailoring food stimuli to individual preferences, stop and stop-change responses in the training task (selected only) would be associated with foods that participants liked and would like to eat the most, which would be crucial for changing food evaluations and cravings. The remaining selected foods were assigned as targets (healthy) and non-targets (unhealthy) for no-signal trials. Non-selected food stimuli were randomly assigned to training task trials, as shown in Figure 3.2 (panel C). The food categories were represented by two different exemplars in the training tasks and the original exemplars shown in the food selection pages only appeared in the test phase as 'novel' stimuli (see section 3.3.7).

3.3.5 Training phase

Inhibitory control training paradigm

The ICT paradigm employed in this study has been primarily adapted from the stop-signal paradigm, which has been previously used as a training intervention for food-related behavioural outcomes (see Allom et al., 2016; Jones et al., 2016). The ICT paradigm included a training task which adopts the principles of the stop-change paradigm (Logan, 1982). The novel element of stop-change responses has been added because common everyday behaviours, such as refraining from eating unhealthy energy-dense foods and making healthier food choices, do not require 'pure' response inhibition, but an updating of behaviour (i.e., action plans) after the cancellation of planned or initiated actions (Boecker et al., 2013). In an effort to reflect more ecologically valid behaviours, the ICT paradigm also required continuous motor responses with the computer mouse, instead of keyboard responses. This has previously been developed in a study by Maizey (2016) and has been modified to match the requirements of a training intervention. Participants were randomly assigned to one of three groups. There were two experimental groups where stop and stop-change training tasks were performed and a control group where participants completed a go task (only no-signal trials and go responses). Participants did not know the 'treatment group' to which they had been assigned and the training tasks were exactly matched for all three groups and only responses in signal trials were manipulated, as described below.

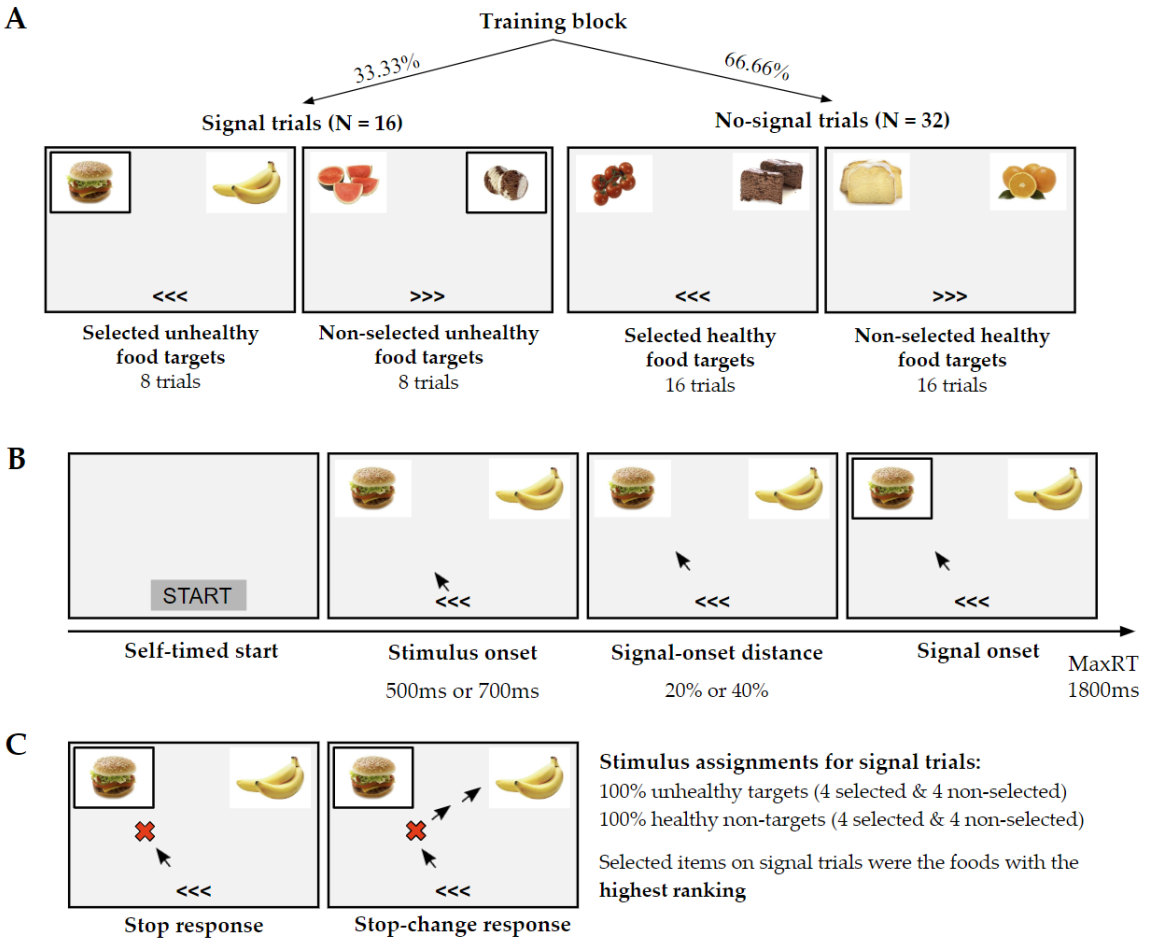


Figure 3.2: Inhibitory control training paradigm and task design.A. There were 48 trials in each training block, which consisted of 32 no-signal trials (66.66%) and 16 signal trials (33.33%). A 100% contingency mapping was used for targets in signal and no-signal trials in terms of food healthiness. For healthy and unhealthy targets there was an equal probability of the stimuli being either selected or non-selected in the initial food selection task. **B.** Participants begin a trial by clicking on a 'START' box and after a stimulus onset time of either 500ms or 700ms the food stimuli (target and non-target) appear on the screen together with a direction cue (e.g., <<<), indicating which target participants have to move their mouse towards to. Participants can then initiate the movement towards the target and on signal trials, when the mouse cursor reaches the signal-onset distance (20% or 40% from starting point), the signal is presented. On no-signal trials as well as signal trials in the control training group, participants have to reach the target within the time limit (1800ms). **C.** On signal trials, participants in the stop group were required to stop their mouse movement and cancel their initiated response towards the target. In the stop-change group, participants were instructed to stop their initial response and move the mouse towards the other stimulus (non-target).

Training task design

All participants were required to move their mouse as quickly and as accurately as possible towards a target stimulus located on either the top right or top left of the screen area as indicated by a set of arrows (<<< or >>>). Trials were self-timed

and participants were required to click on a 'start' box located on the bottom of the screen to begin. There were 48 trials in each training block and a total of four blocks in the training phase (192 trials in total). Each block consisted of 16 signal trials (33.33%) and 32 no-signal trials (66.66%). A 100% contingency was used for healthy targets in no-signal trials and unhealthy targets in signal trials. The healthiness of the foods was always opposite for targets and non-targets (e.g., non-target stimuli in signal trials were always healthy foods). The selection condition, that is whether stimuli have been selected by the participants during the initial food selection task or not, was applied with equal probability for both trial types, as shown in Figure 3.2 (panel A). Each selected and non-selected food was represented by two exemplars in the training phase, that have been matched as much as possible for visual consistency. The target location (left or right) was fully counterbalanced across all design cells and on a block-by-block basis for the two exemplars of each food category. There were no more than four consecutive signal trials in any of the training tasks. As mentioned in section 3.3.4, the four unhealthy foods that had the highest ranking were assigned as targets on signal trials and the four healthy foods with the highest ranking were used as non-targets on signal trials.

For the experimental groups, signal trials were manipulated so that fixed signal-onset distances would define the timing of the signal presentation, which is consistent with the concept of fixed stop-signal delays in response inhibition tasks (Verbruggen & Logan, 2009). The signal-onset distance was defined as the distance on the y-axis from the initial y mouse coordinate when participants began moving their mouse from the start location. Signal-onset distances were thus tailored to individual responses on a trial-by-trial basis and the fixed values that were used were 20% and 40% from the start location. The fixed signal onsets occurred with equal probability for all design cells. In a total of four blocks, there were 32 observations per signal-onset distance. As shown in Figure 3.3.3 (panel B), the visual signal was a bold black border appearing around the picture, similar to previous approaches (e.g., Lawrence et al., 2015). The type of responses associated with the signal presentation differed between the two experimental groups (stop and stop-change), but in each task participants were required to cancel an initiated response toward an unhealthy food. It should be noted that the continuous motor responses ensured that a response had been initiated before the motor response had to be inhibited. In the stop group, participants were instructed to stop moving their mouse and not respond to the target when the signal appeared. In the stop-change group, the signal indicated that participants had to change their initiated response and move towards the non-target stimulus on the

other side of the screen (see Figure 3.3.3, panel C). In theoretical terms, the difference between the two training protocols was the type of action updating. In the stop group, only response inhibition, or inhibitory action updating occured, whereas in the stop-change group, correct responses required both inhibitory and responsive action updating. There has been evidence to suggest that the stop-change task may require a go process, an inhibition process and a response re-engagement process, which may be operating in a serial, independent manner and not in parallel (see Boecker et al., 2013 for review; Verbruggen et al., 2008). On signal trials of the training task administered to the control group, there was no visual signal presented, but participants did respond to unhealthy targets, keeping the overall format of the trials consistent across tasks. Specifically, all groups were 'exposed' to the same number of healthy and unhealthy foods so that no potential confounds due to visual exposure were introduced.

On each trial, the stimulus onset time was either 500ms or 700ms (see Figure 3.2) and each timing occurred with equal probability. The maximum reaction time (maxRT) was set to 1800ms and the direction cues stayed on the screen until maxRT was reached. At 1800ms the food stimuli were masked by grey rectangles which stayed on the screen for 500ms, as a controlled inter-trial interval (ITI). The stimuli did not disappear from the screen until maxRT was reached in order to match visual exposure time to foods for all participants. On signal trials, the black border around the target stimulus also remained on the screen until the end of the trial with the aim to reduce attentional demands associated with the quick detection of a signal while a continuous motor response was being executed.

Training practice

Training practice differed between groups: the control group received only 12 practice trials (no-signal), whereas the experimental groups completed 24 trials to account for 12 signal and 12 no-signal trials. To avoid disclosing the aims of training during practice, there were both healthy and unhealthy images for all trials (50:50). Feedback was given after every trial on the accuracy of the responses, detected slowing and/or stopping of the mouse as well as slow initiation times (<= 750ms). When the initiation time threshold was exceeded participants were presented with the instructions "It is important to start moving your mouse sooner, even if you are not entirely sure of your answer!" (cf. Gillebaart, Schneider, & De Ridder, 2016). The practice blocks were repeated (maximum of three blocks) if and when the proportion of correct go responses was less than 75%. For the experimental groups, in addition to the benchmark for go responses, the practice blocks were repeated if the proportion of correct signal

responses was less than 50%. Participants were not allowed to proceed with the study if they did not meet these performance criteria for successful training practice after three practice blocks.

3.3.6 Manipulation check: go tests

A block of no-signal (go) trials, was presented before the training phase and after the test phase as a manipulation check for the expected behavioural outcomes of training. Each block consisted of 32 trials and required responding to an equal number of healthy and unhealthy food stimuli. In each set of 16 food stimuli, half were selected and half non-selected exemplars. Importantly, the healthy stimuli used as targets were stimuli that were used as non-targets on signal trials during training and the unhealthy stimuli were the targets from signal trials. The non-targets used in the go test blocks were non-selected healthy and unhealthy food stimuli from no-signal trials. Consistent with the training task design, targets and non-targets that were presented together were always opposite in terms of healthiness.

3.3.7 Explicit evaluation task

In the test phase, two main training outcomes were examined via a novel explicit evaluation task (EET): food evaluations and state cravings. The EET required continuous motor responses and explicit ratings of tastiness (evaluations) and desire to eat (cravings). In contrast to other explicit measures, the designed task had added time pressure to the visual analogue scale (VAS) responses. It was assumed that the imposed time limit would promote impulsive responses that were, to a certain extent, not affected by conscious changes of mind and/or demand characteristics. It should be noted that training outcomes were only tested for foods associated with signal trials in training and the EET did not include any stimuli from no-signal trials. The EET had self-timed trials consistent with the training tasks and a food stimulus was presented on each trial after an onset time of either 500ms or 700ms (see Figure 3.3). The stimulus appeared on the bottom of the screen and stayed on until the end of the trial. The dimensions of the stimuli were matched for both the ICT tasks and EET. The VAS had positive and negative anchors with the text descriptions “Very much” and “Not at all”. The side of the scale on which these anchors appeared was randomised across participants but kept consistent throughout the task for each individual. The relative width of the VAS was 80% of the task screen area, which differed in online settings according to the participants’ display resolution. Participants were instructed to move

their mouse towards the VAS as soon as possible (MaxRT = 2000ms). Responses were registered via left mouse button presses (i.e., clicks) on the scale. Upon registration, a blue marker appeared on the scale to indicate that their final response had been recorded. The questions used for the ratings were "How tasty do you rate this item to be?" and "How much do you desire to eat this item right now?". Questions appeared above the VAS and always stayed on the screen.

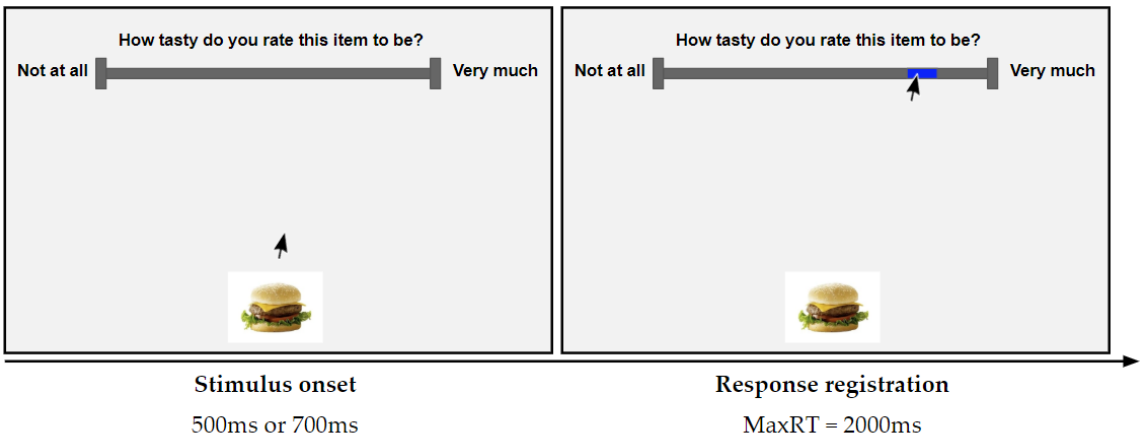


Figure 3.3: Example trial from the explicit evaluation task. This figure depicts the visual design of the explicit evaluation task. After participants begin a trial by clicking on a 'start' box (not shown here), the stimulus appears after 500 or 700ms. The visual analogue scale was located on the top of the screen. In this example trial, participants have to rate how tasty the item is, as specified by the question above the scale. The side on which the positive and negative anchors appeared was randomised across participants. Participants have to click on the scale to registered their response within a maximum reaction time (MaxRT) of 2000ms and a blue marker appeared on the scale to indicate their response was recorded.

There were two types of blocks for the training outcomes: tastiness and desire to eat. The latter was always presented last so that the visualisations of food consumption did not affect ratings of tastiness. The first four trials of each block served as practice trials for participants to familiarise themselves with the task. In each block there was a total of 32 trials, excluding these practice trials, and there was an equal number of healthy and unhealthy foods. For each set of 16 foods, there were eight selected and eight non-selected exemplars. Stimulus novelty was examined by including both food exemplars that appeared during training (i.e., old) and the original food exemplars from the initial food selection task (see section 3.3.4), which were not included in the ICT tasks (i.e., novel). Stimulus novelty was fully counterbalanced across all design cells.

3.3.8 Survey measures

In the eligibility survey participants provided their date of birth and their height and weight for BMI calculation, as part of the screening process. Individuals also had to specify whether they had a past and/or current history of eating disorders for subsequent data exclusion (see section 3.4.3). After screening, participants were asked to answer several questions relating to demographics and eating-related behaviours (see Appendix G). Demographic questions included gender and ethnicity and a history of drug and/or alcohol abuse was recorded. Participants were also asked whether they had currently or in the past been diagnosed with any psychiatric and/or neurological disorder(s) and were instructed to specify the diagnosed disorder if they answered "Yes". For eating-related behaviours, participants were asked to answer whether they were following a vegan or vegetarian diet and the hours since they had a last meal, with the options of "Less than 1 hour ago", "1-2 hours ago", "2-3 hours ago", "3-4 hours ago" and "More than 4 hours ago". Finally, they used a slider ranging from one to nine (one-point increments) to provide their hunger state at the time of the study (i.e., 1= "Not at all"; 9= "Very").

3.4 Analyses

3.4.1 Measures & indices

Data transformations

Data were collected in both laboratory and online settings and therefore mouse coordinates corresponded to different display resolutions. For this reason, x-y coordinates were transformed into a standardised space compatible with the aspect ratio used for the experimental task window (2×1.5). The x-axis coordinates were mapped as a [0, 2] vector and y-axis coordinates were mapped as [0, 1.5]. This transformation was only applied to data from the training tasks and go tests. Mouse coordinates from the explicit evaluation task would undergo a different transformation, as described below.

In the EET, participants provided ratings of tastiness and desire to eat for healthy and unhealthy foods associated with signal trials in the ICT tasks. These ratings were processed as normalised x coordinates to account for differences in computer display screen resolutions. The normalised coordinates ranged from 0 to 100. Ratings were obtained from successful trials, where participants clicked on the scale within the time limit. The side on which the positive end of the VAS appeared (left or right) was

approximately counterbalanced across participants and coordinates were all aligned to the positive end for statistical computations across participants.

Reaction times and accuracy in training

The timing in ICT and go test trials was defined in terms of samples, where each sample corresponded to a screen refresh interval of 17ms at a refresh rate of 60Hz. The time window (MaxRT) for all trials was fixed to 106 samples; t_1, t_1, ..., t_{106}. Reaction time measures were therefore calculated based on the number of samples (or t_n) multiplied by the latency of each sample (17ms). The coordinates of the computer mouse cursor were recorded at each sample.

In the ICT tasks, participants' responses on go trials (i.e., no-signal trials for experimental groups and all trials for the control group) were recorded as correct when the target simulus was reached within the time limit (MaxRT). Reaction times on go trials (GoRTs) were registered when participants stopped moving their mouse after reaching the target, as they were instructed to stop moving their mouse once they had reached the target and wait for the next trial to begin. For GoRTs, stopping was defined as a difference in the Euclidean distance in the transformed x-y coordinates smaller than 0.01, to account for the natural movement of the mouse (i.e., pixel tolerance[4]. When stopping occured for at least three samples (i.e., $\geq$ 50ms), the first sample was used as the timepoint for the registration of a GoRT.

For signal trials in the stop group, a successful stop was considered as a lack of mouse movement, as defined above, for 12 samples, which is approximate to 200ms[5] The timepoint for successful stops was defined as the first sample when stopping was observed. In addition to successful stopping, a correct response on stop-signal trials was dependent on whether the mouse cursor was on the correct side of the screen after signal onset (e.g., the cursor could be on the left side of the screen when the target was presented on the right). For both no-signal and signal trials, responses were also considered inaccurate if the non-target stimulus was reached at any point. The stop-signal reaction time (SSRT) was defined as the time between the signal onset (i.e., when the signal-onset distance was reached) and the successful stop timepoint,

[4]In the preregistered study protocol, pixel tolerance was set to $\pm$20 pixels, which did not account for the coordinate transformation and was not based on the Euclidean distance between pairs of mouse coordinates.

[5]Upon data inspection, it was observed that many participants stopped for at least six samples, which was the preregistered criterion for successful stopping, but initiated movement again and there were several recorded stopping occurences. For this reason, I have increased the threshold to at least 12 samples. For several participants who still had more than one recorded stopping point, the last occurence was selected for accuracy and reaction time registration.

as mentioned above.

For the stop-change group, change accuracy was determined by whether participants responded to the non-target stimulus within time limit (MaxRT) by changing direction after signal onset. Participants also had to initiate a response towards the correct direction before signal onset. Thus, both pre-signal and post-signal mouse coordinates were examined. The change-signal reaction time (CSRT) was defined as the time from signal onset until a correct change in direction was registered for at least three samples, that is $\geq$ 50ms, accounting for natural movements of the mouse.

Differences between groups for performance on the go tests were examined via difference scores for pre-to post-training correct GoRTs (ΔGoRT = $\text{GoRT}_{\text{post}}$ - GoRT_{pre}), where a positive score indicates participants were slower to respond after training. ΔGoRT was calculated for healthy and unhealthy foods and selection condition was not taken into account for the confirmatory analyses. $\Delta\text{GoRT}_{\text{healthy}}$ and $\Delta\text{GoRT}_{\text{unhealthy}}$ were then compared for the experimental groups compared to the control.

3.4.2 Preregistered analyses

Data pre-processing and analyses were primarily conducted in R (R Core Team, 2017) via RStudio (RStudio Team, 2016). Bayesian analyses were performed using the 'BayesFactor' package (Morey & Rouder, 2018) and linear mixed-effects models (LMMs) were fitted via the *lmBF* function. Training outcomes were examined with selected LMMs that treated participants and exemplars as random effects to account for by-subject and by-item variability. For fixed effects in the LMMs the "medium" prior setting was selected, which corresponds to an r scale value of 1/2. For random effects, r was equal to 1, which represents a "nuisance" setting for medium-to-large effects that are not formally examined, such as by-subject variability (see Rouder et al., 2012 for details on specification of priors for fixed and random effects). For each training outcome, eight LMMs were run and the best fitting models were identified. These are presented below in a generic form, as 'Ratings' can refer to tastiness ratings for healthy or unhealthy foods and desire to eat ratings for healthy or unhealthy foods.

Model 1: Ratings $\sim$ training group $\times$ selection condition $\times$ stimulus novelty
Model 2: Ratings $\sim$ training group $\times$ selection condition + stimulus novelty
Model 3: Ratings $\sim$ training group $\times$ selection condition
Model 4: Ratings $\sim$ training group + selection condition

Model 5: Ratings ∼ training group × stimulus novelty + selection condition
Model 6: Ratings ∼ training group + stimulus novelty + selection condition
Model 7: Ratings ∼ training group
Model 8: Ratings ∼ selection condition

Preregistered hypotheses indicated that the best fitting model would be a model that includes the main fixed effects of training group and selection condition and an interaction term for the two effects, while stimulus novelty would not interact with these fixed effects. The best model would therefore be model 3 for all training outcomes. If the training effects did not transfer to novel stimuli that appeared during the EET, model 1 would be favoured instead. The top-down model selection procedure was implemented for four training outcomes, as outlined in H1, H2, H3 and H4 (see section 3.2). The full models are shown below, where *ID* refers to participant IDs as an additive effect which is treated as a random factor and *item* represents the specific exemplar that was being rated during the EET. All models were therefore tested against the null model (denominator) which only included the random effects of ID and item. Supplementary frequentist analyses were conducted using the 'lme4' package (Bates, Mächler, Bolker, & Walker, 2015). Please note that although model comparison results were reported together from both Bayesian and frequentist analyses, model fitting procedures with the 'BayesFactor' and 'lme4' R packages are not entirely matched[6], but this reporting approach may increase the utility of findings from confirmatory analyses in potential replication studies. The *p*-values for model comparison were attained with likelihood ratio tests and models were refitted using Maximum Likelihood (Bolker et al., 2009; Pinheiro & Bates, 2000).

H1: $\text{Evaluations}_{\text{unhealthy}}$ ∼ training group × selection condition × stimulus novelty + ID + item
H2: $\text{Cravings}_{\text{unhealthy}}$ ∼ training group × selection condition × stimulus novelty + ID + item
H3: $\text{Evaluations}_{\text{healthy}}$ ∼ training group × selection condition × stimulus novelty + ID + item
H4: $\text{Cravings}_{\text{healthy}}$ ∼ training group × selection condition × stimulus novelty + ID + item

[6]See https://rdrr.io/cran/BayesFactor/f/vignettes/compare_lme4.Rmd for details on comparing parameter estimates from models fitted using *lmer* and *lmBF* functions.

The expected two-way interaction between training condition and selection condition for all training outcomes was followed-up by Bayesian independent samples t-tests with the default prior settings (Rouder, Speckman, Sun, Morey, & Iverson, 2009) in JASP (JASP Team, 2018). Although parameter estimates could be obtained for fixed effects and interactions through LMMs (see Appendix C.3), Bayesian t-tests would allow the interpretation of evidential thresholds through BFs which was necessary for the study sampling plan[7]. As supplementary frequentist statistics, Welch's t-tests, or unequal variance t-tests, were conducted in JASP. The Welch's t-test was preferred due to potential unequal variances and unmatched sample sizes across groups (Ruxton, 2006). Welch's t-tests were two-tailed and effect sizes were given by Cohen's *d*. Bayesian independent samples t-tests were also conducted to examine the secondary hypotheses for the manipulation check of training mechanisms. All tests are outlined below.

H1a. $\text{Evaluations}_{\text{unhealthy-selected}}$: Stop-change group < Go group
H1b. $\text{Evaluations}_{\text{unhealthy-non-selected}}$: Stop-change group < Go group
H1c. $\text{Evaluations}_{\text{unhealthy-selected}}$: Stop group < Go Group
H1d. $\text{Evaluations}_{\text{unhealthy-non-selected}}$: Stop group < Go Group

H2a. $\text{Cravings}_{\text{unhealthy-selected}}$: Stop-change group < Go group
H2b. $\text{Cravings}_{\text{unhealthy-non-selected}}$: Stop-change group < Go group
H2c. $\text{Cravings}_{\text{unhealthy-selected}}$: Stop group < Go Group
H2d. $\text{Cravings}_{\text{unhealthy-non-selected}}$: Stop group < Go Group

H3a. $\text{Evaluations}_{\text{healthy-selected}}$: Stop-change group > Go group
H3b. $\text{Evaluations}_{\text{healthy-non-selected}}$: Stop-change group > Go group
H3c. $\text{Evaluations}_{\text{healthy-selected}}$: Stop group ≠ Go Group
H3d. $\text{Evaluations}_{\text{healthy-non-selected}}$: Stop group ≠ Go Group

H4a. $\text{Cravings}_{\text{healthy-selected}}$: Stop-change group > Go group
H4b. $\text{Cravings}_{\text{healthy-non-selected}}$: Stop-change group > Go group
H4c. $\text{Cravings}_{\text{healthy-selected}}$: Stop group ≠ Go Group
H4d. $\text{Cravings}_{\text{healthy-non-selected}}$: Stop group ≠ Go Group

[7]We preregistered that planned comparisons would follow the LMM analyses, but the study protocol did not specify which tests would be used although this was already taken into account. The analysis strategy reported in this first preregistered study protocol was overall inadequate, but informed the robustness of subsequent protocols (e.g., see Chapter 4).

H5a. $\Delta\text{GoRT}_{\text{unhealthy}}$: Stop-change group > Go group
H5b. $\Delta\text{GoRT}_{\text{unhealthy}}$: Stop group > Go group
H5c. $\Delta\text{GoRT}_{\text{healthy}}$: Stop-change group < Go group

3.4.3 Data exclusions

Eligible participants who completed the study would be excluded from preregistered analyses for potential exploratory subgroup analyses based on the following criteria: if they had past and/or current diagnosis of psychiatric and/or neurological disorder(s), past and/or current history of drug and/or alcohol abuse and were following a vegan or vegetarian diet. Several data exclusion criteria based on training task performance were also applied. First, participants were excluded if the proportion of correct responses on no-signal trials was below 0.85. This criterion applied to all training groups. It has been shown that the extent to which successful inhibition takes place in signal trials of ICT tasks is significantly associated with the effect size of training outcomes, with smaller effect sizes in studies where appetitive stimuli were not ultimately paired with successful inhibition (Jones et al., 2016). Hence participants in the stop group who had a proportion of correct responses on signal trials (StopPC) lower than 0.65 were excluded from preregistered analyses. Due to the expected difficulty of the stop-change training task and its novelty, participants with a proportion of correct responses on signal trials (ChangePC) lower than 0.50 were excluded. In all training groups, participants who had a mean GoRT (RTs from correct responses on no-signal trials) greater than 3 standard deviations (SDs) from the group mean were excluded. The same criterion was applied to change-signal reaction times (CSRTs). Participants who had a mean CSRT (correct responses only) greater than 3 SDs from the group mean were excluded. A more conservative threshold was used for the stop group, that is, mean SSRTs had to be less than 2 SDs from the group mean. Data exclusion criteria for these signal-related RT measures were checked after accuracy-based critera were implemented (e.g., StopPC < 0.65 criterion applied first and then data were inspected for mean SSRTs > 2 SDs from group mean).

3.4.4 Preregistration deviations

In the preregistered study protocol there were a number of hypotheses which were descriptive statements of expectations for potential differences between training effect

sizes related to the primary outcomes of food evaluations and cravings[8]. For example, it was hypothesised that stop-change training would lead to a greater decrease in positive evaluations and cravings for unhealthy foods than response inhibition (stop) training, compared to the go group. There was a larger focus on the preregistration of methods rather than hypotheses and analyses in the first preregistered protocol which led to lack of specificity in the description of statistical analyses for confirmatory hypotheses. For this reason, hypotheses and exclusive statistical tests have been restructured to increase clarity and aid in the interpretation of findings. The Bayesian independent samples t-tests that informed the stopping rule in the study sampling plan during data collection were the same as the tests described in section 3.4.2. The secondary hypotheses regarding RTs in the pre-and post-training go tests (see section 3.3.6) were not tested via LMMs first as the primary training outcomes, but examined with directional (Bayesian) independent samples t-tests. Other minor deviations (e.g., changes in terminology) have been noted throughout this Chapter.

3.5 Results

3.5.1 Sample characteristics

A total of 458 individuals participated in the study and data collection was primarily conducted in laboratory group settings (79.69%). All recruitment details can be seen in Figure 3.4. Many participants were excluded before completing the study because they did not meet the performance criteria for successful training practice (see section 3.3.5). Exclusions of participants who completed the study for potential exploratory subgroup analyses were preregistered due to the expected large size of the sample (per group). Subgroup analyses would be reported separately for participants who had a past and/or current history of psychiatric disorders, drug and/or alcohol abuse and a small subgroup of participants with binge eating disorder. Participants who reported following a vegan or vegetarian diet would also be included in separate exploratory analyses. Five participants with self-reported drug and/or alcohol abuse and one participant with binge eating disorder were excluded. For the criterion of psychiatric disorders, participants who provided a definite answer about a diagnosis were excluded, while others who responded “Not sure” were included in preregistered analyses. All abovementioned exclusions were applied, as shown in Figure 3.4, but participants

[8]Version 2 of the preregistered study protocol can be found at https://osf.io/y7fsk/ and all analyses were described on pages 17-18.

who reported following a vegetarian or vegan diet were included in preregistered analyses. Additional data exclusions were implemented after the inspection of training performance in all groups according to the specified preregistered criteria (see section 3.4.3).

Table 3.1: Descriptive statistics of sample characteristics for all training groups

	Go group		Stop group		Stop-change group	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Age (Years)	21.11	5.10	21.60	5.72	21.30	5.99
Gender (% Female)	79.49	40.55	76.04	42.91	75.31	43.39
Ethnicity (% White)	84.35	36.49	80.21	40.05	82.72	38.05
Hunger (1-9)	4.43	2.18	3.87	2.39	4.12	2.36
Body-mass index (kg/m^2)	22.54	2.93	22.22	2.79	21.97	2.50
Diet (% Vegan or vegetarian)	11.11	31.56	12.90	33.71	12.35	33.10

Note. The descriptive statistics reported in this table have been obtained from final sample after data exclusions separately for the go (N = 117), stop (N = 96) and stop-change groups (N = 81). For the descriptive statistics of body-mass index there are missing values in the go (N = 15), stop (N = 15) and stop-change (N = 6) groups due to invalid self-reported height and/or weight measurements. Two participants in the go group selected the "Do not wish to answer" option on the ethnicity question.

The final sample size consisted of 294 participants in total. The number of participants was not exactly matched for the go group (N = 117), stop group (N = 96) and stop-change group (N = 81). Sample characteristics for the experimental groups and the control group are shown in Table 3.1. The sample was generally not diverse, as it consisted primarily of undergraduate students at Cardiff School of Psychology, but all training groups were approximately matched on gender, ethnicity and age. The average BMI in all groups was in the healthy-weight category (18.5 – 24.9 kg/m^2). Participants' self-reported hunger levels at the time of the study were not high across groups. This is likely due to the fact that the majority of participants in the control group (82.91%) and experimental groups (stop: 80.21%; stop-change: 83.95%) had a meal less than three hours prior to the study. A minority of participants in each training group reported that they were following a vegan or vegetarian diet.

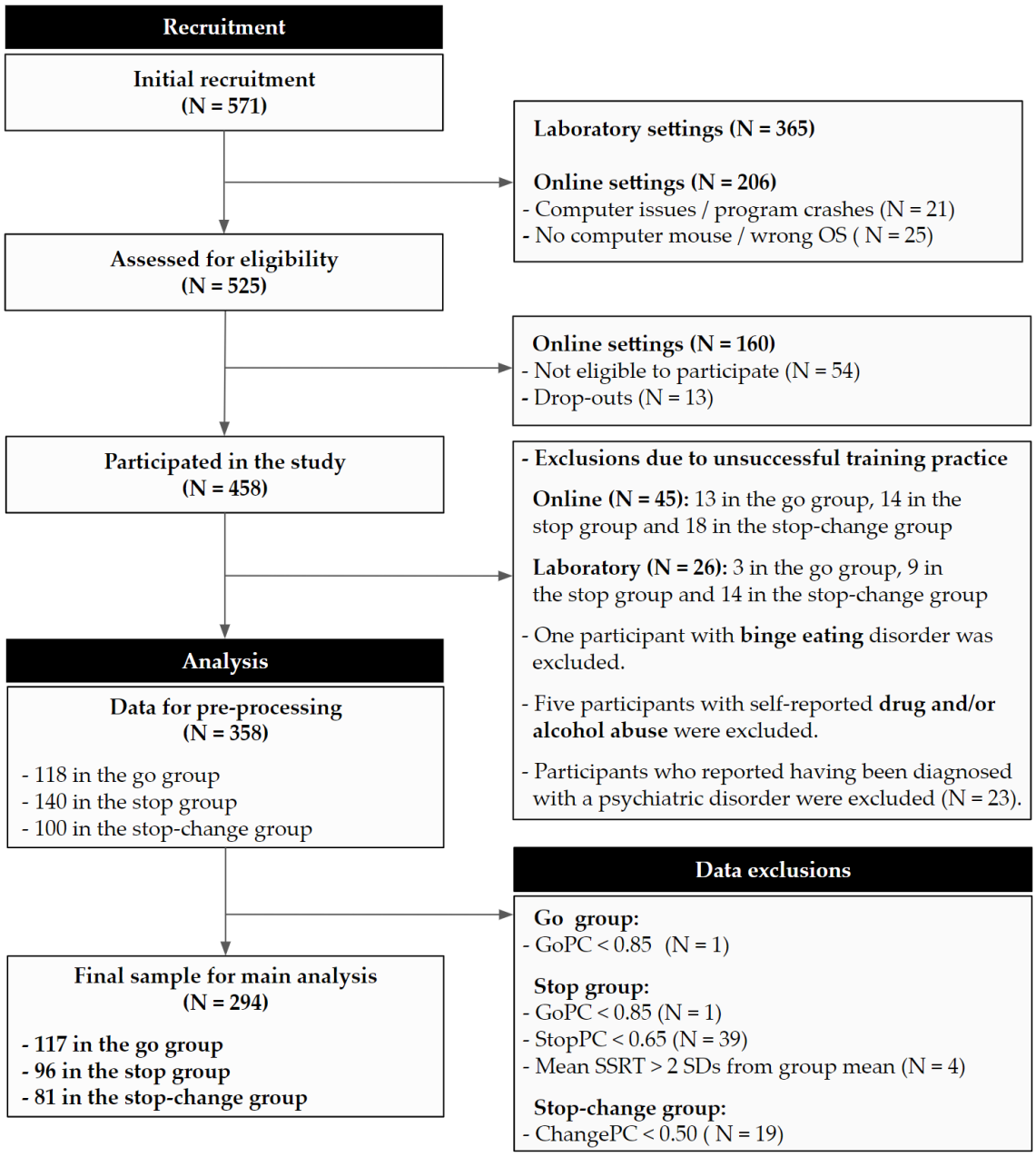


Figure 3.4: Schematic of study recruitment process and data exclusions. *Note.* All data exclusion criteria are described in detail in section 3.4.3.

3.5.2 Findings from confirmatory analyses

Linear mixed-effects models

As described in section 3.4.2, linear mixed-effects analyses for all training outcomes were performed. The best, or maximal, models for each of the training outcomes were expected to include the fixed effects of training condition (go, stop, stop-change) and selection condition (selected or non-selected) and an interaction term for these fixed

effects. An interaction with stimulus novelty would contradict the hypothesis that any training effects transfer to novel exemplars of the food categories being associated with signal-related responses. Tastiness and desire to eat ratings were measured after training for all participants (see section 3.3.7) and reflect food evaluations and cravings, respectively. Food evaluations and cravings were tested separately for healthy and unhealthy foods in line with the preregistered analysis plan and model comparisons were conducted for four distinct training outcomes. For all training outcomes (H1 - H4), the three best fitting models are presented in Table 3.2. Visual inspection of LMM diagnostic plots (see Figure C.3) revealed potential violations of the homoscedasticity (i.e., constant variance of residuals) assumption for all full models. Heteroskedasticity can result in unreliable *t*-values and confidence intervals for parameter estimates and inferential statistics were therefore not computed. Parameter estimates without the potentially biased standard errors have been plotted for the two-interaction models for all outcomes using the 'sjPlot' R package (Lüdecke, 2019), which can be seen in Figure C.2 in the Appendix. Inferences for specific directional hypotheses (e.g., H1a, H1b) were only based on the follow-up Bayesian independent samples t-tests.

As predicted, the best fitting models for the evaluations of unhealthy (H1) and healthy foods (H3) specified the main fixed effects of training group and selection condition as well as an interaction between these effects. There was *strong* evidence in favour of the model with the interaction term over the model with only the additive effects for the evaluations of unhealthy foods ($BF_{10} = 13.61$, $\chi^2(2) = 15.81$, $p < 0.001$) and *extreme* evidence for the two-way interaction model fitted to the evaluations of healthy foods ($BF_{10} = 306.92$, $\chi^2(2) = 22.17$, $p < 0.001$). For the $\text{evaluations}_{\text{unhealthy}}$ models, an additive effect of stimulus novelty was supported and comparison with the full model showed *extreme* evidence that a three-way interaction between all fixed effects was not preferred ($\text{Log}(BF_{01}) = 603.58$, $\chi^2(5) = 6.46$, $p = 0.264$). An additive effect of stimulus novelty was also supported for $\text{evaluations}_{\text{healthy}}$ models, but there was again *extreme* evidence against the three-way interaction of fixed effects ($BF_{01} = 95858.07$, $\chi^2(5) = 2.66$, $p = 0.753$).

The best fitting models for desire to eat ratings, that is cravings for unhealthy (H2) and healthy foods (H4), indicated that training group, selection condition and stimulus novelty were important fixed effects, while there was support for an interaction between training group and selection condition. Model comparison yielded *extreme* evidence that the two-way interaction was preferred compared to only the additive effects of training group and selection condition for $\text{cravings}_{\text{unhealthy}}$ ($BF_{10} = 188392.60$, $\chi^2(2) = 35.27$, $p < 0.001$) and $\text{cravings}_{\text{healthy}}$ ($BF_{10} = 129.40$, $\chi^2(2) = 20.28$, $p <$

0.001). There was *extreme* evidence that a three-way interaction including stimulus novelty was not supported over a two-way interaction model with the additive effect of stimulus novelty for both $\text{cravings}_{\text{unhealthy}}$ ($BF_{01} = 13783.84$, $\chi^2(5) = 6.34$, $p = 0.275$) and $\text{cravings}_{\text{healthy}}$ ($BF_{01} = 247247.80$, $\chi^2(5) = 0.44$, $p = 0.994$).

Table 3.2: Best fitting Bayesian linear mixed-effects models for training outcomes

Training outcome	Model	Log(BF_{10})
H1. Evaluations:	[1] selection condition	1468.42
Unhealthy foods	[2] group × selection condition	1468.18
	[3] group × selection condition + stimulus novelty	1465.90
H2. Cravings:	[1] group × selection condition	1917.08
Unhealthy foods	[2] group × selection condition + stimulus novelty	1914.83
	[3] selection condition	1905.97
H3. Evaluations:	[1] group × selection condition	1847.56
Healthy foods	[2] group × selection condition + stimulus novelty	1845.84
	[3] selection condition	1845.73
H4. Cravings:	[1] group × selection condition	2080.86
Healthy foods	[2] selection condition	2079.56
	[3] group × selection condition + stimulus novelty	2078.99

Note. All models include the random effects for participants and items (.. + ID + item) and were tested against the null model including only these random effects. Log(BF_{10}): Natural logarithm of BF_{10}; all log values in this table indicate *extreme* evidence in favour of the fitted model compared to the null model (denominator).

Follow-up test results

All results from the Bayesian independent samples t-tests and supplementary Welch's t-tests[9] are presented in Table 3.3 and effect sizes can be seen in Figure 3.6. There was *moderate* evidence that evaluations of selected unhealthy foods were reduced in the stop-change group ($M = 81.15$, $SD = 14.73$) compared to the control group (H1a; $M = 85.78$, $SD = 10.30$), but only *anecdotal* evidence for this effect in the stop group ($M = 82.57$, $SD = 10.97$) compared to the control (H1c). In contrast, there was *moderate* evidence for the null compared to the alternative hypotheses for both H1b and H1d. Participant's evaluations of non-selected unhealthy foods were not reduced from the

[9]The detection of normality violations did not require further data transformations according to the preregistered analysis plan. However, exploratory Mann-Whitney tests were conducted and revealed no major deviations in the p-values that would alter the conclusions.

stop-change group ($M = 55.80$, $SD = 17.52$) and stop group ($M = 55.96$, $SD = 18.70$) compared to the control group ($M = 55.90$, $SD = 16.81$). Training effects on cravings for unhealthy foods were in a similar direction. There was *moderate* evidence for a reduction in cravings for selected unhealthy foods from the stop-change group (H2a; $M = 68.72$, $SD = 26.35$) relative to the control group ($M = 76.65$, $SD = 21.53$) and *strong* evidence for the same effect in the stop group (H2c; $M = 67.89$, $SD = 23.59$). There was only *anecdotal* evidence for the null compared to the alternative for H2b, as participants' cravings for non-selected unhealthy foods were not reduced from the stop-change group ($M = 37.54$, $SD = 21.34$) compared to the control group ($M = 40.01$, $SD = 20.38$). There was also *moderate* evidence that stop training did not reduce cravings for non-selected unhealthy foods ($M = 39.03$, $SD = 21.93$) relative to go training (H2d).

Contrary to initial predictions, there was *strong* evidence that stop-change training did not lead to an increase in evaluations for selected healthy foods ($M = 80.74$, $SD = 12.28$) relative to go training (H3a; $M = 82.18$, $SD = 11.53$). As expected, there was *anecdotal* evidence that evaluations of selected healthy foods did not change as a result of stop training (H3c; $M = 79.21$, $SD = 14.00$). There was *moderate* evidence that evaluations for non-selected healthy foods were not increased from the stop-change group ($M = 46.27$, $SD = 17.11$) compared to the control group (H3b; $M = 44.83$, $SD = 18.43$). As predicted, there was *moderate* evidence that stop training did not lead to increased evaluations of non-selected healthy foods ($M = 47.01$, $SD = 17.13$) compared to the control group (H3d). Consistent with these results, there was *moderate* evidence that cravings for selected healthy foods were not reduced from the stop-change group ($M = 71.79$, $SD = 22.34$) relative to the control group (H4a; $M = 73.08$, $SD = 17.15$) and there was *anecdotal* evidence that there were no differences between the stop group ($M = 69.70$, $SD = 19.94$) and the control group (H4c). There was *anecdotal* evidence for the null compared to the alternative for H4b, as participants' cravings for non-selected healthy foods were not increased from the stop-change group ($M = 33.31$, $SD = 19.38$) to the control group ($M = 30.93$, $SD = 17.31$). As expected, there was *moderate* evidence that there were no differences between cravings for non-selected healthy foods between the stop group ($M = 33.03$, $SD = 17.99$) and the control group (H4d).

Table 3.3: Statistical test results for confirmatory hypotheses under predictions H1-H4.

	BF_{10}	t	df	p	Evidence interpretation
H1a	7.12	2.44	196	0.016	*Moderate* evidence for H1 compared to H0
H1b	0.16	0.40	196	0.968	*Moderate* evidence for H0 compared to H1
H1c	2.81	2.18	211	0.030	*Anecdotal* evidence for H1 compared to H0
H1d	0.15	-0.06	211	0.979	*Moderate* evidence for H0 compared to H1
H2a	3.79	2.24	196	0.026	*Moderate* evidence for H1 compared to H0
H2b	0.34	0.82	196	0.415	*Anecdotal* evidence for H0 compared to H1
H2c	12.23	2.80	211	0.006	*Strong* evidence for H1 compared to H0
H2d	0.20	0.34	211	0.736	*Moderate* evidence for H0 compared to H1
H3a	0.09	0.83	196	0.407	*Strong* evidence for H0 compared to H1
H3b	0.26	-0.57	196	0.572	*Moderate* evidence for H0 compared to H1
H3c	0.58	1.66	211	0.098	*Anecdotal* evidence for H0 compared to H1
H3d	0.22	-0.89	211	0.373	*Moderate* evidence for H0 compared to H1
H4a	0.11	0.44	196	0.660	*Moderate* evidence for H0 compared to H1
H4b	0.37	-0.89	196	0.377	*Anecdotal* evidence for H0 compared to H1
H4c	0.34	1.31	211	0.191	*Anecdotal* evidence for H0 compared to H1
H4d	0.21	-0.86	211	0.389	*Moderate* evidence for H0 compared to H1

Note. All hypotheses are statistically defined in section 3.4.2.

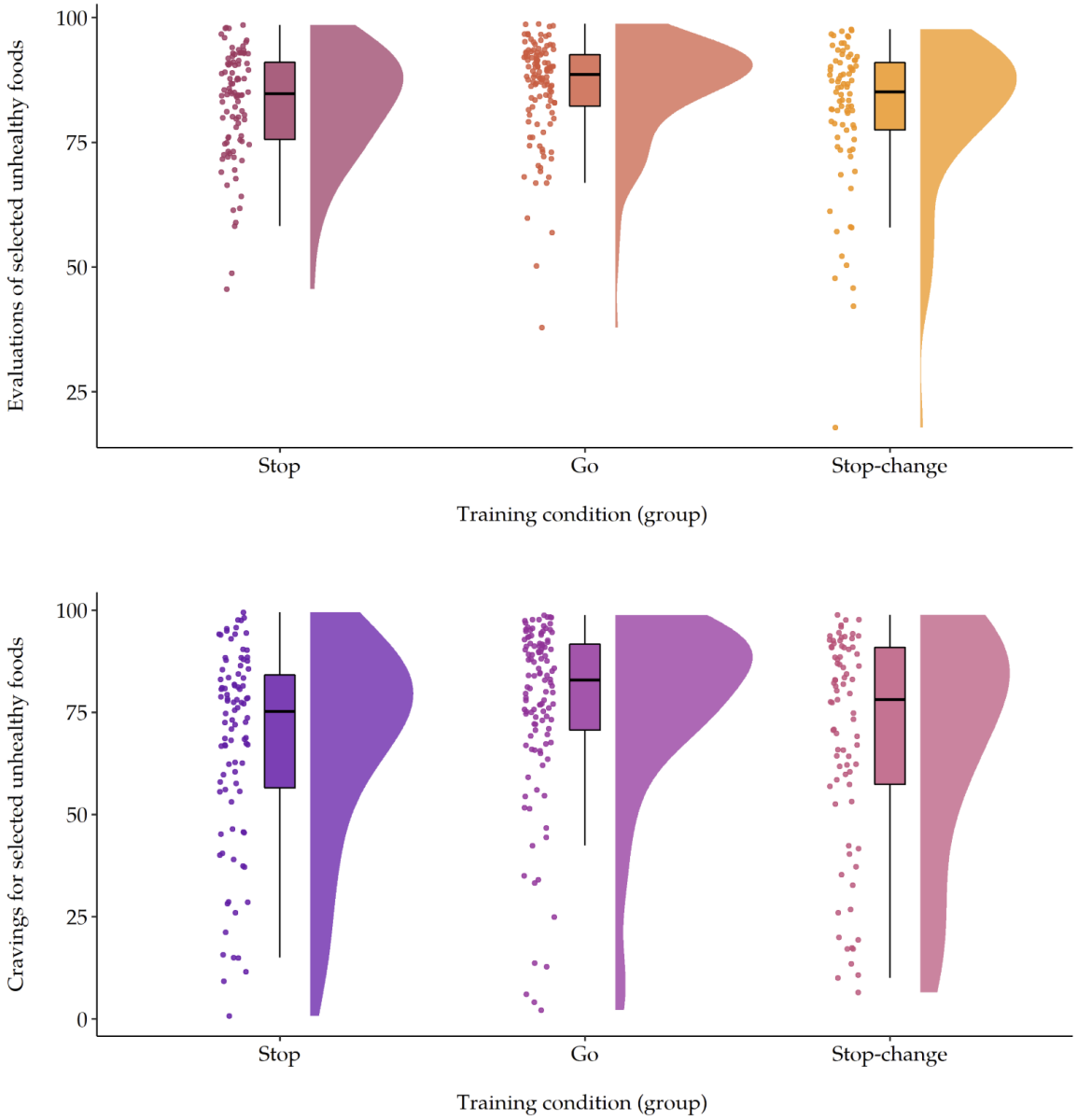


Figure 3.5: Raincloud plots of unhealthy food evaluations and cravings in the selected condition. Mean tastiness ratings (i.e., evaluations) for selected unhealthy foods are largely clustered around the postiive end of the scale, but for desire to eat ratings the range of ratings is much greater. *Note.* The 'split-half violin' elements in the plot show smoothed distributions and boxplot vertical lines represent the range, excluding outliers based on the Interquartile Range.

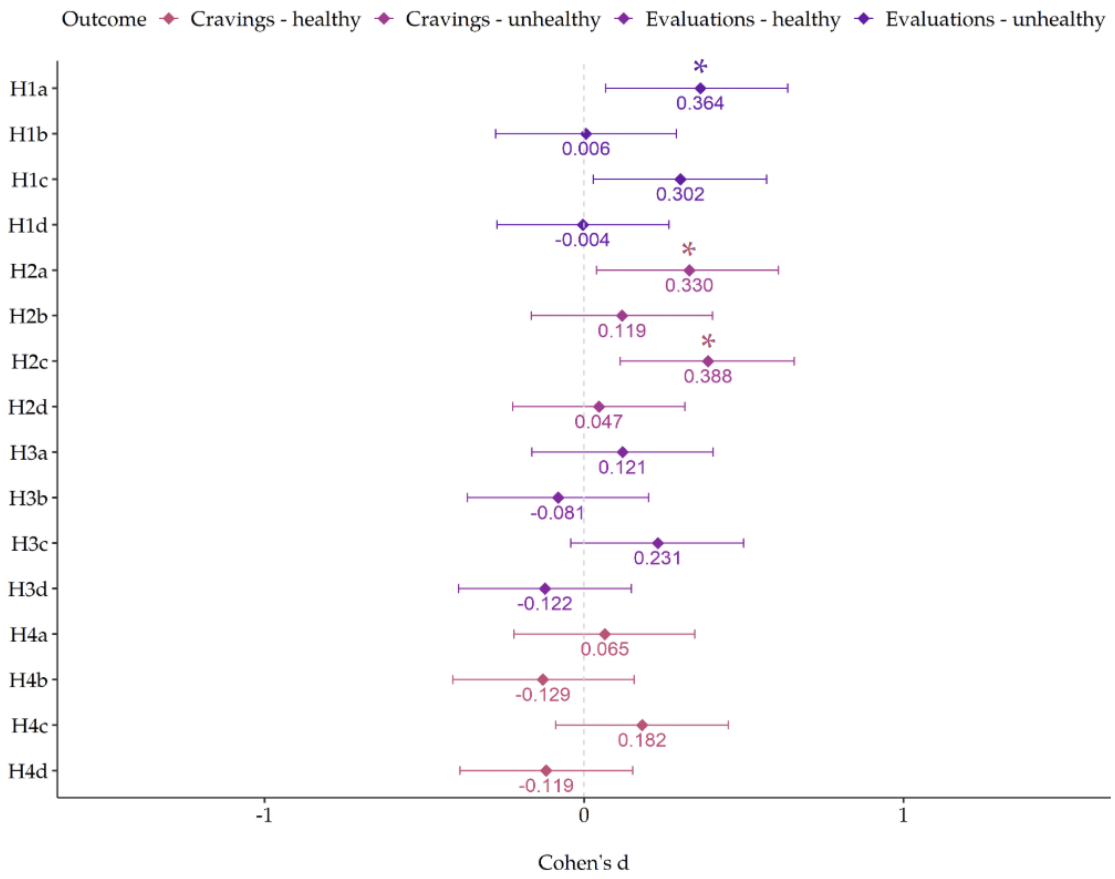


Figure 3.6: Effect sizes for confirmatory independent samples t-tests. The reduction in cravings for selected unhealthy foods was slighlty greater in the stop group (H2c) than the stop-change group (H2a) compared to the control group. The effect sizes were both in the small-to-medium range. Although there was only *anecdotal* evidence for a reduction in evaluations of selected unhealthy foods in the stop group compared to the control group (H1c), the effect size was smaller in the stop relative to the stop-change group (H1a). *Note.* The asterisk denotes effect sizes that correspond to hypotheses for which there was *moderate* evidence for the alternative compared to the null. The bars represent the 95% confidence intervals for Cohen's d values.

Stimulus-response associations

It was hypothesised that stimulus-stop and stimulus-go associations could be observed in terms of correct GoRTs in the go test blocks that were administered before and after training (H5). There was only *anecdotal* evidence that participants in the stop-change group were not slower to respond correctly towards unhealthy foods in the go test after training (M = -28.68, SD = 96.85) compared to participants in the go group (M = -40.40, SD = 84.14) [H5a; BF_{01} = 2.69, $t(196)$ = -0.88, p = 0.379, d = -0.13, 95% CI for d = -0.41, 0.16]. There was *strong* evidence that GoRTs towards unhealthy foods were not slower after training in the stop group (M = -63.39, SD = 123.55) compared to the go group [H5b; BF_{01} = 16.50, $t(211)$ = 1.55, p = 0.123, d = 0.22, 95% CI for d

= -0.06, 0.48]. The GoRTs for unhealthy food targets for both pre- and post-training go test trials can be seen in Figure 3.7. There was *moderate* evidence that participants in the stop-change group were not faster to respond correctly towards healthy foods in the go test after training (M = -45.16, SD = 90.73) compared to participants in the go group (M = -43.66, SD = 79.15) [H5c; BF_{01} = 5.41, $t(196)$ = 0.20, p = 0.846, d = 0.03, 95% CI for d = -0.26, 0.31].

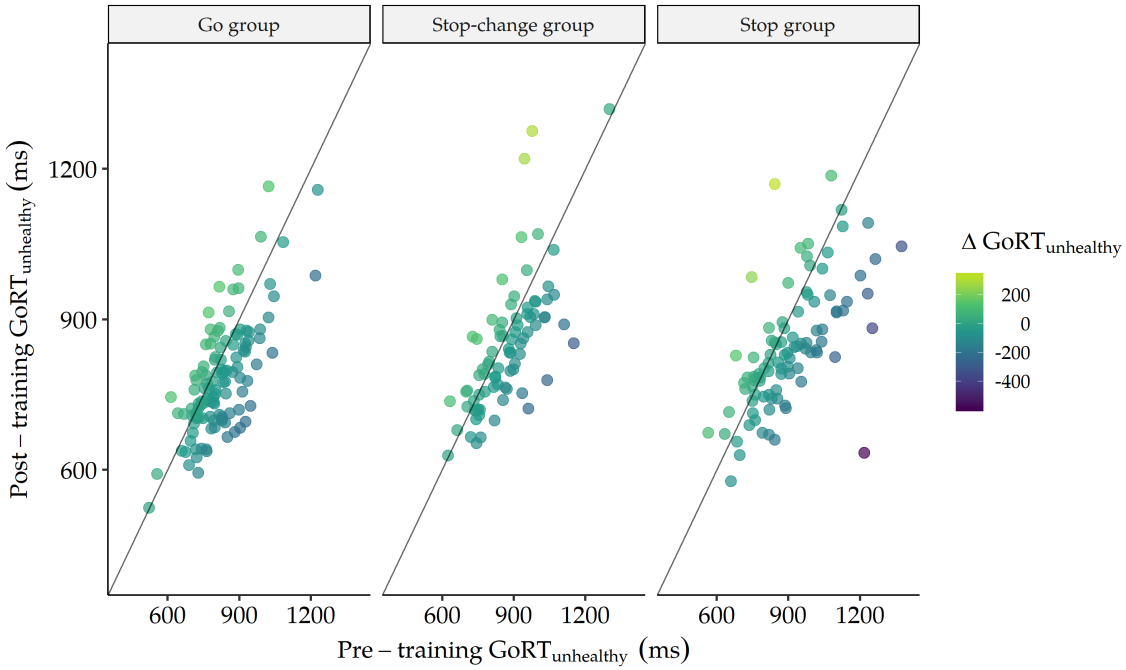


Figure 3.7: Mean go reaction times for unhealthy targets pre-and post-training across groups. The scatterplots show the mean go reaction times (GoRTs) from correct go trials pre-and post-training when the targets were unhealthy foods from signal trials during training. There is a general improvement in performance after training relative to baseline across groups, which could be attributed to practice effects associated with the continuous computer mouse movements. ΔGoRT$_{\text{unhealthy}}$ was calculated by subtracting the mean GoRTs on post-training go test trials from GoRTs on pre-training trials for each participant.

3.5.3 Findings from exploratory analyses

Relationship between unhealthy food evaluations and cravings

The mean ratings of unhealthy foods in the tastiness and desire to eat EET blocks were examined together in order to explore the relationship between unhealthy food evaluations and cravings. It was expected that there would be a large positive correlation between the two outcomes for all groups. Correlations were tested using Bayesian and supplementary frequentist correlation pairs. For Bayesian analyses, the default prior settings were employed with a streched beta prior width of 1 (Wagenmakers,

Verhagen, & Ly, 2016) and Pearson's correlation, denoted by r, is reported for all one-tailed correlations (i.e., positive). The mean ratings for selected unhealthy foods were included in this analysis due to the finding that a reduction in evaluations and cravings in the experimental groups compared to the control was only obtained for selected foods. There was *extreme* evidence for medium-to-large positive correlations between unhealthy food cravings and evaluations in the go group [$r = 0.51$, $\text{Log}(BF_{10}) = 15.79$, $p < 0.001$, 95% CI for $r = 0.39, 1.00$], stop group [$r = 0.41$, $\text{Log}(BF_{10}) = 6.95$, $p < 0.001$, 95% CI for $r = 0.26, 1.00$] and the stop-change group [$r = 0.56$, $\text{Log}(BF_{10}) = 12.94$, $p < 0.001$, 95% CI for $r = 0.41, 1.00$]. The mean ratings from all participants included in preregistered analyses can be seen in Figure 3.8 below. It is possible that the effects of stop and stop-change training on food evaluations of selected unhealthy foods were linked to stimulus devaluation. If the food evaluations are highly correlated with cravings, a reduction in the evaluations of selected unhealthy foods would also translate into a reduction in the desire to eat these foods at that time.

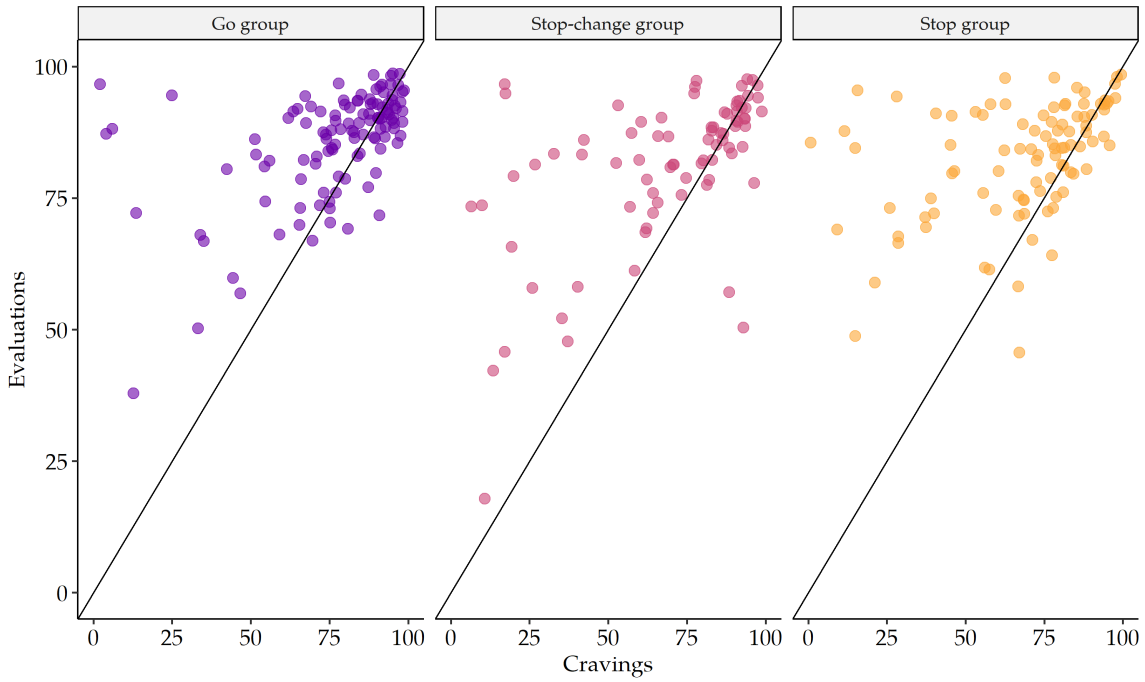


Figure 3.8: Relationship between unhealthy food evaluations and cravings. The scatterplots show the mean tastiness and desire to eat ratings from the explicit evaluation task that represent selected unhealthy food evaluations and cravings.

Training performance across groups

The average proportion of correct go responses was matched across the stop (M = 0.996, SD = 0.008), stop-change (M = 0.996, SD = 0.008) and go groups (M = 0.996, SD = 0.009).There was a relatively high number of participants who were excluded due to not meeting the accuracy criteria for performance on signal trials in the stop group (N = 39). The proportion of correct responses on signal trials in the final group sample was satisfactory (M = 0.84, SD = 0.09). Training performance in the stop and stop-change groups was inspected further for SSRTs and CSRTs as well as proportion of correct responses on signal trials. All statistical comparisons were conduncted using non-directional Bayesian and supplementary frequentist paired samples t-tests with the default prior settings (i.e., $\sqrt{2}/2$ scale parameter for the Cauchy distribution; Rouder, Speckman, Sun, Morey, & Iverson, 2009).

As expected, there was *extreme* evidence that the proportion of correct responses on signal trials (i.e., successful inhibitions) was higher when the signal-onset distance was set at 20% (M = 0.88, SD = 0.09) rather than 40% from the start location (M = 0.79, SD = 0.13) [Log(BF_{10}) = 21.49; $t(95) = 7.95$, $p < 0.001$, d = 0.81, 95% CI for d = 0.58, 1.04]. Although it was easier for participants to stop when the signal was presented relatively early during their initiated movements, the sample means of the individual median SSRTs were in the opposite direction. There was *extreme* evidence that participants were slower to stop when the signal-onset distance was 20% (M = 274.22, SD = 60.36) compared to 40% from the starting point (M = 220.20, SD = 50.16). It would be theoretically sound to assume that if there was a conflict between the approach tendency to move towards a selected unhealthy food target on signal trials and the need to inhibit the motor response, differences would be observed for SSRTs between selected and non-selected targets. Taking into account the differences observed between SSRTs and proportion of successful inhibitions between the two signal-onset distances, tests were performed for each distance separately. However, there was *moderate* evidence that SSRTs did not differ between selected (M = 277.84, SD = 65.64) and non-selected foods (M = 272.55, SD = 68.54) at the 20% signal-onset distance [BF_{01} = 6.53; $t(95) = 0.79$, p = 0.430, d = 0.08, 95% CI for d = -0.12, 0.28]. Similarly, there was *moderate* evidence that SSRTs for selected (M = 221.71, SD = 55.23) and non-selected foods (M = 218.17, SD = 54.72) were not different at the 40% signal-onset distance [BF_{01} = 6.32; $t(95) = 0.83$, p = 0.406, d = 0.09, 95% CI for d = -0.12, 0.29].

In the stop-change group, the individual median CSRTs were calculated and compared within-subjects to check whether there were differences between the two

signal-onset distances. Consistent with the aforementioned results for SSRTs, there was *extreme* evidence that participants were slower to change direction when a stop-change signal was presented at a 20% distance from the starting point (M = 258.99, SD = 65.26) rather than at a 40% signal-onset distance (M = 224.40, SD = 91.66) [Log(BF_{10}) = 17.70; $t(80) = 7.28$, $p < 0.001$, $d = 0.81$, 95% CI for $d = 0.56, 1.06$]. There was *extreme* evidence that the proportion of correct responses on signal trials in the stop-change group (ChangePC) was on average higher when the signal-onset distance was 20% (M = 0.87, SD = 0.12) rather than 40% (M = 0.75, SD = 0.15) [Log(BF_{10}) = 20.91; $t(80) = 8.03$, $p < 0.001$, $d = 0.89$, 95% CI for $d = 0.63, 1.15$]. In line with the previous results, there was *moderate* evidence that CSRTs did not differ between selected (M = 253.90, SD = 59.65) and non-selected foods (M = 259.65, SD = 90.66) when the signal-onset distance was 20% from the start location [BF_{01} = 5.52; $t(80)$ = -0.90, p = 0.371, d = -0.10, 95% CI for d = -0.32, 0.12]. *Moderate* evidence was also obtained for the absence of differences between CSRTs on trials where selected (M = 220.41, SD = 91.77) and non-selected foods (M = 221.26, SD = 115.73) were presented with a signal-onset distance of 40% [BF_{01} = 8.13; $t(80)$ = -0.10, p = 0.923, d = -0.01, 95% CI for d = -0.23, 0.21].

For both SSRTs and CSRTs in the stop and stop-change groups, respectively, participants were not faster to stop or change their responses when the signal was presented early on during their movements compared to when it appeared relatively late. It was expected that it would be harder to stop or change a response when the signal-onset distance was set to 40% rather than 20% from starting point. This was observed in the proportion of correct responses on signal trials, but not on reaction times. A potential explanation for these findings is that the 20% signal-onset distance could have been reached during movement acccelaration, therefore requiring more time for the motor response to be inhibited and/or re-directed.

Insights from mouse trajectories

There was no evidence for formed stimulus-stop associations in the stop and stop-change groups compared to the control group (see section 3.5.2) and as shown in Figure 3.7, mean GoRTs from correct trials seemed to be reduced after training across all groups, indicating the presence of practice effects. In order to check whether mouse trajectories did not differ between the pre- and post-training go tests across groups, the velocity profiles of correct go test trials were inspected (see Figure 3.9). Mouse trajectories from correct go test trials were split into 21 time bins of 84ms and velocity was calculated for each time bin. Velocity was defined as the Euclidean distance

between consecutive x and y coordinates divided by the time elapsed. The coordinates were transformed into a standardised coordinate space (see section 3.4.1). The mean velocity was calculated at a participant level for all time bins and conditions of interest (i.e., training group, go test block) only for trials where selected unhealthy food targets were presented. These targets were chosen for further inspection because training effects were only observed for selected unhealthy foods.

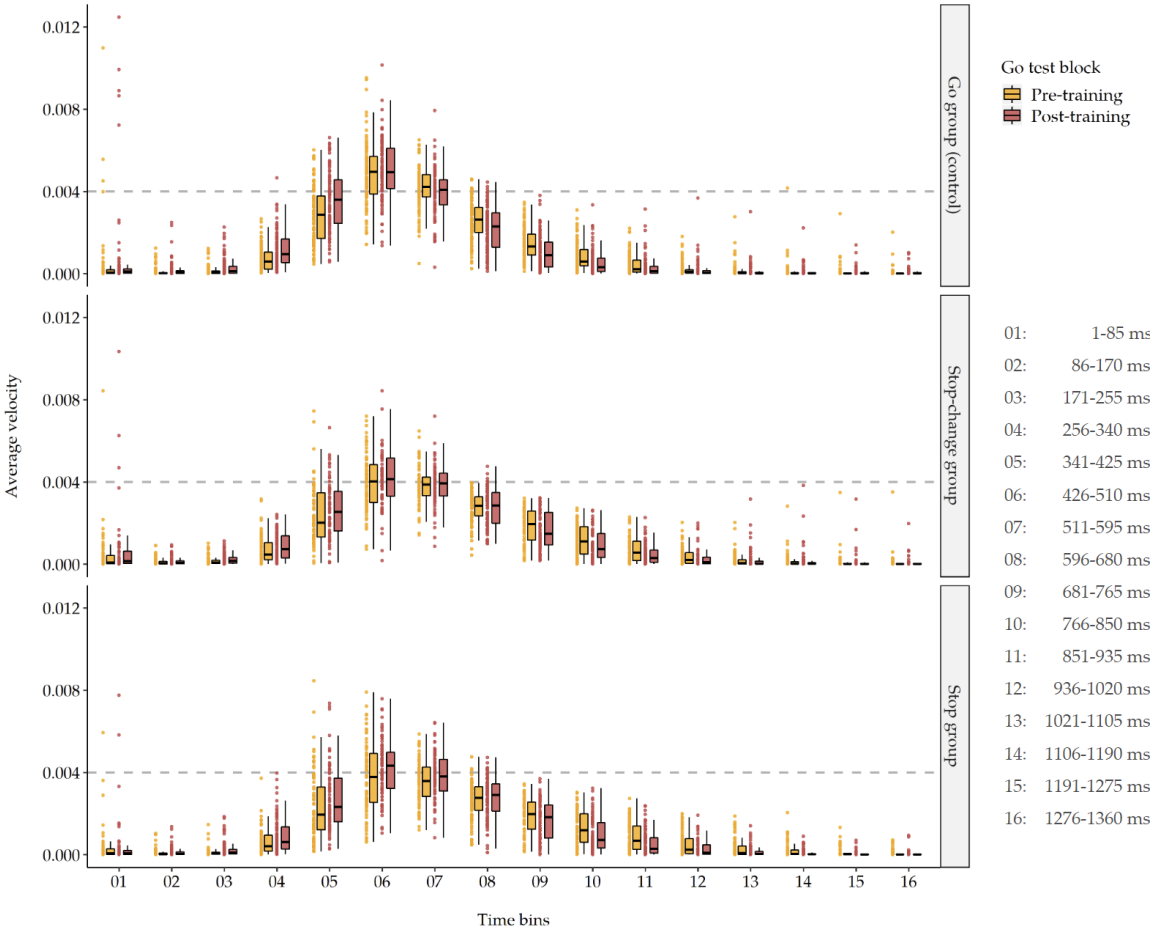


Figure 3.9: Velocity profiles of mouse movements over time for selected unhealthy food targets in the go test blocks. The average velocity for each time bin was calculated at a participant level and has been plotted for pre- and post-training go test trials in the go, stop and stop-change groups. Only go test trials where selected unhealthy food targets were presented were included in this plot. The velocity profiles are almost identical across groups. Movement acceleration occurs between the 4th and 6th time bin, when peak velocity is reached. After movement initiation, velocity is increased during the 340ms and 510ms time window and movements gradually slow down close to response completion. Across go test blocks, the peak average velocity was ranged between 0.004-0.005. Average velocity during the acceleration of movements appears higher after training, which could be attributed to practice effects. *Note.* Time bins 17 to 21 are not shown due to the very low frequency of long GoRTs, as it can be seen for time bins 15 and 16.

Data from participants who were recruited online were not not included because

their mouse settings were not controlled by the experimenter. In line with previous guidelines (Fischer & Hartmann, 2014), the computer mouse settings in the laboratory were changed to reduce the speed at which the mouse cursor moved (i.e., sensitivity setting 4 on Windows 7) and the default mouse acceleration option was disabled. The final sample for the inspection of velocity profiles consisted of 257 participants (go group = 101, stop group = 81, change group = 75). As discussed in Figure 3.9, the velocity profiles of correct go responses were approximately matched across groups. The difference in GoRTs (i.e., faster after training) seem to arise during the 340ms and 510ms time window when movement acceleration is observed and peak velocity is reached. Inspection of the velocity profiles for correct go responses towards selected unhealthy food targets shows that the task design may indeed not be sensitive enough to capture stimulus-stop associations.

Mouse trajectories were also inspected for EET data in an attempt to show the potential influence of response bias, such as changes of mind, in explicit measures. The mouse trajectories from the tastiness rating trials where selected unhealthy foods were presented in the stop group (N= 81) have been plotted in Figure 3.10. It is clear that while a proportion of participants have very smooth trajectories from the starting point to their selected rating with no major changes on the x-axis (e.g., see participants with IDs 92, 118, 181), other participants could have had changes of mind during their movements, as there were either consistent changes in direction for all trials or abrubt shifts on the x-axis for specific stimuli (e.g., see participants with IDs 187, 217, 114, 189). Some participants had erratic mouse movements (e.g., see participants with IDs 64, 111) which should potentially be discarded from further analyses. However, exclusion criteria based on visual inspection of mouse trajectories may require further testing in a preregistered manner (Kieslich, Henninger, Wulff, Haslbeck, & Schulte-Mecklenbeck, 2018). The smooth and abrupt shifts in direction (x-axis) could also indicate response uncertainty. If the explicit evaluations, for example, are determined by both affective and cognitive (e.g., healthiness) attributes of the foods (Marty et al., 2017), participants may show uncertainty or ambivalence during their continuous motor responses. The curvature of the mouse trajectories could be further explored via advanced mouse-tracking analyses (Hehman, Stolier, & Freeman, 2015; Kieslich & Henninger, 2017).

Figure 3.10: Mouse trajectories in the explicit evaluation task. The plotted mouse trajectories exhibit a number of spatial characteristics, such as abrupt and smooth shifts in direction (x-axis), which may indicate changes of mind or uncertainty. Trajectories were plotted for all completed tastiness ratings for selected unhealthy foods in the stop group (N = 81) and these are visualised in different colours. Each plot component corresponds to a single participant with a unique ID. The positive end of the visual analogue scale was on the top right of the screen for all participants after coordinate transformation (see section 3.4.1). Participants initiated their movements from the bottom center of the screen. The visualisation of completed mouse trajectories indicates that explicit ratings may be influenced by underlying response bias and warrants further investigation.

3.6 Discussion

The novel ICT protocol employed in this study was developed in an attempt to assess the efficacy of a training intervention that requires cognitive control to be exerted when appetitive food cues are presented, but is more ecologically valid in terms of real-world eating behaviours. Although ICT protocols based on the stop-signal task (SST) have been shown to be less effective compared to GNG training tasks (Allom et al., 2016; Aulbach et al., 2019; Jones et al., 2016; Turton et al., 2016), controlled response inhibition acquired through SST training may have more promising transfer effects than automatic inhibition in the GNG (Spierer et al., 2013). Taking into account that daily eating behaviours may require more than "pure" response inhibition, such as response re-engagement processes (Boecker et al., 2013) when choosing a healthier food, ICT tasks can be extended to include stop-change responses.

The current study assessed the feasibility and efficacy of a novel ICT protocol which implements stop and stop-change tasks tailored to influence participants' evaluations and cravings for unhealthy foods. In a mixed design, participants were randomly assigned to a training group, and training outcomes were assessed post-training via a timed explicit evaluation task. Participants provided tastiness (i.e., evaluations) and desire to eat (i.e., cravings) ratings for healthy and unhealthy food categories which were presented on signal trials during training. It was hypothesized that unhealthy food evaluations and cravings would be reduced in the experimental groups compared to the control group. For the stop-change training manipulation, we considered the possibility that participants would have increased evaluations and cravings for healthy food categories associated with a stop-change response relative to the control group. A crucial manipulation in the ICT design was whether the food categories were selected by the participants as most liked during an initial food selection task or not (i.e., selection condition: selected vs non-selected). In the EET, food stimuli differed in terms of novelty, that is participants rated food exemplars that were presented during training (old) or only appeared during the food selection task (novel). It was hypothesised that any training effects would transfer to stimuli of the same food category.

The feasibility of the novel ICT protocol was established and both stop and stop-change training tasks had comparable effects on explicit food ratings for tastiness and desire to eat. Results from confirmatory analyses showed that food evaluations and cravings for unhealthy foods were reduced in the experimental groups compared to the control group, but only when the foods had been selected by the participants in

the initial food selection task. The evaluations and cravings for healthy foods were not increased in the stop-change group relative to the control group. Findings from confirmatory and exploratory analyses are further discussed below along with key limitations of the current study and recommendations for future research.

3.6.1 Training effects on food evaluations and cravings

Linear mixed-effects model analyses supported a two-way interaction between training group (go, stop, stop-change) and selection condition, but not a three-way interaction that included stimulus novelty as an effect for all training outcomes. This indicated a food-specific rather than a stimulus-specific effect of training. The two-way interaction was examined via a series of preregistered hypotheses. Assumptions regarding the importance of selection condition are contingent on which theoretical account of stimulus devaluation and related training mechanisms is followed. According to the BSI theory (Chen et al., 2016; Veling et al., 2008), stimulus devaluation occurs only when highly appetitive stimuli are associated with response inhibition during training, as an initial approach tendency towards these stimuli can lead to aversive conflict signals when responses towards them need to be inhibited. The findings from confirmatory analyses are in agreement with the BSI theory as food evaluations were reduced in the experimental groups compared to the control group, only when selected unhealthy foods were associated with a signal response (i.e., stop or stop-change). However, the BSI theory mostly relates to GNG training studies where automatic response inhibition is trained for food stimuli that appear on 50% of trials (see Veling et al., 2017). Nevertheless, Chen et al. (2016) have shown that robust devaluation effects can occur when no-go trials are rare (25% - Experiment 4a), but not when they are more frequent (75% - Experiment 4b), which indicates that the stop-signal paradigm, where the proportion of stop-signal trials is relatively low, could lead to a reduction in positive food evaluations. The findings of the current study provide further support for this assumption.

Cravings for selected unhealthy foods were also reduced in the experimental group relative to the control group, which would suggest a link between food evaluations and cravings. Medium-to-large correlations between selected unhealthy food evaluations and cravings were indeed observed in exploratory analyses (see section 3.5.3). Contrary to prior expectations, healthy food evaluations and cravings were not increased in the stop-change group compared to the control group. It was hypothesised that the re-engagement process targetted to healthy foods during stop-change signal trials

could lead to an increase in evaluations and potentially cravings for these foods. It is possible that the response inhibition required for successful change responses on signal trials actually transfers to a certain extent to the non-target stimuli participants had to respond to. Although the effect size was negligible (see Figure 3.6), evaluations of selected healthy foods were slightly reduced in the the stop-change group compared to the control group.

Stop and stop-change training tasks led to reduced food evaluations and cravings, which suggests that stop-change training could be equally effective as an ICT intervention. However, the effect sizes for training outcomes were all in the small-to-medium range (0.30 - 0.39), in line with with the findings from recent meta-analyses of SST training effects on food intake (e.g., see Turton et al., 2016). For food evaluations, stop-change training had a relatively larger effect compared to stop training, whereas for food cravings, stop-training had a slightly greater effect relative to stop-change training. These observations were not statistically examined in a more meaningful way however, as the current design did not allow for such comparisons. It is therefore recommended that stop and stop-change training tasks are compared directly in studies that employ a within-subjects baseline (control condition). For example, stop and stop-change groups could be compared directly when the difference scores for training outcomes are computed for each participant by employing both pre-and post-training measurements. Go foods and/or untrained foods (see Chen et al., 2016) could serve as baselines for training effects within each group.

3.6.2 No evidence for stimulus-response associations

A manipulation check for training mechanisms was implemented in order to examine whether stimulus-response associations would be observed in participants' reaction times when they had to respond to stimuli which were presented on signal trials during training. It was expected that stimulus-stop and potentially stimulus-go associations would be learned during training (Best et al., 2019; Verbruggen et al., 2014a). However, there was evidence that reaction times on the go test trials (correct GoRTs) towards unhealthy targets did not differ between the experimental groups and the control group. Similarly, GoRTs towards healthy non-targets from signal trials were not faster in the stop-change compared to the control group. Visual inspection of GoRTs from pre- and post-training go test trials across groups revealed that participants could have been generally faster to complete a go response in the go test after training, which could simply be attributed to practice effects.

The absence of RT differences in pre-to post-training go tests between groups as well as within groups could also be explained by the underlying mechanisms of training. Taken together, the evidence for stimulus devaluation effects which were only present for selected unhealthy foods and the lack of stimulus-response associations provide further support for the BSI theory (Chen et al., 2016; Veling et al., 2008). The BSI theory and stimulus-stop association accounts are of course not mutually exclusive (Veling et al., 2017), but the current study showed that devaluation occured in the absence of such observed associations. These findings should be interpreted with caution, however, as other explanations for the lack of RT differences in the go tests could be presumed (also see *Challenges of the continuous tasks* below). For example, participants familiarised themselves with a go task and after several blocks of training this go task was administered again, but participants in the experimental groups were explicitly instructed that no signals would appear. Hence in all groups, strong practice effects would be very likely to occur and in the experimental groups attention to the food stimuli could be decreased as participants were aware that they would not need to detect a signal anymore (i.e., the border around the pictures). Other studies have used explicit instructions or experimental manipulations to increase attention to the food stimuli (e.g., see Best et al., 2016; Bowditch, Verbruggen, & McLaren, 2016). It should be noted that stimulus-stop associations are often inferred when response inhibition is facilitated for no-go food stimuli, which could be evidenced by fewer errors over the course of training, but slowing of GoRTs towards no-go stimuli provides evidence for trained automatic inhibition, rather than a top-down inhibitory control mechanism (see Veling et al., 2017; Verbruggen et al., 2014a). In future research, all potential training mechanisms (see Veling et al., 2017 for review) could ideally be investigated via preregistered hypotheses.

3.6.3 Challenges of the continuous tasks

The demands of continuous motor movements using the computer mouse should be taken into account as this is a novel element of the ICT paradigm which has not been properly examined in this context. First, the ICT tasks had increased difficulty for many participants, as shown by the high number of exclusions due to unsuccessful practice and proportion of correct responses on signal trials in the stop and stop-change groups (see Figure 3.4). Task difficulty is an important issue to be considered in designed ICT protocols that employ SST and/or SCT task variants which pair food stimuli with a signal-related response in a minority of trials. If the proportion of

correct responses on signal trials is not high, the final number of stimulus-signal pairings is reduced even further and can diminish training effects. This has been shown in a recent meta-analysis (Jones et al., 2016) where the proportion of successful inhibitions was a significant moderator of training outcomes and this is a potential explanation behind GNG training resulting in larger effects compared to SST training (Veling et al., 2017).

A second issue with the continuous task variant was that correct responses did not depend on attention and processing of the food stimuli. Both the training and go test blocks in all groups required the perception of a direction cue (left/right) and decision-making processes were not explicitly linked to the content of the food pictures. In common mouse-tracking studies, where participants respond with a computer mouse and the continuous trajectories are recorded (see Hehman et al., 2015 for overview), the stimulus of interest appears on the start location (i.e., bottom of the screen) and participants move towards two, often conflicting, response boxes. Mouse trajectories can then be analysed to infer how and when response competition occurs and when underlying cognitive processes may occur during the motor movements. In the current study, however, the categorisation did not require the processing of a food stimulus and therefore it is possible that motor responses were not very informative. Specifically, it could be assumed that participants decided on the correct direction to follow before movement initiation was observed and then completed a relatively simple motor response towards the target. Exploratory inspection of the velocity profiles in correct go test trials (see section 3.5.3) revealed there were no apparent differences between groups and that responses were characterised by a common pattern, that is, participants initiated a response within a time window of 256-340ms and then a ballistic movement was observed (i.e., acceleration and decrease in velocity close to response completion). If motor movements were not sensitive enough to affective and/or cognitive influences, then acquired stimulus-response associations would also not be captured in the go tests.

Although for the ICT protocols continuous motor responses can pose a challenge for the reasons outlined above, mouse trajectories from the explicit evaluation task (see section 3.5.3) indicated that there is an unexplored avenue in the analyses of explicit measures. The responses in the EET were timed in order to promote more impulsive responses that were not guided by response bias, such as demand characteristics. However, there was a great variability in how participants responded in the EET. For example, participants may be initially inclined to respond more negatively towards an exemplar in the tastiness block but then change their direction towards the more

positive end of the scale (i.e., change of mind). Future research can employ robust mouse-tracking task designs (e.g., Sullivan, Hutcherson, Harris, & Rangel, 2015) to investigate how ICT protocols can influence *explicit* food evaluations and potentially affect *implicit* evaluations as well (e.g., see design for capturing ambivalence in evaluations; Schneider et al., 2015). The spatial complexity of the mouse trajectories in the EET overall warrants further investigation in the driving processes behind explicit measures employed in the ICT literature, as there is currently not enough evidence to suggest that training can have an effect on *implicit* evaluations (see Jones et al., 2016 and study in Chapter 5).

3.6.4 Concluding remarks

The current study employed an ICT protocol and explicit evaluation task that both had several novel elements, such as continuous motor responses that were completed under time pressure. Findings from preregistered analyses provided evidence for the feasibility and potential efficacy of the ICT protocol, but the stop-change training task variant needs to be explored further. Within-subjects experiments with large sample sizes could shed more light into the potential advantages of SCT training compared to SST training. In particular, it would be interesting to examine whether a keyboard-variant of the SCT with a higher proportion of signal trials (e.g., 40-45%) that encourages participants to pay attention to food stimuli presented in the central visual field can have comparable or even greater effects than GNG training. Although the results of the study are promising in that SST and SCT tasks led to reduced unhealthy food evaluations and cravings, it is paramount that the efficacy of the SCT is assesed for eating behaviours, such as food intake in both single- and multi- session studies.

Chapter 4

The affective priming paradigm as an implicit measure of food attitudes and related choice behaviour

4.1 Introduction

There is an emerging need for a greater understanding of attitudes towards foods that may drive unhealthy eating behaviours, such as overeating. Attitudes reflect "object-evaluation associations" that can be retrieved from memory and influence behaviour towards the attitude object (Klauer & Musch, 2003). For example, individuals may respond positively to a food that contains intrinsically rewarding ingredients (e.g., sugar, fat), with the positive evaluation automatically activated by the learned association between reward and consumption. Evaluations of foods arise from both affective and cognitive components of attitudes (Marty et al., 2017). The affective component reflects an individual's hedonic reaction to the sensory properties of foods, commonly referred to as food liking, which is a central determinant of dietary choice (Eertmans et al., 2001). The cognitive component may involve thoughts about the nutritional value of a food item and potential health consequences (Trendel & Werle, 2015). This study examined the methodological validity of an implicit measure of attitudes - the affective priming paradigm (APP; Fazio et al., 1986; Fazio & Olson, 2003; Hermans et al., 2001; Klauer & Musch, 2003) and the extent to which priming measures were sensitive to affective (i.e., liking) and cognitive (i.e., healthiness)

components of food attitudes. The association between priming measures and food choice behaviour was also investigated.

The interplay between affective and cognitive components of attitudes may be paramount to the understanding of eating behaviours, including food choices. Appetitive foods and their cues, such as sight or smell, can induce positive affective reactions (Blechert et al., 2014) and activate the brain's reward circuits associated with "wanting" and "liking" (Berridge et al., 2010). In food-rich societies, where high-calorie foods are heavily promoted, such cue-evoked positive reactions are frequent and can drive impulsive food choices (Zoltak et al., 2018) that likely contribute to overeating and other unhealthy eating behaviours (Berridge et al., 2010; Lawrence et al., 2012; Sato et al., 2016). These impulsive food choices are not guided by deliberate processes, such as the consideration of consequences (Veling, Chen, et al., 2017). Cognitive components of attitudes include social norms and individual beliefs about the attitude object (i.e., foods), such as nutrition and health consequences and should be considered as determinants of eating behaviours (Eertmans et al., 2001). Interestingly, cognitive and affective components of attitudes can interact, as implicit measures can be influenced by various sources of valence, such as caloric content, economic cost and effects on one's health (Verhulst, Hermans, Baeyens, Spruyt, & Eelen, 2006). For example, unhealthy foods can be perceived to be tastier than healthy foods and chosen for consumption more frequently, even if individuals are not consciously aware of the association between healthiness and tastiness (Ackermann & Palmer, 2014; Raghunathan, Naylor, & Hoyer, 2006).

Previous research has largely focused on the use of explicit measures to study individual food attitudes in various contexts. Explicit food attitudes are derived from deliberate, conscious thoughts and feelings and can be assessed with self-report measures (e.g., questionnaires), but their relationship with implicit attitudes in food choice research remains controversial (Ellis et al., 2014). It has long been acknowledged that individuals' responses may be affected by social desirability and other strategic response bias (see Podsakoff et al., 2003 for review), potentially rendering direct, or explicit measures less sensitive to the measurement of certain attitude concepts/objects, such as foods and other appetitive cues (e.g., alcohol, tobacco, drugs). In an effort to control for such limitations, a number of 'implicit' measures have been developed for the investigation of attitudes. The APP has been previously applied to the food domain as an implicit, or indirect, measure of attitudes (e.g., Lamote, Hermans, Baeyens, & Eelen, 2004; Roefs et al., 2005). It is important to note that 'implicit' measures do not always measure implicit attitudes. The term implicit often refers to

unconscious processes and may be confused with the notion of measuring participants' unconscious attitudes. Although strategic control of responses may be avoided under strict time constraints of implicit reaction times tasks, such as the APP, participants could still be aware of their attitudes towards the measured concepts/objects (Fazio & Olson, 2003).

The current study employed a variant of the APP where attitude objects are presented as primes and are unrelated to the primary task of identifying the evaluative connotation of target words presented after the primes (Fazio & Olson, 2003). Participants were asked to perform an evaluative categorisation task, identifying target words as either positive or negative when preceded by either most liked (i.e., positive) or least liked (i.e., negative) food primes (see Figures 4.1 and 4.3). Here, the main outcome of interest is the affective priming effect, which manifests as faster responses (and/or lower error rates) on affectively congruent (i.e., most liked food-positive target or least liked food-negative target) than incongruent trials (i.e., most liked food-negative target or least liked food-positive target). In contrast to other indirect measures of (food) attitudes, such the implicit association test (Greenwald et al., 1998), this APP task variant does not require an evaluative response towards the prime and participants are explicitly instructed to not pay attention to the primes (pictures or words). Affective priming effects can be explained by response competition/facilitation processes (Fazio & Olson, 2003), as the primes can be defined as being congruent or incongruent to the required response to the target (Wentura & Degner, 2010). Theoretically, however, it is also possible that the perception of the prime activates the "object-evaluation association" from memory, increasing the accessibility of valence for the targets when these are congruent with the prime compared to incongruent (see Fazio, 2001; Herring et al., 2013). In the evaluative categorisation task, this distinction between the *encoding* and *response* perspectives cannot be inferred from observed priming effects.

The APP in the food domain has been shown to capture the evaluation of foods (i.e., liking) through observed priming effects for both reaction times and error rates (Lamote et al., 2004), even when attitudes were only recently acquired in laboratory settings (Verhulst et al., 2006). Lamote et al. (2004) employed the picture-word variant of the evaluative categorisation task and reported evidence for priming effects with food stimuli that were associated with both "moderate" (Experiment 1) and "strong" evaluations (Experiment 2), as rated by the participants during the first phase of the experiment (pleasantness scale). Interestingly, the strength of the priming effect was not influenced by 'prime extremity' (i.e., the strength of the evaluations). This lack

in sensitivity could be attributed to the premise that the APP captures affect in terms of valence (positive or negative), but cannot provide a more granular assessment of food liking (Lamote et al., 2004; also see Herring et al., 2013). In line with this finding regarding the affective components of food attitudes, previous studies have yielded mixed evidence for its utility in identifying the influence of cognitive components, such as health-related values. While some studies have found that healthiness, or fat content, may not affect the affective priming effect (Becker et al., 2015; Roefs et al., 2005), other evidence suggests that priming can reflect preference for low fat over high fat palatable foods, potentially attributed to health concerns (Roefs, Stapert, et al., 2005). If priming measures are influenced by both affective and cognitive components of attitudes, it would also be of theoretical and methodological value to examine whether observed priming effects for food stimuli are associated with impulsive food choice behaviour.

Overall, there has been moderate evidence to suggest that the APP can tap into the affective components of foods. This study aimed to address three questions that are central to establishing the methodological utility of the APP in eating behaviour. First can priming effects be obtained for most liked and least liked foods, as expected by previous findings? Second, is this paradigm sensitive to cognitive components of attitudes, such as the healthiness of the foods? Finally, are priming effects for foods that vary in liking and healthiness associated with impulsive choices to consume these foods?

4.2 Hypotheses

The study tested several confirmatory hypotheses regarding the utility of the APP as an implicit measure of food attitudes. Priming effects were examined using both median reaction times for correct responses (RTs) and error rates (ERs). The relationship between priming measures and impulsive food choices were also investigated. A schematic diagram of the APP contrasts and selected hypotheses is shown in Figure 4.1. In section 4.4.2, statistical tests for four categories of predictions (H1-H4) are outlined. These were the exclusive set of a priori hypotheses. For confirmatory analyses, all hypotheses were tested and reported with no changes to the specified IVs, DVs or any other variables, variable derivations, stated statistical transformations, or data exclusions within each test. The hypotheses, analyses, manipulated and non-manipulated variables, and measurements in sections 4.3 and 4.4 were therefore complete, necessary, immutable and exclusive for all preregistered confirmatory outcomes.

H1. Positive priming effect for non-food primes as a manipulation check for the APP. The robustness of the employed manipulation check had previously been demonstrated in a series of pilot experiments, which are summarised in section 4.3.3 and are described in detail in Appendix D.

H1a. RTs would be on average faster in congruent than incongruent non-food prime trials.

H1b. ERs would be on average lower in congruent than incongruent non-food prime trials.

H2. Priming effects (RTs) for healthy and unhealthy foods

H2a. RTs would be on average faster in congruent than incongruent food prime trials.

H2b. RTs would be on average faster in congruent than incongruent *healthy* food prime trials, specifically.

H2c. RTs would be on average faster in congruent than incongruent *unhealthy* food prime trials, specifically.

H2d. The priming effect (RT difference scores) would be on average greater for unhealthy than healthy most liked food prime trials (see section 4.4.1 for priming effect calculation).

H3. Priming effects (ERs) for healthy and unhealthy foods

H3a. ERs would be on average lower in congruent than incongruent food prime trials.

H3b. ERs would be on average lower in congruent than incongruent *healthy* food prime trials, specifically.

H3c. ERs would be on average lower in congruent than incongruent *unhealthy* food prime trials, specifically.

H3d. The priming effect (ER difference scores) would be on average greater for unhealthy than healthy most liked food prime trials.

H4. Relationship between food choices and observed priming effects (RTs)

H4a. The probability of choosing a most liked over a least liked food from within a pair of healthy food stimuli would positively correlate with the priming effect

(RTs) in healthy food prime trials.

H4b. The probability of choosing a most liked over a least liked food from within a pair of unhealthy food stimuli would positively correlate with the priming effect (RTs) in unhealthy food prime trials.

H4c. The probability of choosing an unhealthy over a healthy most liked food would positively correlate with the difference in priming effects (RTs) between unhealthy and healthy most liked food prime trials.

Preregistered hypotheses for priming effects were proposed for both speed (RT) and accuracy (ER) measures. In response priming procedures without strict time windows (e.g., 300-450ms) priming effects are most commonly observed in RTs (Wentura & Degner, 2010), but we assume that such effects may be observed in either speed and/or accuracy performance ($RT_{con} < RT_{inc}$ and/or $ER_{con} < ER_{inc}$). In addition, accuracy data should be inspected for potential speed-accuracy trade-offs (SATs). For example, participants could purposefully delay their responses on incongruent trials to improve accuracy, producing a priming effect for RTs but a reverse effect for error rates (i.e., $ER_{con} > ER_{inc}$). Therefore, support for observed priming effects would be dependent on both speed and accuracy hypotheses, as shown in the expression[1] below, where there should be no effects in the opposite direction ($RT_{con} > RT_{inc}$ or $ER_{con} > ER_{inc}$) and there should be evidence for either RT or ER priming effects ($RT_{con} < RT_{inc}$ or $ER_{con} < ER_{inc}$).

$$\{\neg\,[(RT_{con} > RT_{inc}) \vee (ER_{con} > ER_{inc})]\} \wedge [(RT_{con} < RT_{inc}) \vee (ER_{con} < ER_{inc})]$$

A contingent analysis plan for testing these hypotheses (i.e., follow-up tests) when the effects were not in the expected direction was preregistered (see section 4.4.2).

[1] Logical operators: $\neg$ = 'not'; $\vee$ = 'or'; $\wedge$ = 'and'

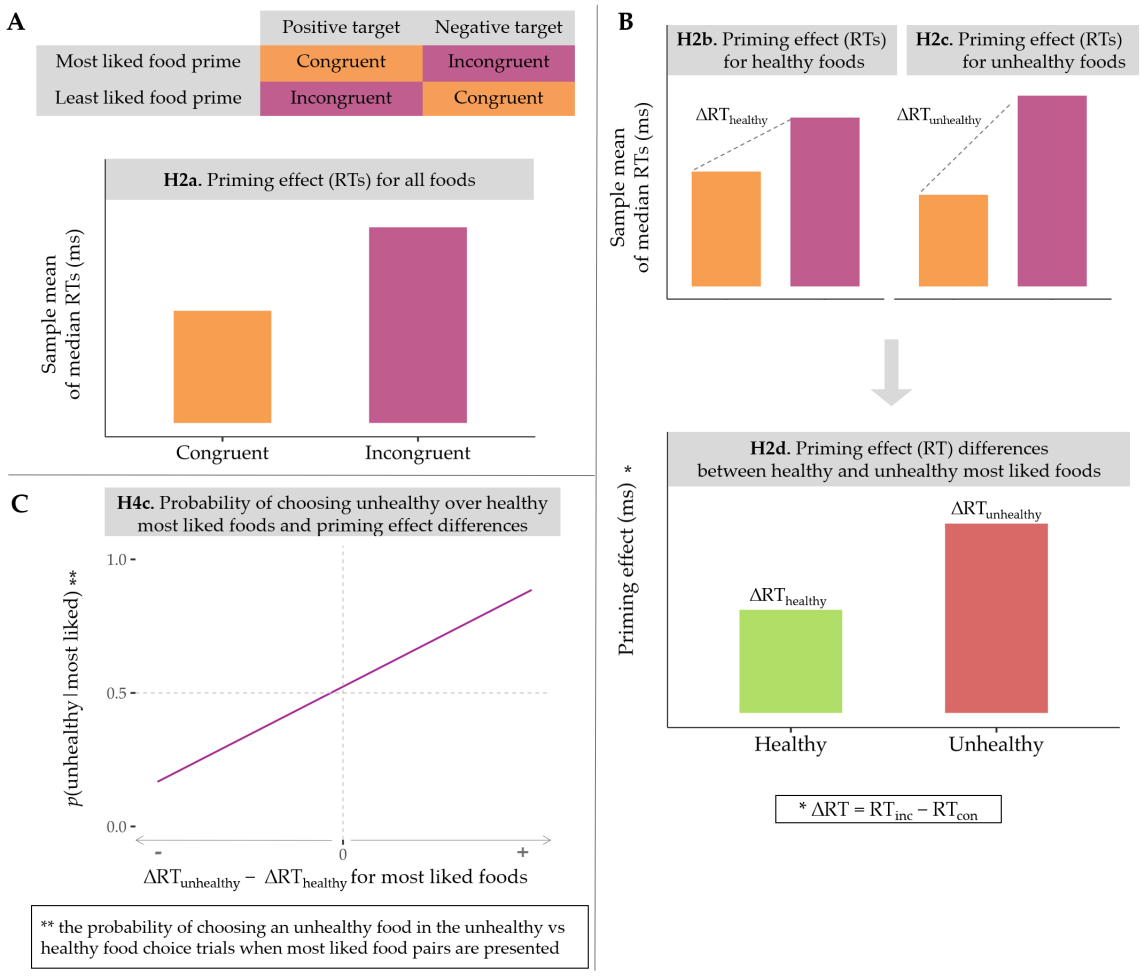


Figure 4.1: Schematic diagram of affective priming paradigm contrasts and selected hypotheses. A. Congruence in the affective priming paradigm is defined by the prime-target pairs. The trial is classified as *congruent* when a most liked food prime is paired with a positive target, and *incongruent* when paired with a negative target. Additionally, the trial is *congruent* when a least liked food prime is paired with a negative target, and *incongruent* when paired with a positive target. A priming effect for all foods (H2a) would be shown by lower sample means of median RTs (ms) in congruent vs. incongruent trials ($RT_{con} < RT_{inc}$). Details for all RT calculations can be found in section 4.4.1. Priming effects for RTs (H2) are shown here only for demonstration purposes, but the priming effects in terms of ERs are in the same direction ($ER_{con} < ER_{inc}$; see H3 predictions). **B.** Priming effects were expected for both healthy (H2b) and unhealthy food primes (H2c). It was also hypothesised that the priming effect would be greater for unhealthy than healthy food primes (H2d). The RT priming effect was calculated as the difference in median RTs for incongruent and congruent trials ($medianRT_{inc} - medianRT_{con}$) at the participant level and the sample means of these difference scores were then compared across conditions (healthy vs unhealthy). **C.** The probability of choosing unhealthy over healthy most liked foods in the unhealthy vs healthy food choice task trials was hypothesised to positively correlate (linearly) with individual differences in RT priming effects between unhealthy ($\Delta RT_{unhealthy}$) and healthy ($\Delta RT_{healthy}$) most liked food prime trials (H4c). The latter was examined using difference scores ($\Delta RT_{unhealthy} - \Delta RT_{healthy}$) in which a positive value indicates participants had a larger priming effect for unhealthy most liked food primes. H4a and H4b are not shown here, but also posit expected positive linear correlations between variables. *Note.* Hypotheses graphs are not based on actual or simulated data and are for illustrative purposes only. RT: reaction time; RT_{con}: RTs in congruent trials; RT_{inc}: RTs in incongruent trials; ΔRT: RT difference score (as shown in the formulas)

4.3 Methods

4.3.1 Data collection protocol

Participants

Recruitment was conducted via advertisements at Cardiff University and Prolific[2] (https://www.prolific.ac/) and data were collected in both laboratory and online settings (see section 4.3.1). 254 individuals were recruited via Prolific and 18 drop-outs were recorded. There were 30 recruited individuals who were not eligible to participate and quit the study (see section 4.5.1). In laboratory settings, a total of 114 participants was recruited. 43 participants recruited via the Experimental Management System (EMS) received course credits when eligible (e.g., undergraduate students) and 71 participants not eligible for course credits received monetary reimbursement (£6). Participants performing the study via Prolific were rewarded £4.50 upon completion[3].

The complete and exhaustive set of inclusion and exclusion criteria for participation in the study were as follows. Eligible participants were at least 18 years of age, had normal or corrected-to-normal vision, including normal colour vision, and spoke English as their first or second language. Exclusion criteria included being on a diet and/or have recently been taking diet pills, a past and/or current history of eating disorders and food allergies and/or intolerances. Screening survey questions can be found in Appendix G and all criteria were based on self-report. Further post-hoc exclusions of participants from preregistered analyses are explained in section 4.4.3 and presented in section 4.5.1.

The study was approved by the local Research Ethics Committee at the School of Psychology, Cardiff University. All eligible participants provided informed consent and were debriefed. The study employed a within-subjects design and blinding of participants and/or experimenters was not applicable. However, participants were not made aware of the study aims before completion. Also, the contact between the experimenter and participants was minimised as data was collected online and in group laboratory settings, as explained in the next section.

[2]Prolific requires pre-screening of participants and the current country of residence was set to UK for two reasons: 1) consistency of subject pools between laboratory and online settings; and 2) food brands included in the behavioural tasks might not have been popular outside the UK.

[3]A £6.00/h rate was used for both Prolific and EMS participants. On Prolific, the estimated time of completion was 45 minutes, and, in the laboratory, the study was expected to last 60 minutes due to the coordination of group testing settings and the time it would take to provide all participants with the chosen food items (see section 4.3.2).

Study setting

The study was undertaken in both laboratory (group testing) and online settings using Inquisit 5 (Millisecond Software, 2017). The study protocol was matched for the two collected data sets, which were analysed and reported separately. The primary dataset stemmed from the laboratory setting, as this would allow us to examine consequential food choices (see section 4.3.4). The online dataset would directly replicate any findings on the APP as an implicit measure of food attitudes (H1-H3) and examine whether priming measures were associated with non-consequential food choices (i.e., choices are not motivated by the offer of real food at the end of the experiment). This data collection protocol would also provide insights into data quality and potential differences in the utility of the APP between laboratory and online settings (see section 4.5.4).

Sampling plan

A Sequential Bayes Factor (SBF) design with maximal N (Schönbrodt et al., 2017) was employed, whereby data collection continued until either the desired level of evidence for all confirmatory hypotheses was obtained within each study setting separately (online and laboratory), or the maximal N had been reached. A minimum sample size, or *nmin*, of 40 was set for each study setting and the maximum number of participants, or *nmax*, was 200[4]. A threshold of $BF_{10} \geq 10$ would indicate *strong* evidence for the alternative hypothesis (H1) compared with the null (H0) while threshold of $BF_{01} \geq 10$ would correspond to *strong* evidence for H0 relative to H1 (see Lee & Wagenmakers, 2013). Interim analyses were conducted for every 10 participants. The evidential value and hence interpretation of the results was exclusively based on Bayes factors, but frequentist statistics have also been reported ($\alpha = 0.05$). Although frequentist power analysis was not appropriate for an SBF design, a Bayes Factor Design Analysis (BFDA; see Figure 4.2) was conducted to assess the probability of the proposed design generating misleading evidence (Schönbrodt & Wagenmakers, 2018). Analyses were performed for all preregistered hypotheses, as in directional t-tests for priming-related hypotheses (H1-H3) and directional correlations for food choice task predictions (H4), as shown in panels A and B of Figure 4.2, respectively. The design priors were consistent with the analysis priors that would be employed for Bayesian t-tests and

[4]For the purposes of the present thesis, I need to report that *nmax* has not yet been reached for the laboratory cohort due to limited time and availability of participants at Cardiff University during the preceding months of final thesis submission. Data collection has been set to continue after a specified date: 05/11/2019.

correlations (see section 4.4.2). Only the BFDA results were considered for the design of the study and no other power analyses were conducted.

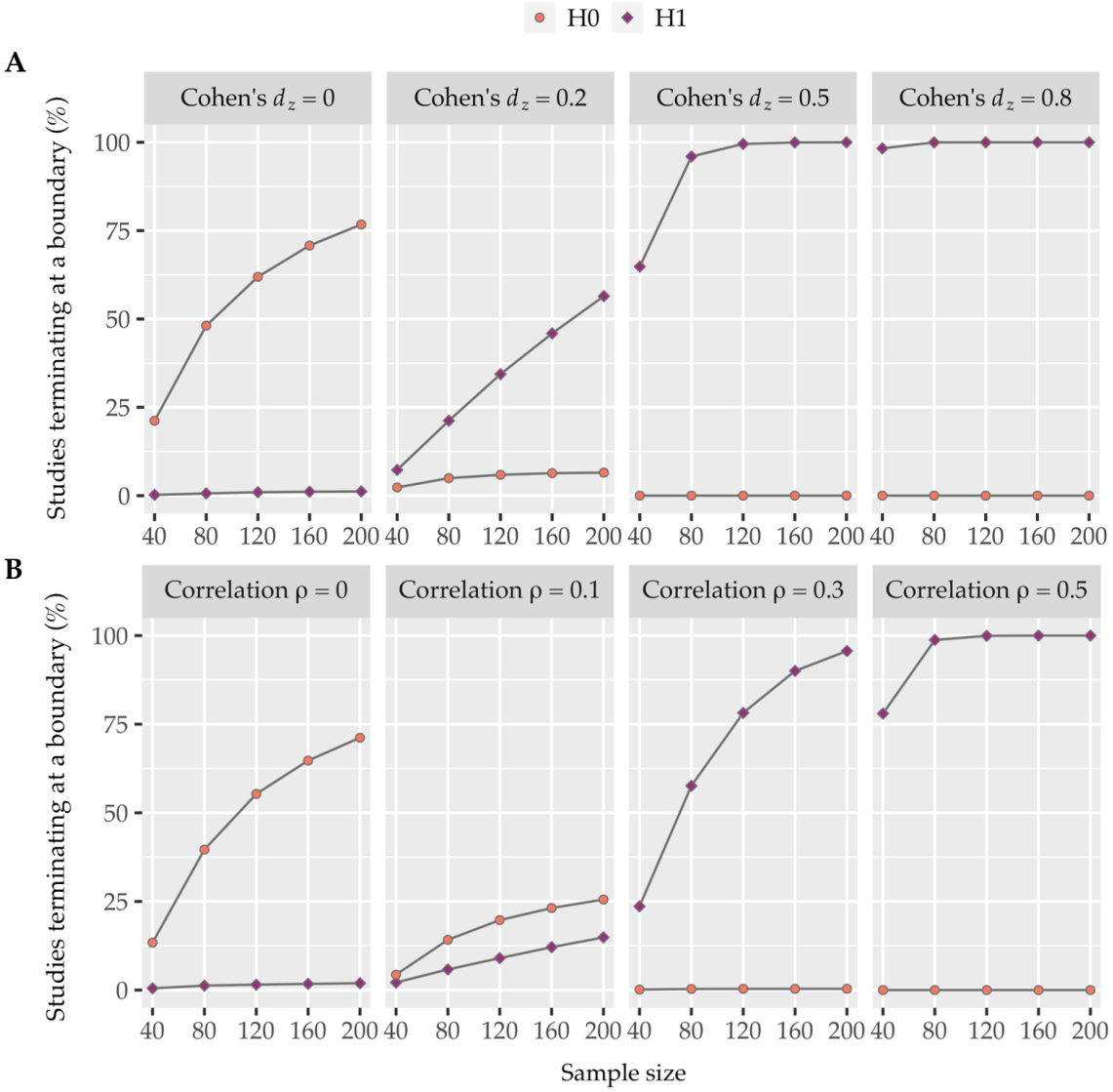


Figure 4.2: Bayes factor design analysis (BFDA) results for H0 and H1 at different sample and effect sizes in a simulated sequential design. The graphs show the percentage of simulated studies (10000) terminating at a boundary (H1 and H0) when the threshold is set to $BF_{01} \geq 10$ and $BF_{10} \geq 10$. BFDA has been conducted for the sample sizes of 40 (*nmin*), 80, 120, 160 and 200 (*nmax*). The Cohen's d_z and correlation ρ (rho) values reflect the potential of the true effect size being either zero (i.e., H0 is true), 'small' ($d_z = 0.2$; $\rho = 0.1$), 'medium' ($d_z = 0.5$; $\rho = 0.3$) or 'large' ($d_z = 0.8$; $\rho = 0.5$). These benchmarks are used for demonstration purposes only. **A. This panel shows the BFDA results for the planned directional Bayesian paired-samples t-tests (H1-H3).** For H0, 77.04% of all simulated studies correctly terminate at the H0 boundary when *nmax* has been reached. However, the probability of obtaining false positive evidence is low, with only 1.5% of the studies incorrectly stopping at the H1 boundary. At n = 40, the probability is very low, with only 0.36% of studies incorrectly stopping at the H1 boundary.

Assuming a small true effect size for H1 ($dz = 0.2$), at *nmax* 57.7% of simulated studies terminate at the correct H1 boundary and 5.9% of studies stop at the H0 boundary (i.e., probability of obtaining false negative evidence). Assuming a medium true effect size ($dz = 0.5$), at a sample size of 120, 99.7% of all studies correctly terminate at the H1 boundary and no studies (0%) stop at the H0 boundary. For a large true effect size ($dz = 0.8$), 80 participants would be adequate to correctly support H1 with 100% of simulated studies correctly reaching the H1 boundary. **B. This panel shows the BFDA results for the planned directional Bayesian correlations (H4).** Assuming the absence of a positive correlation (H0) at *nmax*, 71.19% of all simulated studies correctly terminate at H0 and 1.92% incorrectly stop at the H1 boundary. For a small true effect size ($\rho = 0.1$), only 14.85% of studies correctly terminate at H1 when *nmax* is reached and 25.54% of studies stop at H0. For a medium true effect size ($\rho = 0.3$), at *nmax* 95.65% of all studies correctly provide strong evidence for H1 and for a large effect size ($\rho = 0.5$) at the sample size 120, 99.94% of all simulated studies correctly terminate at the H1 boundary. Note. The design priors were consistent with the planned analysis priors (see section 4.4).

4.3.2 Procedure

Recruited participants confirmed their eligibility and proceeded to provide their consent and choose their study setting (laboratory or online). Participants also indicated their dominant, or preferred, hand for performing the study tasks. A schematic of the study procedure is shown in Figure 4.3. The prime selection process required participants to complete a rating task where they rated how much they like food and non-food stimuli (see section 4.3.3). Participants completed a short APP practice block (16 trials), where they received feedback on both the speed and accuracy of their responses. Participants completed eight blocks of the task in total, with short breaks in between and instruction reminders.

After the APP, participants performed a food choice task (FCT; see section 4.3.4), consisting of two blocks in total. In laboratory settings, participants received a food item chosen during the task at the end of the study. In online settings, food choice was not consequential in terms of real consumption. Ratings for all primes and targets (see section 4.3.5) were provided after the FCT for exploratory analyses. Participants were presented with three short questionnaires[5] (see section 4.3.6). The total duration of the study per participant was 40-50 minutes, after which participants were debriefed.

[5]Questionnaire items may prime participants to pay attention to health- or weight-related information and therefore were presented after the behavioural tasks had been completed.

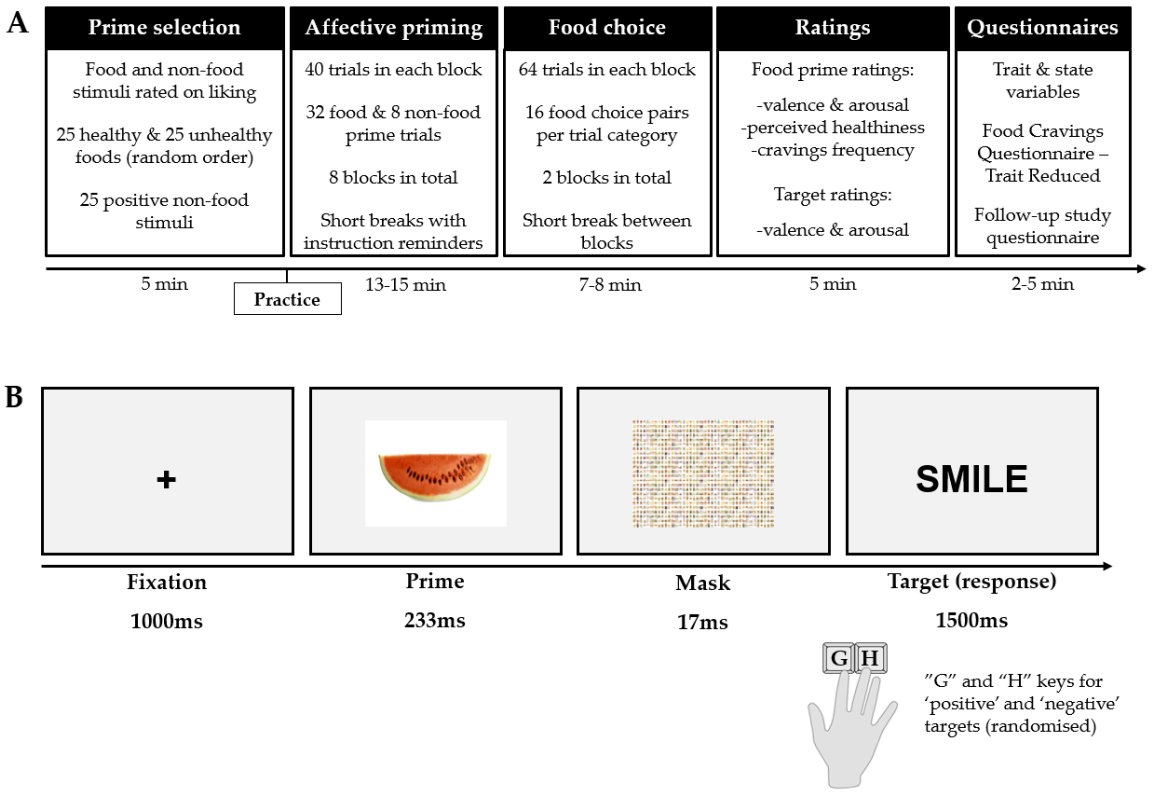


Figure 4.3: Schematic of the study procedure and affective priming paradigm. A. Primes for the affective priming paradigm (APP) were selected based on participants' liking ratings, with the subsequent APP consisting of eight blocks, including 32 food and 8 non-food prime trials per block. The food choice task followed the APP and included two blocks of 64 trials. Participants then rated all primes and targets and were presented with three short questionnaires in the depicted order. **B.** The APP involved an evaluative categorisation task, where participants categorised target words as positive or negative as quickly and accurately as possible. After a central fixation cross (1000ms), a prime (food or non-food) was presented for 233ms, followed by a mask. Participants must respond within 1500ms of target onset using the "G" and "H" keys for positive/negative (randomised across participants) using their index and middle fingers. Finger placement on the assigned keys depended on the participant's dominant hand.

4.3.3 Affective priming paradigm

Prime selection

The food primes were selected from 25 healthy and 25 unhealthy foods which were rated on liking, as measured using a visual analogue scale (VAS) ranging from -100 ("Strongly dislike") to 100 ("Strongly like"). Four unhealthy and four healthy foods that had the maximum rating were selected as 'most liked' primes, and four unhealthy and healthy foods that had the minimum rating were chosen as 'least liked' primes. For each selected food category (e.g., apples for healthy- most liked), there were two exemplars in the APP. Instructions highlighted that "the rating task includes foods

that could be either liked or disliked" to minimise the potential of social desirability bias whereby participants consistently rate foods on the positive end of the scale. Non-food primes were selected from 25 positive images from various categories such as animals, that comprised of several items (e.g., kitten, puppy, panda). The food ratings were always presented first and the order of healthy and unhealthy food rating blocks was randomised across participants. Foods in each block were presented in a random order. More details about the food and non-food stimuli can be found in Appendix E.1.

Task design

The APP involved an evaluative categorisation task (see Figure 4.3) in which participants categorised target words as either positive or negative. The targets were preceded by either 'positive' or 'negative' food primes, as well as positive non-food primes (manipulation check). The food prime trials involved a $2 \times 2 \times 2$ design with the manipulated variables of healthiness (healthy versus unhealthy), affective congruence (congruent versus incongruent) and liking (most liked versus least liked). Non-food prime trials differed only in affective congruence. Each block of 40 trials consisted of 16 healthy and 16 unhealthy food prime trials as well as 8 non-food prime trials. Congruent and incongruent prime-target pairs appeared with equal probability for all trials. There were 32 positive and 32 negative targets in total (see Appendix E.2), which appeared randomly with equal probability across two consecutive blocks for food prime trials. Targets for non-food prime trials were presented randomly across eight blocks[6].

Participants were instructed to categorise the words as quickly and as accurately as possible. Participants responded using the "G" and "H" keys, as explained in Figure 4.3. Each trial commenced with a central fixation cross followed after 1000ms by the prime. Following a 233ms inter-stimulus interval (ISI), the prime was succeeded by a backward mask (17ms) to limit subjective awareness of the primes, constructed from a mosaic of various food stimuli with different colour compositions (Wentura & Degner, 2010). The stimulus-onset asynchrony (SOA) between prime and target was 250ms. The response window begun on target onset (i.e., 1250ms) and participants had a maximum reaction time (MaxRT) of 1500ms. Each trial ended either when a response was registered or when the maximum total trial duration was reached (2750ms). A trial was considered incorrect if the target categorisation was wrong or participants

[6]Due to the separate randomisation of targets for food and non-food prime trials, certain targets may have appeared twice in a block.

did not respond within 1500ms. All stimuli were presented centrally and pictures had their relative dimensions set to 40% of the vertical and horizontal width of the presentation window. The targets and fixation cross (+) were presented in black, bold Arial fonts. Words were presented in upper-case letters against a uniform grey background.

Paradigm development

The study protocol was assessed for its feasibility in both laboratory and online settings in a series of pilot experiments, which are described in detail in Appendix D. In Experiments 1a (N = 44) and 1b (N = 26) we obtained inconsistent findings regarding the robustness of the proposed manipulation check (i.e,. RT priming effect for positive non-food primes). Considering that non-food primes were not selected by the participants but were pre-defined according to assumed valence, in Experiment 2 (N = 37) participants chose non-food stimuli as "most liked" in a selection task, which was also employed in Chapter 3. In Experiment 2, I introduced a follow-up survey to identify potential limitations of the APP from the participants' perspective. An RT priming effect for non-food primes was obtained, providing further support for the proposed manipulation check. A thematic analysis of the participants' open-ended responses on the survey shed light into certain methodological issues that were addressed in the final study protocol and were incorporated in the follow-up study questionnaire in a systematic manner (see section 4.3.6). A major improvement in the APP task design was the increased number of targets that varied in subsequent blocks to reduce the influence of practice effects on the observed priming effects. Additionally, the target stimuli (i.e., words) in the final pilot experiment were selected based on normative ratings of valence. The robustness of the proposed manipulation check was established in this final pilot (Experiment 3; N = 41), where RT priming effects for non-food primes were successfully replicated in online settings.

4.3.4 Food choice task

The FCT involved binary food choices, adapted from previous literature (Veling, Chen, et al., 2017; Zoltak et al., 2018). Participants were instructed to choose the foods that they would prefer to eat at the end of the experiment. To measure consequential food choices, in laboratory settings, participants were instructed that one of their choices would be selected by the researcher(s) and they would be given the food item they had chosen on that occasion. The selection of the food was not random due to the

unsuitability of certain foods for laboratory storage (e.g., fast decay of fruits). The proposed selection process was in line with instructions used in previous literature (Veling, Chen, et al., 2017). The researcher(s) selected an item from the list of suitable foods and restricted selection to foods rated as 'most liked' by the participants (see Appendix E.1 for details). In online settings, participants did not receive a food item at the end of the study and thus choices were not consequential. In the laboratory, we also provided participants with bottled water after screening to minimise the potential impact of thirst levels on food choices.

Each trial in the FCT (see Figure 4.4) involved the simultaneous presentation of two food items on the left and right of a central fixation cross, which participants would choose between using the "C" and "M" keys[7]. A response had to be registered within a maximum of 1500ms and participants would then be presented with response feedback (500ms) where their confirmed choice would be highlighted (i.e., a yellow frame around the selected food). A central fixation cross was presented during the intertrial interval (duration = 1000-2000ms[8]).

Participants were instructed to make their choices quickly and time pressure would help ensure that food choices were not deliberate, reducing the probability of demand characteristics (Veling, Chen, et al., 2017). Feedback was presented if participants did not respond within 1500ms, instructing them to choose faster ("Please try to choose faster" - 1000ms). To avoid loss of data, missed trials were repeated and only one repetition per trial was allowed. For each design cell of the APP (healthiness × liking) there were four food categories included in the FCT. All food prime categories were included in the FCT and represented by the primary exemplars (i.e., stimuli used in prime selection). Two main types of trials were presented and each type had two categories (see panel B in Figure 4.4). The FCT comprised 128 binary choices in total and was split into two blocks of 64 trials with a short intervening break.

4.3.5 Prime & target ratings

Participants explicitly evaluated all prime categories and targets for exploratory analyses. Food primes were evaluated for valence, arousal, perceived healthiness and frequency of cravings. Non-food primes were also evaluated for valence and arousal. Ratings were only obtained for the primary exemplars. All targets were evaluated for

[7]We purposefully deviated from the previous literature on single-hand responses, due to the possibility of learned associations (e.g., between the index/middle finger commands for 'positive' and 'negative' in the APP and food choices). Here, participants responded using both hands, by placing their index fingers on the "C" and "M" keys.

[8]Random selection in steps of 100ms.

valence and arousal. Rating scales can be found in Appendix E.3.

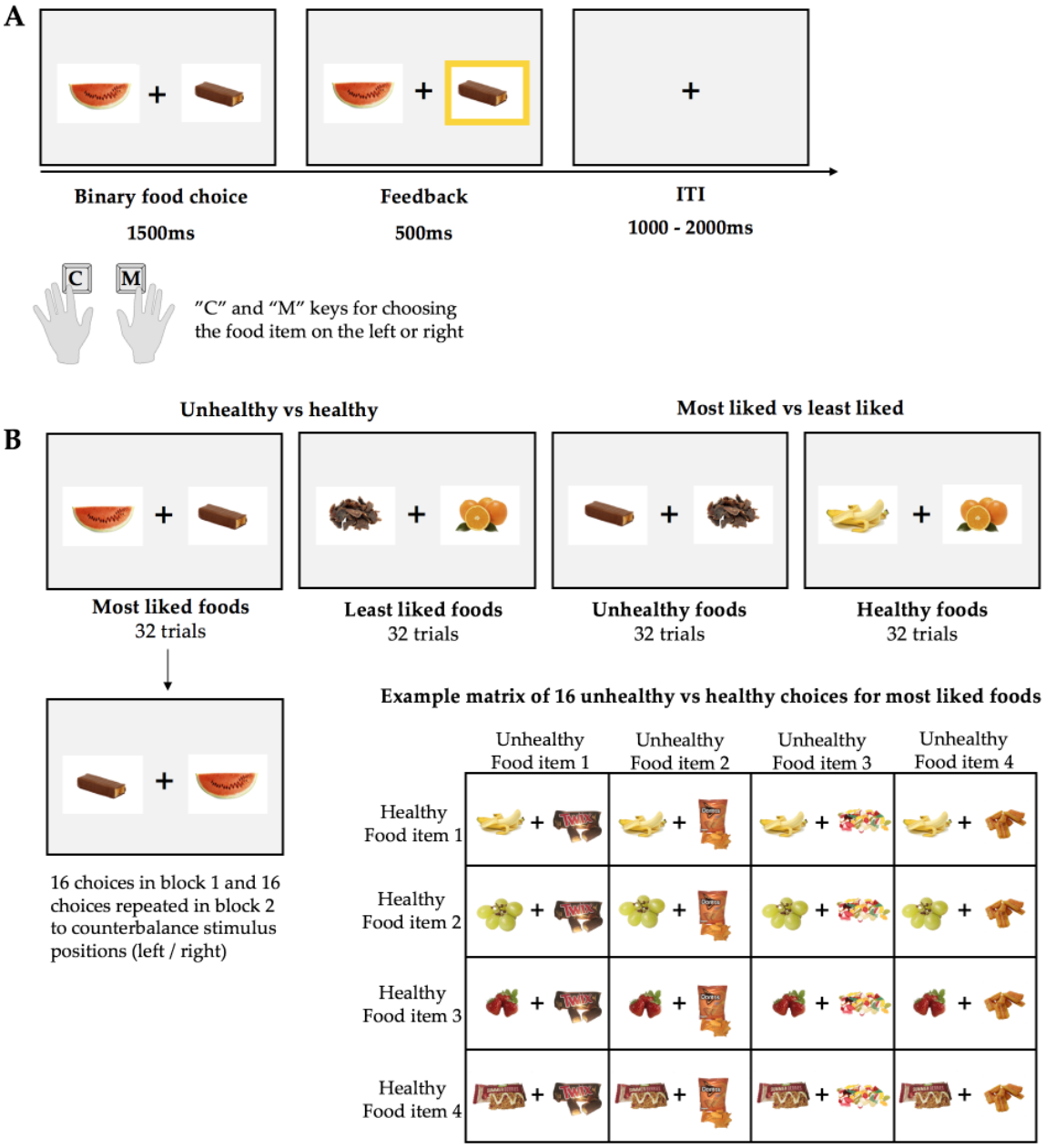


Figure 4.4: Schematic of the food choice task and different trial types. A. Participants made binary food choices within 1500ms between two food items presented on the left and right of a central fixation cross. Their response was followed by visual feedback (500ms). The intertrial interval (ITI) varied randomly (1000-2000ms). **B.** The two main trial types involved unhealthy vs healthy and most liked vs least liked choices. There were two categories of food pairs for each trial type. In *unhealthy vs healthy* trials (N = 32 per block), participants chose between most liked foods (N = 16) or least liked foods (N = 16), as shown in the example matrix. In *most liked vs least liked* trials, participants chose between unhealthy (N = 16) or healthy foods (N = 16). There were two blocks in total and choices were repeated in block 2 to counterbalance stimulus positions, as shown above.

4.3.6 Questionnaires

Trait & state variables

An initial questionnaire recorded several trait and state variables that could be associated with eating behaviours and related information (see Appendix G). These variables included how long ago participants had their last meal, whether they followed a specific diet and hunger levels. Self-reported height and weight was recorded in order to calculate the participants' body mass index (BMI: kg/m^2). Participants also indicated their gender and ethnicity (optional). Together these measures ensured that all relevant sample characteristics would be reported for potential use in meta-analyses and/or study replications.

Food Cravings Questionnaire- Trait Reduced

Participants completed the short version of the Food Cravings Questionnaire - Trait - Reduced (FCQ-T-r; Meule et al., 2014) in order to examine trait food cravings as a potential moderator of affective priming effects. FCQ-T-r consists of 15 items scored on a 5-point scale ("strongly disagree" to "strongly agree"). The subscales included in the FCQ-TR are 'lack of control over eating', 'thoughts or preoccupation with food', 'intentions and plans to consume food', 'emotions before or during food craving', and 'cues that may trigger food craving'.

Follow-up study questionnaire

At the end of the study participants completed a follow-up study questionnaire (see Appendix E.4), where they were asked to answer questions about their performance in the APP (e.g., response strategies) and report which target words, if any, they considered ambivalent or unclear. The significance of these questions is discussed together with findings in section 4.5.4. Items for this questionnaire were conceived and standardised via thematically analysed open-ended responses from participants who completed a pilot experiment for this study (see Appendix D.3.3 for details).

Participants also indicated the number of occasions they were interrupted during the word task (see Waters & Li, 2008). The survey included an instructional manipulation check (IMC) which has been designed to examine whether participants are paying attention to the instructions as well as a questionnaire attention check measure (Kees, Berry, Burton, & Sheehan, 2017). These measures are further explained in Appendix E.4 and section 4.5.4. Participants' performance on the data quality assurance

measures would be later compared for online and laboratory settings in exploratory analyses.

4.4 Analyses

4.4.1 Measures & indices

All planned comparisons are outlined in section 4.4.2, where RT_{con} and RT_{inc} denote the sample mean of individual median correct RTs in congruent and incongruent trials, and ER_{con} and ER_{inc} refer to the mean error rates in congruent and incongruent trials, respectively. At the level of participants, median RTs were used as they are less sensitive to outliers and may provide a more accurate measure of central tendency in positively-skewed distributions. The median RTs were computed for each participant and then a Bayesian paired-samples t-test was conducted for the alternative hypothesis that the population mean of the difference in median RTs is smaller than 0 (or greater than 0 for H2d and H3d). The difference in median RTs for each participant between congruent and incongruent trials ($\text{median}RT_{inc} - \text{median}RT_{con}$) was then calculated for further testing of RT priming effects. The sample means of these difference scores were then compared across conditions (e.g., $\Delta RT_{unhealthy} > \Delta RT_{healthy}$ in H2d) and are referred to as ΔRT. Similarly, ΔER was defined as the priming effect for error rates, where $\Delta ER = ER_{inc} - ER_{con}$. For the calculation of error rates at the participant level, accuracy is recoded as 1 = incorrect and 0 = correct.

With regards to FCT analyses, p(unhealthy|most liked) refers to the conditional probability of choosing an unhealthy food in the unhealthy vs healthy food choice trials when most liked food pairs were presented (see Figure 4.4 for trial types). Accordingly, p(most liked|healthy) denotes the conditional probability of choosing a most liked food in the most liked vs least liked trials where healthy food pairs are presented, and p(most liked|unhealthy) indicates the conditional probability of choosing a most liked food on trials where the unhealthy food pairs were presented. Choices were recoded according to trial types to compute these probabilities. For example, in trials where participants chose between most liked and least liked foods and the foods presented were healthy, choices were coded as 1 = most liked and 0 = least liked. Then the mean was calculated and denoted the probability that participants chose a most liked food in these most liked vs least liked (healthy) choice trials, that is p(most liked|healthy). Probability values were calculated from the number of completed trials. The difference in priming effects (RTs only) between unhealthy and healthy most liked food prime

trials is represented by $\Delta RT_{unhealthy} - \Delta RT_{healthy}$.

4.4.2 Preregistered analysis plan

Bayesian paired-samples t-tests (Rouder et al., 2009) employed a prior with the $\sqrt{2/2}$ scale parameter for the half-Cauchy distribution. Bayesian correlation pairs had a stretched beta with the parameter $\gamma = 1$, which corresponds to a uniform prior (Wagenmakers et al., 2016). Every directional Bayesian test would be reported with the equivalent frequentist test (see 4.3.1). Analyses were conducted separately for the online and laboratory datasets and results were reported independently (see section 4.3.1). Pre-processing of the data and confirmatory analyses were conducted in R (R Core Team, 2017) via RStudio (RStudio Team, 2016) and all scripts are available on the Open Science Framework (OSF; https://osf.io/3hrmy/). For Bayesian t-tests and correlations the 'BayesFactor' package (Morey & Rouder, 2018) was used and for the reported frequentist tests the 'jmv' (jamovi) package (Selker, Love, & Dropmann, 2018) was employed.

H1, H2 and H3 were exclusively tested using directional Bayesian paired- samples t-tests, as outlined below.

H1a. $RT_{con} < RT_{inc}$ for non-food prime trials
H1b. $ER_{con} < ER_{inc}$ for non-food prime trials
H2a. $RT_{con} < RT_{inc}$ for food prime trials
H2b. $RT_{con} < RT_{inc}$ for healthy food prime trials
H2c. $RT_{con} < RT_{inc}$ for unhealthy food prime trials
H2d. $\Delta RT_{unhealthy} > \Delta RT_{healthy}$ for most liked food primes

H3a. $ER_{con} < ER_{inc}$ for food prime trials
H3b. $ER_{con} < ER_{inc}$ for healthy food prime trials
H3c. $ER_{con} < ER_{inc}$ for unhealthy food prime trials
H3d. $\Delta ER_{unhealthy} > \Delta ER_{healthy}$ for most liked food primes

H4 was only examined via directional Bayesian correlation pairs, as shown below. The reported correlation coefficient was Pearson's rho. Definitions of probabilities have been described in detail above (see section 4.4.1).

H4a. $\Delta RT_{healthy}$ for most liked primes positively correlates with p(most liked|healthy)

H4b. $\Delta RT_{unhealthy}$ for most liked primes positively correlates with p(most liked|unhealthy)

H4c. $\Delta RT_{unhealthy} - \Delta RT_{healthy}$ (for most liked primes) positively correlates with p(unhealthy|most liked)

As a contingent analysis plan, Bayes factors for hypotheses H1, H2 and H3 in the opposite direction would also be reported if differences between means were descriptively in the unexpected direction, such as $RT_{con} > RT_{inc}$ for food prime trials. The decision to report the positive one-sided tests would be based on descriptive values and not on Bayes factors, as support for the null in a directional Bayesian t-test does not exclude the possibility that there is greater evidence for an effect in the opposite direction. For example, even if there is adequate evidence for H0 and the null hypothesis is preferred to the negative hypothesis ($RT_{con} < RT_{inc}$), the positive hypothesis ($RT_{con} > RT_{inc}$) may still be favoured over the null (see Morey, 2014).

Although statistical tests were not conducted for performance in the FCT alone, such as reaction time differences between trial types, we would report descriptively the probabilities of choosing most liked food items in the most liked vs least liked trials when both healthy and unhealthy food pairs were presented, which should be above 0.5 if prime selection according to liking was successful (see also Veling, Chen, et al., 2017).

For all t-tests (H1-H3), Cohen's d_{av} was reported, which uses the average standard deviation of both measures in a paired-samples comparison and can be similar to Cohen's d_s effect size for between-subject designs, increasing its utility for potential meta-analyses (Lakens, 2013). The formula for the calculation, as presented below, was obtained from Lakens (2013). The mean difference of the two repeated measures (mean of the difference scores) is divided by the average standard deviation of both measures. The R code has been adapted from an existing script from Anvari & Lakens (2019), available at https://osf.io/cfd6e/. The script also provides code for the calculation of confidence intervals (CIs) for Cohen's d_{av}, which were also reported.

$$Cohen's \quad d_{av} = \frac{Mean \quad difference}{\sqrt{\frac{SD_1^2 + SD_2^2}{2}}}$$

The Shapiro-Wilk test of normality was conducted for every t-test under H1, H2 and H3. If the normality assumption was violated under alpha < 0.005 for any of

planned comparisons in a set of predictions for RTs (H1a, H2a-H2d), only the results with log-transformed values (e.g., $\text{logRT}_{\text{con}} < \text{logRT}_{\text{inc}}$ for H1a) would be reported. For example, if normality was violated for H2c under H2 (i.e., only RT difference scores for unhealthy food prime trials), we would log-transform RTs for all comparisons (H2a, H2b, H2c, H2d). For error-related predictions (H1b, H3a-H3d), Bayesian t-tests would be conducted as planned. However, as part of the supplementary frequentist statistics, Wilcoxon signed rank tests would also be performed. In section 4.5, p_W denotes the p-value from the Wilcoxon signed rank tests for clarity. As explained in section 4.3.1, conclusions would only be drawn based on Bayesian tests.

4.4.3 Data exclusions

Error rates in the APP were inspected for food and non-food prime trials separately and participants with ERs greater or equal to 0.4 from within either set of trials were excluded from all respective analyses. This obviated the need for further inspection of the distribution of missed or inaccurate responses across conditions. The FCT data were inspected for missed responses, where participants did not respond within 1500ms. Analyses conducted for H4a, H4b, and H4c would not include participants who had more than 50% of missed trials across the two blocks in any trial type examined under H4 (i.e., < 16 out of 32 trials).

Data were also inspected for timing delays in trial events in the APP due to the possible occurrences of technical issues during online testing (e.g., slow broadband). Timing delays were defined as trial events that last two or more screen refreshes than originally programmed. The trial events that were inspected were the presentation of the prime (233ms) and mask (17ms) and trials with timing delays would be removed from analyses. If a participant had more than 25% of trials removed, they would then be excluded from all analyses.

4.5 Results

4.5.1 Sample characteristics

From the recruited online sample (N = 236), excluding drop-outs, there were 30 individuals who were not eligible to participate in the study. Ten Prolific users were not native or bilingual English speakers and ten users reported not having normal or corrected-to-normal vision. Four individuals also reported being on a diet at the time of the study, while five indicated they had food allergies/intolerances. One individual

was excluded for having a past and/or current history of an eating disorder.

Collected data were inspected for potential exclusions, as outlined above (see section 4.4.3). No participants were excluded due to timing delays in the APP from the laboratory sample. We removed delayed trials from nine participants (only one to five trials each) who completed the study online. Two participants were excluded based on their total proportion of error rates in the APP (>=0.4) from the laboratory sample and four participants were removed from the online data. The final samples for APP analyses (H1-H3) were 112 and 202 for laboratory and online settings, respectively. For FCT analyses (H4), one participant from the laboratory sample and two participants from the online sample were also excluded because they had missed more than 25% of FCT trials. The final sample sizes for FCT analyses were 111 and 200 for laboratory and online settings, respectively. Although *nmax* was set to 200, due to the exclusions based on FCT missed trials, data was collected from two additional participants to reach the desired sample size for H4 analyses and therefore the final sample size for the APP analyses was 202.

Descriptive statistics of demographics and other sample characteristics, as measured towards the end of the study (see section 4.3.6), can be found in Table 4.1. Overall, the laboratory and online cohorts were approximately matched, but online testing led to a considerably more diverse sample in terms of gender, age and BMI. Participants in both cohorts were generally not very hungry at the time of the study. In the laboratory sample, 56.76% of participants self-reported eating 1-3 hours before the study and 19.82% of participants had a meal just before the study ("Less than 1 hour ago"). In the online sample, 53.54% of participants self-reported eating 1-3 hours before the study and 21.21% of participants had a meal less than one hour before the study. 84.69% of participants from the laboratory cohort reported that they were not following any specific diet, while 6.31% were vegetarian and 6.31% pescetarian. Similarly, 89.40% of participants from the online cohort did not follow a specific diet, 7.07% were vegetarian and 2.53% followed a vegan diet.

The descriptive statistics of baseline liking measures, provided for selected primes that were included in the APP, were also inspected. Both food and non-food prime stimuli were on average rated appropriately, with 'most liked' primes rated above 80 and 'least liked' primes rated below -50. The mean liking values for 'least liked' foods indicate that the selected set of food categories in this study was variable enough for participants to be able to find several foods not (very) appetitive, so that the 'least liked' manipulation in the APP would be valid. Similarly, the predetermined healthiness of the foods was on average consistent with participants' ratings of perceived healthiness

in both cohorts.

Table 4.1: Descriptive statistics of sample characteristics for laboratory and online cohorts

	Laboratory cohort		Online cohort	
	Mean	*SD*	*Mean*	*SD*
Age (Years)	22.05	5.55	33.53	11.96
Gender (% Female)	79.28	40.71	56.57	49.69
Ethnicity (% White)	80.18	40.05	84.85	35.95
Hunger (1-9)	5.17	2.22	4.55	2.50
FCQ-T-r total score	45.32	10.48	42.97	11.93
Body-mass index (kg/m^2)	22.75	3.60	25.17	5.88
Liking for non-food stimuli	93.11	10.92	89.23	15.70
Liking for most liked unhealthy foods	84.34	17.56	82.81	24.08
Liking for least liked unhealthy foods	-58.04	36.13	-55.87	38.55
Liking for most liked healthy foods	87.75	14.99	84.86	18.16
Liking for least liked healthy foods	-62.36	31.92	-62.45	32.36
Perceived healthiness of healthy foods	7.36	0.74	7.34	0.86
Perceived healthiness of unhealthy foods	2.29	0.75	2.45	0.89

Note. The descriptive statistics shown in this table did not include participants who did not complete the last parts of the study which included relevant questionnaire measures (two from online cohort) and excluded participants based on both error rates in the affective priming paradigm and proportion of missed trials in the food choice task (see section 4.4.3). The sample sizes for the variables presented here are 111 and 198 for laboratory and online cohorts, respectively. Ethnicity was not provided ("do not wish to answer") by two participants in the online cohort. Calculated BMI was considered invalid for two participants in the laboratory cohort and three participants in the online cohort (< 15 or > 60). Hunger was measured on a 9-point Likert scale (1 = "Not at all" to 9 = "Very"). Liking was measured using a visual analogue scale that ranged from -100 (“Strongly dislike”) to 100 (“Strongly like”) and perceived healthiness ranged from 1 ("Very unhealthy") to 9 ("Very healthy"). FCQ-T-r: Food Cravings Questionnaire - Trait - reduced

4.5.2 Findings from confirmatory analyses

Manipulation check

Extreme evidence was obtained for the expected RT priming effects on non-food prime trials (H1a), as presented in Tables 4.2 and 4.3. In the laboratory cohort, participants were faster to respond in congruent ($M = 544.63$, $SD = 63.51$) compared to incongruent non-food trials ($M = 564.09$, $SD = 65.76$). This effect was replicated

in the online cohort, with participants having, on average, lower median RTs on congruent ($M = 563.60$, $SD = 71.40$) rather than incongruent non-food trials ($M = 585.92$, $SD = 73.29$). RT priming effects from non-food prime trials can be seen in Figure 4.5.

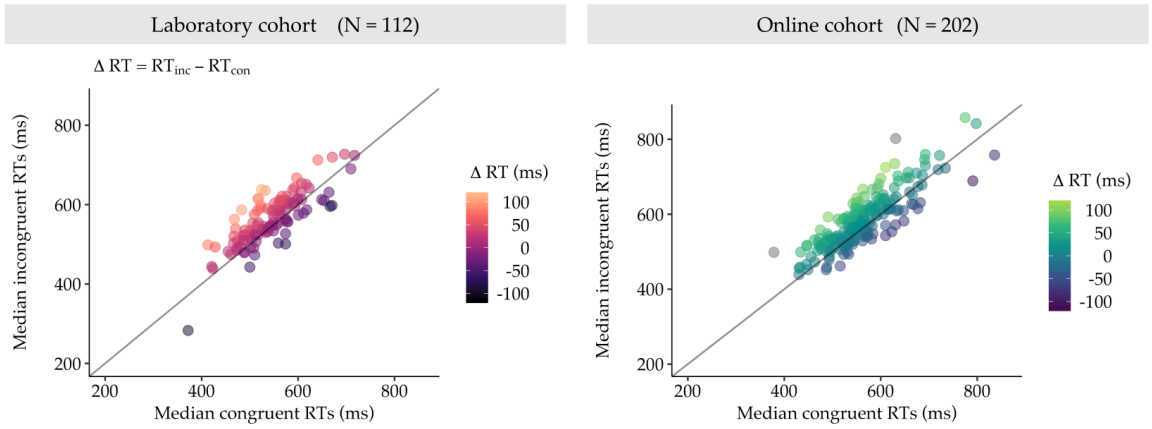


Figure 4.5: Plots showing the observed reaction time priming effects for non-food primes in the laboratory and online cohorts. The scatterplots show the individual median reaction times (RTs) calculated for non-food prime trials at the participant level and how they differ for each level of affective congruence. As expected, participants were faster to respond on congruent compared to incongruent trials in both the laboratory and online cohorts. The RT priming effect, or ΔRT, was calculated as the difference between incongruent and congruent RTs ($RT_{inc} - RT_{con}$). Any value shown above the unity line on these plots corresponds to a positive priming effect, whereby incongruent RTs (y-axis) are larger compared to congruent RTs (x-axis). The magnitude of ΔRT (ms) can be visualised using the colour gradient applied to plotted data points.

In support of H1b, an overall priming effect for error rates in the expected direction was observed. In the laboratory cohort, there was *very strong* evidence that participants had lower error rates on congruent ($M = 0.06$, $SD = 0.07$) compared to incongruent non-food trials ($M = 0.09$, $SD = 0.08$) [$W = 962.00$, $p_W < .001$]. Similarly, in the online cohort there was *very strong* evidence for error rates being reduced from congruent ($M = 0.04$, $SD = 0.05$) to incongruent non-food trials ($M = 0.06$, $SD = 0.09$) [$W = 3043.50$, $p_W < .001$]. The support for the preregistered hypotheses which were introduced as a manipulation check for the APP was paramount to the validity of the employed task design for food stimuli.

Food priming effects & choice behaviour

Findings from primary laboratory cohort The results of all statistical tests for preregistered hypotheses H2 and H3 from the laboratory cohort (N = 112) are presented in Table 4.2. We obtained *extreme* evidence for an RT priming effect across food prime trials (H2a), as RTs were on average faster on congruent (M = 544.86, SD = 58.30) compared to incongruent trials (M = 558.51, SD = 59.42). In healthy food prime trials (H2b), RTs were also faster on congruent (M = 544.22, SD = 60.00) compared to incongruent trials (M = 558.60, SD = 59.64). There was *extreme* evidence for an RT priming effect across unhealthy food prime trials (H2c), as shown by RTs in congruent (M = 546.03, SD = 57.91) and incongruent trials (M = 559.73, SD = 60.99). Observed priming effects for healthy and unhealthy food prime trials have been visualised using raincloud plots (Allen et al., 2019, 2018), which can be seen in Figure 4.6. Although we expected that the RT priming effect would be greater for unhealthy compared to healthy most liked food prime trials, there was *anecdotal* evidence for the null hypothesis compared to the alternative. The RT priming effect for unhealthy most liked food primes ($\Delta\text{RT}_{\text{unhealthy}}$; M = 22.17, SD = 43.99) was not greater than the RT priming effect for healthy most liked food primes ($\Delta\text{RT}_{\text{healthy}}$; M = 16.03, SD = 49.12).

As explained in section 4.2, it was preregistered that support for any observed priming effects would be dependent on both speed- and accuracy-related hypotheses. There was *extreme* evidence that on average participants made fewer errors on congruent (M = 0.06, SD = 0.04) compared to incongruent food prime trials (M = 0.09, SD = 0.07) [H3a; W = 877.00, $p_W < .001$]. In healthy food prime trials (H3b), error rates were lower on congruent (M = 0.06, SD = 0.05) relative to incongruent trials (M = 0.09, SD = 0.07). There was also *extreme* evidence for the expected differences in error rates between congruent (M = 0.06, SD = 0.05) and incongruent unhealthy food prime trials (M = 0.09, SD = 0.07) [H3c; W = 912.00, $p_W < .001$]. Priming effects for error rates were in the expected direction across food prime trials and therefore we can conclude that any RT effects were not observed due to strategic responding or SATs, such as trading off high accuracy for faster responses. Contrary to predictions about differences in ER priming effects between healthy and unhealthy most liked food primes, there was only *anecdotal* evidence for the null compared to the alternative hypothesis (H3d). The ER priming effect was not on average greater for unhealthy (M = 0.02, SD = 0.07) compared to healthy most liked food primes (M = 0.01, SD = 0.08) [W = 2017.00, $p_W = 0.126$].

Table 4.2: Statistical test results for hypotheses H1 to H3 from the laboratory cohort (N = 112)

					95% CI for d_{av}		
	Log(BF_{10})	$t(111)$	p	d_{av}	Lower	Upper	Evidence interpretation
H1a	10.37	-5.22	< .001	-0.30	-0.42	-0.18	*Extreme* evidence for H1
H1b	4.08	-3.49	< .001	-0.36	-0.57	-0.15	*Very strong* evidence for H1
H2a	20.96	-7.55	< .001	-0.23	-0.30	-0.16	*Extreme* evidence for H1
H2b	11.68	-5.54	< .001	-0.24	-0.33	-0.15	*Extreme* evidence for H1
H2c	15.25	-6.34	< .001	-0.23	-0.31	-0.15	*Extreme* evidence for H1
H2d	-0.84	1.30	0.097	0.13	-0.07	0.33	*Anecdotal* evidence for H0
H3a	14.25	-6.12	< .001	-0.49	-0.66	-0.32	*Extreme* evidence for H1
H3b	10.53	-5.26	< .001	-0.46	-0.64	-0.28	*Extreme* evidence for H1
H3c	10.16	-5.17	< .001	-0.46	-0.64	-0.27	*Extreme* evidence for H1
H3d	-1.04	1.16	0.124	0.13	-0.09	0.35	*Anecdotal* evidence for H0

Note. Evidence is interpreted for the alternative hypothesis (H1) compared to the null (H0) and vice versa. All hypotheses are statistically defined in section 4.4 and results are discussed in detail in section 4.5.2. The effect size is given by Cohen's d_{av}. Log(BF_{10}): Natural logarithm of BF_{10}; e.g. $BF_{10} > 10$ is equivalent to Log(BF_{10}) > 2.3 and $BF_{10} < 1/10$ is equivalent to Log(BF_{10}) < -2.3; $BF_{10} > 100$ is represented by Log(BF_{10}) > 4.61

Bayesian correlation pairs for hypotheses H4a and H4b have yielded conclusive evidence regarding the absence or presence of the expected linear positive correlations. There was *moderate* evidence that the probability of choosing a most liked food over a least liked food from within a pair of healthy food stimuli ($M = 0.97$, $SD = 0.05$) did not positively correlate with the RT priming effect in healthy food prime trials [H4a; $BF_{01} = 8.25$; $\rho = 0.002$, $p = 0.491$, 95% CI = -0.155, 1]. Similarly, there was *strong* evidence that the probability of choosing a most liked over a least liked food from within a pair of unhealthy food stimuli ($M = 0.95$, $SD = 0.06$) did not positively correlate with the RT priming effect in unhealthy food prime trials [H4b; $BF_{01} = 13.07$; $\rho = -0.061$, $p = 0.738$, 95% CI = -0.216, 1]. *Strong* evidence was obtained for the null compared to the alternative hypothesis for H4c. The probability of choosing an unhealthy over a healthy most liked food ($M = 0.56$, $SD = 0.29$) did not positively correlate with the difference in RT priming effects between unhealthy and healthy most liked food prime trials [H4c; $BF_{01} = 11.02$; $\rho = -0.036$, $p = 0.645$, 95% CI = -0.192, 1].

Replication: findings from online cohort The results of all statistical tests for preregistered hypotheses H2 and H3 from the online cohort (N = 202) are presented in Table 4.3. RTs for all comparisons under H2 were log-transformed (logRTs) due to the violation of the normality assumption for H2b, in line with the preregistered analysis plan. Although logRTs are descriptively presented here, RT priming effects with non-transformed RTs can be seen in Figure 4.6. Reaction time and error rate priming effects were replicated in the online cohort. First, there was *extreme* evidence for an RT priming effect across food prime trials, as on average logRTs on congruent trials ($M = 6.34$, $SD = 0.12$) were faster compared to logRTs on incongruent food prime trials ($M = 6.36$, $SD = 0.12$). In healthy food prime trials (H2b), logRTs on congruent trials ($M = 6.34$, $SD = 0.12$) were also faster than logRTs on incongruent trials ($M = 6.36$, $SD = 0.12$). *Extreme* evidence was obtained for an RT priming effect in the expected direction for logRTs on congruent ($M = 6.34$, $SD = 0.13$) and incongruent ($M = 6.36$, $SD = 0.12$) unhealty food prime trials (H2c). The results from laboratory and online cohorts converge for H2d as well, as there was *moderate* evidence that the logRT priming effect for most liked unhealthy foods ($\Delta\text{LogRT}_{\text{unhealthy}}$; $M = 0.03$, $SD = 0.08$) was not greater than the logRT priming effect for most liked unhealthy foods ($\Delta\text{LogRT}_{\text{healthy}}$; $M = 0.02$, $SD = 0.07$).

In line with the findings from the laboratory cohort, priming effects were observed in terms of error rates and the possibility of strategic trade-offs in performance was refuted. As expected for H3a, there was *extreme* evidence that error rates on congruent trials ($M = 0.05$, $SD = 0.05$) were on average lower compared to error rates on incongruent food prime trials ($M = 0.06$, $SD = 0.07$) [$W = 4238.00$, $p_W < .001$]. In healthy food prime trials (H3b), results for error rates on congruent ($M = 0.05$, $SD = 0.05$) and incongruent trials ($M = 0.06$, $SD = 0.07$) were in the same direction. *Strong* evidence was also obtained for an ER priming effect in unhealthy food prime trials, as error rates were on average lower on congruent ($M = 0.05$, $SD = 0.05$) compared to incongruent trials ($M = 0.06$, $SD = 0.08$) [H3c; $W = 4942.50$, $p_W < .001$]. In the online cohort, there was *strong* evidence for the null compared to the altenative for H3d. Potentially due to the increased sample size in the online cohort, there was conclusive evidence that the ER priming effect was not greater for unhealthy ($M = 0.01$, $SD = 0.08$) compared to healthy most liked food primes ($M = 0.01$, $SD = 0.07$) [$W = 7227.50$, $p_W = 0.779$].

In the online cohort, there was *moderate* evidence for the lack of a positive correlation between the probability of choosing a most liked food over a least like food from within a pair of healthy food stimuli, or p(most liked|healthy) ($M = 0.96$, $SD =$

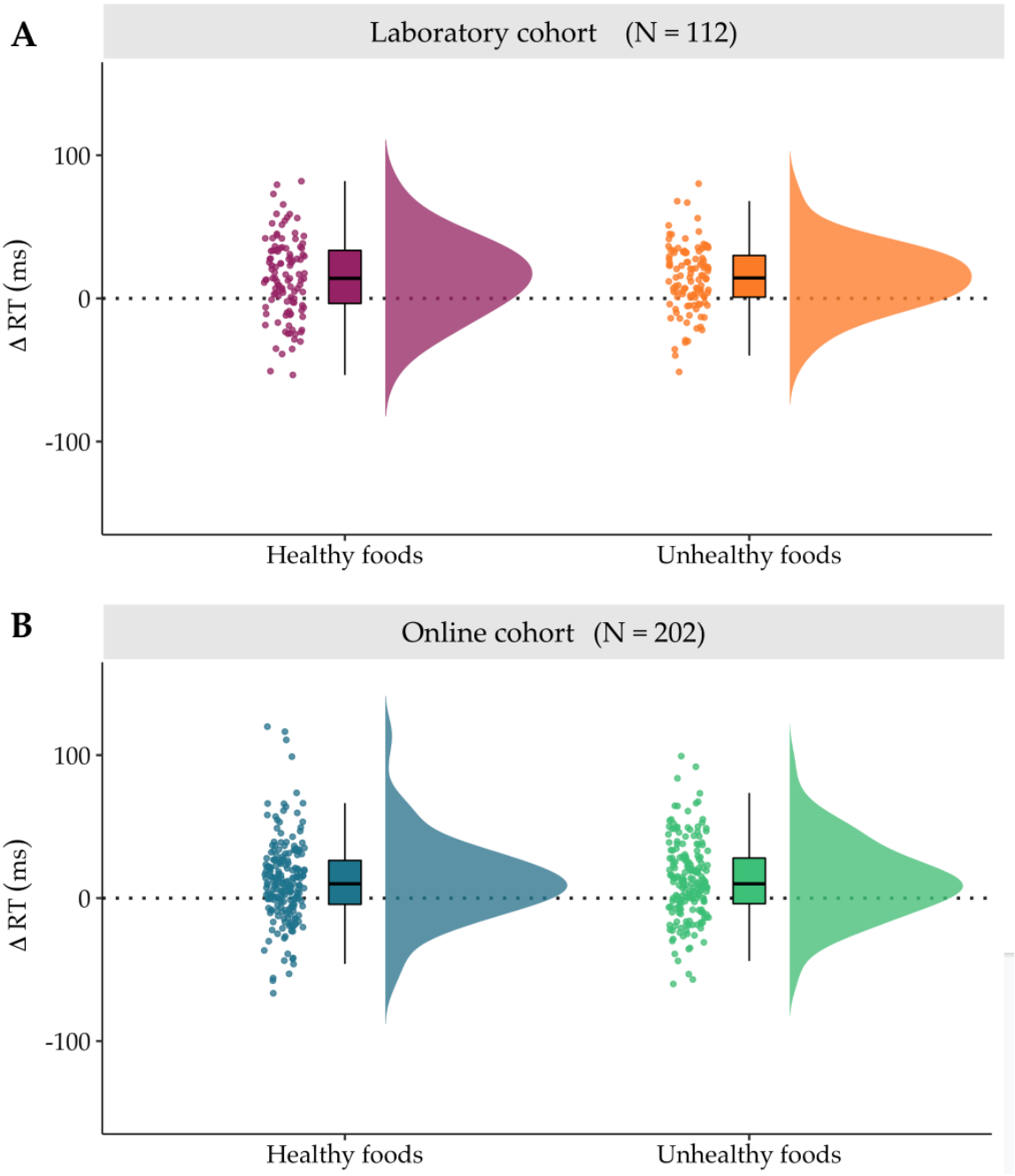


Figure 4.6: Plots showing the observed reaction time priming effects for healthy and unhealthy food primes in the laboratory and online cohorts. The rainclouds show the individual median reaction times (RTs) from trials where healthy and unhealthy foods were presented. ΔRT (ms) refers to the difference between congruent and incongruent trials, where positive scores reflect an RT priming effect. The line drawn at y=0 shows that for both laboratory and online cohorts the distribution of participants' median RTs were overall positive. The spread of the data indicates that on average, priming effects for both healthy and unhealthy foods were reliably observed across participants.

Table 4.3: Statistical test results for hypotheses H1 to H3 from the online cohort (N = 202)

					95% CI for d_{av}		
	Log(BF_{10})	$t(201)$	p	d_{av}	Lower	Upper	Evidence interpretation
H1a	24.94	-7.89	< .001	-0.31	-0.39	-0.23	*Extreme* evidence for H1
H1b	4.07	-3.31	0.001	-0.32	-0.50	-0.14	*Very strong* evidence for H1
H2a	25.92	-8.05	< .001	-0.18	-0.22	-0.13	*Extreme* evidence for H1
H2b	14.77	-6.05	< .001	-0.17	-0.22	-0.11	*Extreme* evidence for H1
H2c	17.70	-6.62	< .001	-0.18	-0.24	-0.13	*Extreme* evidence for H1
H2d	-1.98	0.62	0.269	0.05	-0.10	0.19	*Moderate* evidence for H0
H3a	6.87	-4.30	< .001	-0.28	-0.40	-0.15	*Extreme* evidence for H1
H3b	7.93	-4.56	< .001	-0.30	-0.43	-0.17	*Extreme* evidence for H1
H3c	3.39	-3.30	0.001	-0.23	-0.37	-0.09	*Strong* evidence for H1
H3d	-2.65	-0.13	0.553	-0.01	-0.15	0.13	*Strong* evidence for H0

Note. Evidence is interpreted for the alternative hypothesis (H1) compared to the null (H0) and vice versa. All hypotheses are statistically defined in section 4.4 and results are discussed in detail in section 4.5.2. The effect size is given by Cohen's d_{av}. Log(BF_{10}): Natural logarithm of BF_{10}; e.g. $BF_{10} > 10$ is equivalent to Log(BF_{10}) > 2.3 and $BF_{10} < 1/10$ is equivalent to Log(BF_{10}) < -2.3; $BF_{10} > 100$ is represented by Log(BF_{10}) > 4.61

0.08), and the RT priming effect in healthy most liked food prime trials [H4a; BF_{01} = 4.90; $\rho = 0.061$, $p = 0.195$, 95% CI = -0.056, 1]. There was also *moderate* evidence for the absence of a positive linear correlation between the probability of choosing a most liked over a least liked food from within a pair of unhealthy food stimuli, or p(most liked|unhealthy) ($M = 0.94$, $SD = 0.10$), and the RT priming effect in unhealthy food prime trials [H4b; $BF_{01} = 7.61$; $\rho = 0.032$, $p = 0.328$, 95% CI = -0.085, 1]. As a futher validation of the FCT, both probabilities of choosing a most liked food item in the most liked vs least liked trials were very high and above 0.5. In contrast to the laboratory cohort, where we obtained *strong evidence* for the null compared to the alternative, for H4c, in the online cohort there was only *moderate* evidence for the lack of a positive linear correlation between the probability of choosing an unhealthy over a healthy most liked food, or p(unhealthy|most liked) ($M = 0.55$, $SD = 0.33$), and the difference in RT priming effects between unhealthy and healthy most liked food prime trials [H4c; $BF_{01} = 6.42$; $\rho = 0.044$, $p = 0.27$, 95% CI = -0.073, 1].

4.5.3 Robustness checks

The preregistered hypotheses of the study were tested under different aggregation and reduction conditions, as outlined below. Following the sensitivity analyses, the findings of the study would be considered "robust" if the results were consistent with those of

the main preregistered analyses presented in section 4.4. Given that the exclusions based on error rates in the APP were not strict, a more conservative criterion would be applied as a robustness check for all hypotheses (H1 to H4). However, there were not enough exclusions to deem further analyses informative (< 4 participants would be excluded per cohort). In line with previous literature on affective priming effects in the food domain (Lamote et al., 2004; Verhulst et al., 2006), H1, H3 and H4 were re-analysed with individual means used in place of individual median RTs. Since mean RTs could be more sensitive to outliers compared to median RTs, previously reported criteria for outlier removal were employed. First, trials with RTs shorter than 250ms would be removed, as reported in Lamote et al. (2004). Exclusion of longer RTs (>1500ms) did not apply to the present APP design (MaxRT = 1500ms). Second, RTs that deviated more than 2.5 standard deviations from the mean of each design cell for food (congruence × healthiness × liking) and non-food prime trials (congruence) would be excluded from the data (Verhulst et al., 2006). Considering that only Bayesian statistical tests would inform the conclusions of the study, only $\text{Log}(BF_{10})$ values are provided in the Appendix (see Tables E.4 and E.5). Sensitivity analyses showed that results from preregistered tests were robust to different RT aggregation and reduction criteria. This is an important issue of replicability as it can be inferred that observed priming effects were not affected by different statistical decisions, that can often be subjective.

4.5.4 Findings from exploratory analyses

Differences between laboratory and online settings

Data quality checks The follow-up study questionnaire included an attention check question (Q6; Kees et al., 2017) and the percentage of correct responses was recorded for both laboratory and online cohorts as a data quality check. Although participants could have been paying attention to the questions, the follow-up questionnaire also included a modified instructional manipulation check (IMC; Q1) to examine whether they had read the instructions before answering the questions. The self-reported number of times participants were interrupted during the APP was also recorded (adapted from Waters & Li, 2008), as distractions in online settings may be a potential limitation for experimental studies involving reaction time tasks. All questionnaire items can be found in Appendix E.4.

Contrary to preconceptions about the potential quality of online data, the percentage of participants who carefully read the instructions on the follow-up study

questionnaire and chose the correct answer on the IMC was higher in the online cohort (M = 86.36, SD = 34.40) rather than the laboratory cohort (M = 76.58, SD = 42.54). It is possible that due to the physical absence of a researcher, online participants actually paid more attention to the instructions. The percentage of participants who answered correctly on the attention check question was very high for both laboratory (M = 94.59, SD = 22.71) and online cohorts (M = 94.95, SD = 21.95). The percentage of participants who reported any self-reported interruptions during the APP, irrespective of the number (e.g., one or two), was also examined and there were no considerable differences observed between the laboratory (M = 27.03, SD = 44.61) and online cohorts (M = 24.75, SD = 43.26). In addition to the data quality checks reported above, online testing was highly precise, as shown by the very low number of exclusions based on error rates (0.019% of participants) and the fact that added noise in the APP data, such as outliers, was not observed (e.g. see dispersion of median RTs in Figures 4.5 and 4.6). Most importantly, results for preregistered confirmatory hypotheses were in the same direction for both cohorts. A schematic of the comparison can be seen in Figure 4.7.

Consequential food choices Another potential limitation of the online testing settings was the fact that the FCT did not involve offering participants food items for consumption, which meant that impulsive food choices were not consequential. Both descriptively and statistically, this did not lead to differences in the findings from confirmatory analyses (H4 test results converge between the two samples). Although their choices were not consequential, participants in the online cohort had also very high probabilities of selecting most liked foods on FCT trials where healthy and unhealthy food pairs were presented (see section 4.5.2). However, it was worth exploring whether any differences would be observed for FCT trials where participants had to choose between healthy and unhealthy most liked foods. The distributions of the food choice probabilities for laboratory (N = 111) and online (N = 200) cohorts are presented and discussed further in Figure 4.8.

	Confirmatory hypothesis & test	Laboratory	Online
H1a.	$RT_{con} < RT_{inc}$ for non-food prime trials	Support for H1	Support for H1
H1b.	$ER_{con} < ER_{inc}$ for non-food prime trials	Support for H1	Support for H1
H2a.	$RT_{con} < RT_{inc}$ for food prime trials	Support for H1	Support for H1
H2b.	$RT_{con} < RT_{inc}$ for healthy food prime trials	Support for H1	Support for H1
H2c.	$RT_{con} < RT_{inc}$ for unhealthy food prime trials	Support for H1	Support for H1
H2d.	$\Delta RT_{unhealthy} > \Delta RT_{healthy}$ for most liked foods	Inconclusive	Support for H0
H3a.	$ER_{con} < ER_{inc}$ for food prime trials	Support for H1	Support for H1
H3b.	$ER_{con} < ER_{inc}$ for healthy food prime trials	Support for H1	Support for H1
H3c.	$ER_{con} < ER_{inc}$ for unhealthy food prime trials	Support for H1	Support for H1
H3d.	$\Delta ER_{unhealthy} > \Delta ER_{healthy}$ for most liked foods	Inconclusive	Support for H0
H4a.	$\Delta RT_{healthy}$ for most liked foods positively correlates with p(most liked | healthy)	Support for H0	Support for H0
H4b.	$\Delta RT_{unhealthy}$ for most liked foods positively correlates with p(most liked | unhealthy)	Support for H0	Support for H0
H4c.	$\Delta RT_{unhealthy} - \Delta RT_{healthy}$ for most liked foods positively correlates with p(unhealthy | most liked)	Support for H0	Support for H0

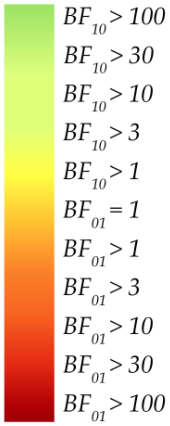


Figure 4.7: Schematic showing the support for confirmatory hypotheses and grades of evidence for laboratory and online cohorts. Grades of evidence based on BF_{10} values have been described in section 4.3.1 and all hypotheses and respective statistical comparisons have been reported in sections 4.2 and 4.4.2 respectively. In the laboratory cohort, H2d and H3d are shown as inconclusive because there was only *anecdotal* evidence for the null (H0) compared to the alternative (H1) in both cases. However, since *nmax* for the laboratory cohort has not yet been reached, it is highly plausible for grades of evidence to converge for both samples when data collection is completed. Overall, the primary findings from the laboratory sample have been successfully replicated in the online sample. *Note.* Evidence for H0 compared to H1 can also be denoted with BF_{01}. For example, *moderate* evidence would be presented as $BF_{01} > 1/3$. $BF_{10} > 3$ and $BF_{01} < 1/3$ indicate support for H1 and H0 respectively. Results were interpreted as inconclusive when the relative evidence for H1 or H0 was *anecdotal*.

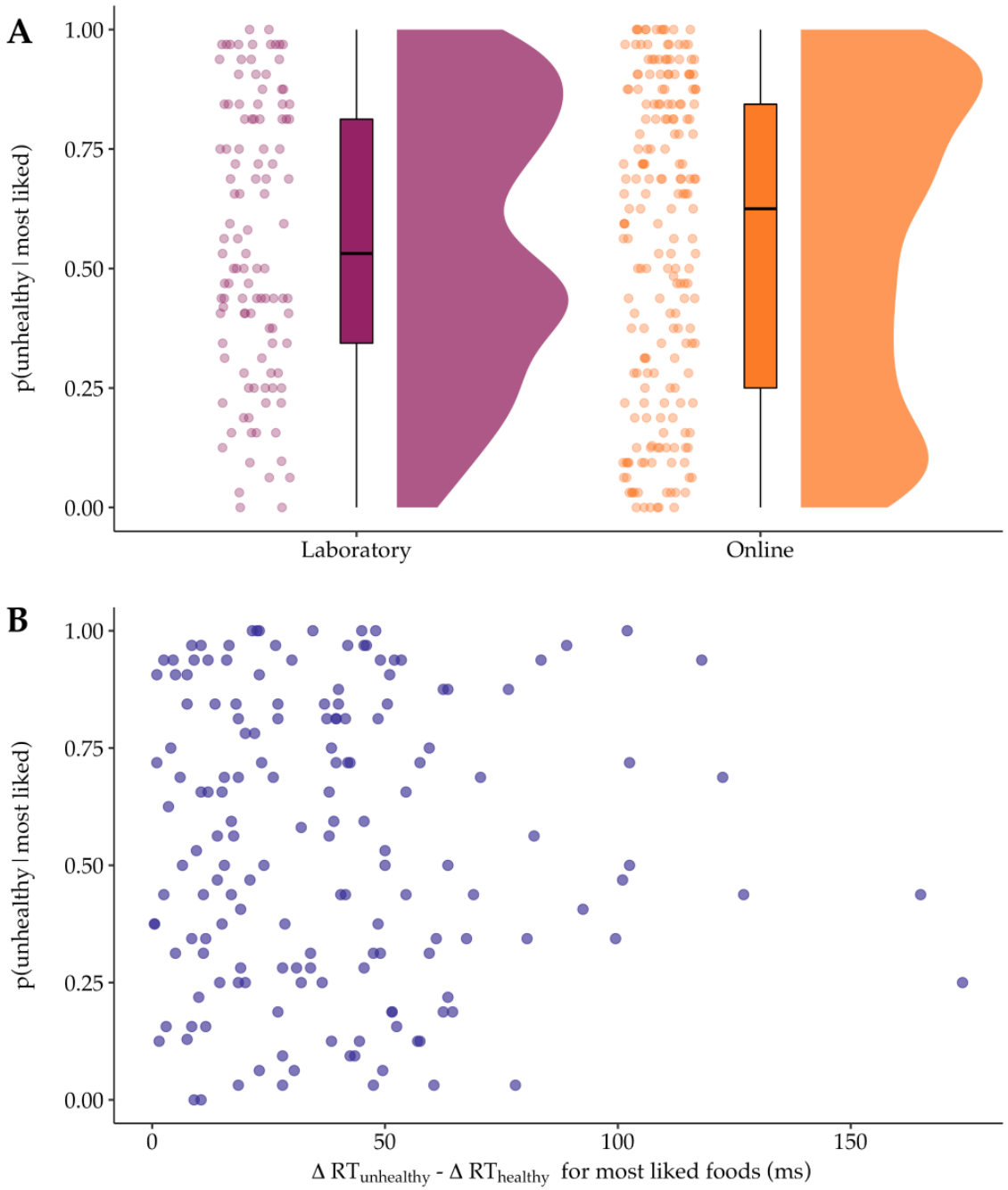


Figure 4.8: Multi-panel plot of p(unhealthy|most liked) distributions for laboratory and online cohorts and sub-group analysis results. A. As previously described (see section 4.4.1), p(unhealthy|most liked) denotes the conditional probability of choosing an unhealthy food in the unhealthy vs healthy food choice trials when most liked food pairs were presented. The probabilities do not follow a normal distribution and there is great variability across participants for both cohorts. However, no clear differences are observed for the two samples, with the exception of a larger cluster of data points below 0.50 for laboratory participants, which may simply be due to unmatched sample sizes. **B.** The sub-group analysis reported in section 4.5.4 revealed that even when the difference between the RT priming effects for unhealthy ($\Delta RT_{unhealthy}$) and healthy most liked foods ($\Delta RT_{unhealthy}$) was positive (> 0), there was no linear correlation between these difference scores (ms) and p(unhealthy|most liked). The sub-group analysis was conducted on merged data from both cohorts (N = 161). *Note.* Individual data points (dots) in panel A have been jittered around the x-axis to avoid overplotting (i.e., multiple overlapping points appearing as one).

Sub-group analysis of food choice behaviour

Confirmatory analyses for the hypothesis that the probability of choosing an unhealthy over a healthy most liked food would positively correlate with the difference in RT priming effects between unhealthy and healthy most liked food prime trials (H4c) showed support for the null compared to the alternative. The difference in RT priming effects was variable in both samples and it was of particular interest to explore whether a linear correlation would be observed when the actual difference was positive. Based on the quality of laboratory and online data as well as the convergence between the results for H4c, the data were merged to increase the sample size for a sub-group analysis. Only participants who had a positive difference score ($\Delta RT_{unhealthy}$ - $\Delta RT_{healthy}$ for most liked food prime trials > 0) were included and the confirmatory statistical tests were repeated. Although the difference in RT priming effects was positive, there was still *strong* evidence for the absence of a positive linear correlation between the difference scores and the probability of choosing an unhealthy food in healthy vs unhealthy trials with most liked food pairs, or p(unhealthy|most liked) [$BF_{10} = 0.077$; ρ = -0.03, $p = 0.630$, 95% CI for ρ = -0.16, 1]. A scatterplot of the individual data points can be seen in Figure 4.8, panel B.

Follow-up study questionnaire results

As mentioned in section 4.3.6, a follow-up study questionnaire was administered at the end of the experiment in order to gather both quantitative and qualitative data regarding issues of awareness and strategic responding in the APP (see Appendix E.4). Please note that validity checks were conducted for all questionnaire responses and participants who were found to provide contradicting responses were excluded from this analysis. For example, on Q7 if a participant responded that they did not use a strategy but also checked one of the other boxes for response strategies, their response was deemed invalid. This validity check was applied to Q2, Q4 and Q7. Participants who had invalid responses in any of these questions were excluded. Participants who did not complete the questionnaire and were excluded from main APP analyses were also not included. The final sample sizes for the results reported in Table 4.4 are 108 and 192 for the laboratory and online cohorts, respectively.

The questionnaire questions and results have been categorised into the following themes: awareness of RT differences (Q2), awareness of prime content (Q3), awareness of affective congruence (Q4), ambivalence of targets (Q5) and response strategies (Q7). Standardised results, excluding open-ended responses, can be found in Table 4.4. An

Table 4.4: Standardized results from the follow-up study questionnaire for laboratory and online cohorts

	Laboratory		Online	
	M	*SD*	*M*	*SD*
Q2. Awareness of RT differences (% selected)				
Faster to categorise positive words	34.26	47.68	23.96	42.79
Faster to categorise negative words	19.44	39.76	14.06	34.85
Faster to categorise words towards the end	21.30	41.13	21.35	41.09
Slower to categorise positive words	6.48	24.73	10.42	30.63
Slower to categorise negative words	22.22	41.77	15.10	35.90
No differences observed	26.85	44.53	42.71	49.59
Q3. Awareness of prime content (1-7)	5.32	1.51	5.63	1.46
1="Never", 4="Occasionally", 7="Always"				
Q4. Awareness of affective congruence (% selected)				
Faster with positive prime-target pairs	65.74	47.68	30.21	46.04
Faster with negative prime-target pairs	40.74	49.36	14.58	35.39
Slower with negative prime-positive target pairs	37.04	48.52	17.71	38.27
Slower with positive prime-negative target pairs	42.59	49.68	20.83	40.72
Responses were not influenced by prime content	21.30	41.13	53.12	50.03
Q5. Ambivalence of targets (% Yes)	67.59	47.02	62.50	48.54
Yes- all words clearly positive or negative				
Q7. Response strategies (% selected)				
Slowed down to be more accurate	25.00	43.50	10.42	30.63
Responded consistently fast, ignoring errors	30.56	46.28	17.71	38.27
No strategy used	46.30	50.10	72.40	44.82

Note. For checkbox questions (Q2, Q4, Q7), participants could select all answers that apply, such as for awareness of affective congruence they could notice they were faster with positive prime-target pairs as well as slower with positive prime-negative target pairs.

important comparison regarding these outcomes is whether the participants in the laboratory cohort had a greater awareness of the task design in general compared to participants recruited from the general population online via Prolific. Recruitment for the laboratory cohort primarily depended on undergraduate students from the School of Psychology at Cardiff University. Although experimental testing in the laboratory may have higher precision compared to online testing, which was not the case in this study, it is also possible for the laboratory sample to show greater bias and demand characteristics in their responses, especially in the presence of a researcher.

The findings presented in Table 4.4 corroborate this assumption, as on average participants in the laboratory cohort were more aware of reaction time differences for types of targets and the effects of affective congruence on their performance for different trial types. For example, 53.12% of participants in the online cohort reported that they believed their responses were not influenced by the content of the pictures (i.e., primes) on Q4, while only 21.30% of participants who completed the study in the laboratory reported their performance was not influenced by the primes. In the laboratory cohort, participants were also more aware of different trial types (affective congruence design cells) with more than 36% selecting all options on Q4. Also, in the online cohort 72.40% of participants reported that they did not purposefully use any kind of strategy to make their responses faster and/or more accurate. The ambivalence of targets which were included in the APP was another issue that was examined using self-reports and for both laboratory and online cohorts many participants indicated that some words were either positive or negative depending on context (e.g. *alone*, *brave*) and that certain words were neutral (e.g., *travel*) or less positive due to personal experiences (e.g., *party*, *hope*) or religious associations (e.g., *heaven*, *angel*). Pooled valence ratings from both cohorts for positive and negative targets can be found in the Appendix (see Figure E.2).

4.6 Discussion

The primary aim of this study was to assess the utility of the affective priming paradigm (APP) as an indirect measure of food liking and related choice behaviour. In a variant of the APP which requires evaluative categorisations that are not semantically related to the content of the primes, participants responded as quickly and as accurately as possible to the valence of word targets. Affective congruence was manipulated so that both healthy and unhealthy foods that have been selected as most liked or least liked via an initial rating task were paired with both positive and negative targets. After the APP, participants completed a binary food choice task (FCT) and impulsive food choice probabilities for different food pairs were measured. The three main research questions of the study were tested via several preregistered confirmatory hypotheses in laboratory settings and replicated in a second cohort of participants who completed the experiment online. The findings for each of these research questions and their implications are discussed at length below, together with recommendations and directions for future research.

4.6.1 Can reliable priming effects for foods be obtained with the APP?

In line with previous findings (e.g., Lamote et al., 2004), reliable priming effects were observed across food prime trials (most liked and least liked foods) for both speed (RTs) and accuracy (ERs). Effects were also shown to be robust for both healthy and unhealthy foods (see Figure 4.6), which were pre-assigned to these categories based on their nutritional characteristics. Participants' individual ratings for all primes corroborated this classification as on average healthy and unhealthy foods were rated appropriately on a 'perceived healthiness' scale. There was conclusive evidence that the APP can be used as an indirect measure of liking for both healthy and unhealthy foods. The interpretation of the findings was strengthened by the success of the manipulation check for the APP, which assessed priming effects for most liked non-food stimuli. Importantly, all results from the laboratory cohort (N = 112) were directly replicated in the online cohort (N = 202). Statistical tests were repeated under different data aggregation/reduction criteria adopted from previous literature (Lamote et al., 2004; Verhulst et al., 2006) in order establish the robustness of the observed priming effects. There were no discrepancies between the results based on the preregistered analysis plan and the alternative analyses, which may suggest that findings were not influenced by the aggregation and outlier removal criteria employed in this study.

4.6.2 Is the APP sensitive to cognitive components of food attitudes?

The differences in priming effects (RTs and ERs) for most liked healthy and unhealthy food primes were investigated to examine whether unhealthy foods are associated with stronger affective reactions as measured by the APP. Contrary to initial predictions, in both laboratory and online cohorts there was no support for the hypotheses that RT and ER priming effects were greater for unhealthy compared to healthy most liked food primes. Previous studies have yielded mixed evidence regarding the sensitivity of the APP in capturing cognitive components of food attitudes, such as the healthiness of the foods. For example, our findings are consistent with the study by Becker et al. (2015), where the authors did not report any differences for the food prime contrasts (healthy, unhealthy, control) in their affective priming paradigm (Study 2). Similarly, Roefs et al. (2005) provided evidence for a priming effect for palatable (most liked) and unpalatable (least liked) foods, but found that fat content (low-fat or

high-fat) did not seem to influence the results. However, Roefs, Stapert, et al. (2005) (Experiment 2) suggested that health concerns may have determined observed priming effects in two groups of participants who differed in terms of BMI and dietary restraint (obese/restrained individuals and normal-weight/unrestrained controls). Specifically, participants in both groups showed a 'preference' for low-fat over high-fat foods. While the interaction between prime fat content and target affect (positive vs negative) for palatable foods was not strong enough to contradict the present findings ($\eta^2 = 0.05$, $p = 0.09$), this study raised an important issue for both methodology and theory regarding the APP as an indirect measure of attitudes that needs to be explored further.

4.6.3 Are priming effects associated with impulsive food choice behaviour?

A novel contribution of this study was the investigation of impulsive food choices using a binary reaction time task, adapted from previous literature (Veling, Chen, et al., 2017; Zoltak et al., 2018). Food liking has a paramount role in dietary choices, which are often impulsive and not guided by deliberate thoughts (Eertmans et al., 2001; Veling, Chen, et al., 2017). If positive affective reactions towards foods can influence impulsive food choices (Zoltak et al., 2018), priming effects obtained via the APP could in theory be associated with the probability of choosing appetitive foods under different conditions, such as choosing a most liked unhealthy food when most liked and least liked foods are presented. Confirmatory analyses provided conclusive evidence for the absence of positive linear correlations between RT priming effects for most liked foods and the probability of choosing a most liked food for both healthy and unhealthy foods. These null findings were replicated in the online cohort. An even more meaningful relationship that was examined was whether the difference between RT priming effects for most liked healthy and unhealthy foods was associated with the probability of choosing an unhealthy food in trials where most liked healthy and unhealthy foods were presented. Again, there was strong support for the null hypothesis compared to the alternative in both laboratory and online cohorts. An exploratory sub-group analysis was also conducted in order to establish whether the absence of a correlation was due to the fact that only a proportion of participants had a greater RT priming effect for most liked unhealthy foods. Interestingly, there was still no evidence for a correlation between the RT difference scores and food choice probabilities.

4.6.4 Experimental design & recommendations

Findings presented here have shown that selected APP design parameters may be important for the robustness and replicability of the observed food priming effects. The paradigm employed in this study was developed via a series of pilot experiments (see Appendix D), which yielded a number of design recommendations. For example, the number of positive and negative targets was increased to allow for the presentation of half the targets in alternating blocks (see section 4.3.3). This design parameter aimed to minimise the possibility of practice effects, which would not only affect performance in the APP (e.g., ceiling effect after several blocks of trials), but also represent a theoretical confound for the interpretation of observed priming effects if responses to targets were simply retrieved from memory and were not influenced by the primes. Although the observed priming effects in this study could be attributed to either a *response* or *encoding* theoretical account (Fazio, 2001; Herring et al., 2013), the standardized follow-up study questionnaire results showed that many participants were aware of the effects of affective congruence on their performance. For example, they believed that the content of the picture influenced their performance when the word they had to categorise was negative and the preceding picture depicted a food they liked the most. In addition to APP performance, potential confounds for primes and targets should be taken into account. Even in cases where robust priming effects fail to be obtained, participants' individual explicit ratings of target valence and prime characteristics can have substantial diagnostic value and provide the basis for the investigation of individual differences. To bridge the gap between explicit and implicit measures of food attitudes, it may be worth pursuing the use of semi-structured questionnaires that measure participants' subjective awareness of performance differences in critical trials (e.g., congruent vs incongruent in the APP) as well as tailored stimulus selection (e.g., selecting primes via an initial rating task). Exploratory analyses also indicated that data from laboratory and online settings did not differ in terms of quality and precision (see section 4.5.4). On the contrary, it is possible that participants in laboratory studies are more aware of experimental procedures, which could lead to increased bias in responses (e.g., demand characteristics). If data quality assurance measures are in place for online testing settings, this is an avenue for data collection that should be followed in studies which require large sample sizes and/or direct replications.

4.6.5 Considerations for future research

The majority of participants in both laboratory and online cohorts were healthy-weight individuals with self-reported frequency and intensity of food craving experiences (i.e., trait food cravings represented by the FCQ-T-r total score) that could not indicate unhealthy eating behaviours, such as binge-eating (Meule, 2018). It is possible that the absence of differences between RT priming effects for most liked healthy and unhealthy foods was due to the fact that participants, on average, did not have stronger affective, or hedonic, reactions towards unhealthy foods. In order to establish whether the APP is sensitive to this cognitive of component of food attitudes, this research question should be addressed in a sample of individuals that are overweight and/or obese, or show higher eating disorder pathology. In such cases, the distinction between cognitive and affective components of food attitudes may be more informative due to increased approach and/or attentional bias towards appetitive cues and the conflict of this bias with health-related goals, such as losing weight (Kakoschke et al., 2015). Accordingly, impulsive food choices that are driven by strong affective reactions towards unhealthy foods should be examined further in a representative sample of individuals that exhibit unhealthy eating behaviours, such as overeating. The present study has shed light into the utility of the affective priming paradigm as an indirect measure of food liking and provided a direct replication of observed priming effects for both speed and accuracy outcomes. The next step in this line of research would be to employ different variants of the APP in an effort to disentangle theoretical explanations of priming effects (e.g., pronounciation task; see Herring et al., 2013 for discussion) and attempt to replicate and extend the presented findings in different samples (e.g., overweight individuals).

Chapter 5

Does go/no-go training lead to food devaluation when indirectly measured via the affective priming paradigm?

5.1 Introduction

Inhibitory control training (ICT) can have potential therapeutic applications for health outcomes related to obesity and unhealthy eating behaviours (Jones et al., 2016, 2018) and current evidence suggests that food-specific go/no-go (GNG) training paradigms produce larger effects compared to stop-signal paradigms (e.g., Allom et al., 2016). Stimulus devaluation has been receiving increasing attention as a potential mechanism behind GNG training outcomes for both healthy-weight and obese individuals (e.g., Chen, Veling, et al., 2018; Chen et al., 2018; Veling et al., 2013a). Although several studies have reported robust devaluation effects for unhealthy no-go foods when these are measured with visual analogue scales (e.g., Chen et al., 2016, 2018), explicit evaluations are limited to self-reports which can be affected by demand characteristics (Podsakoff et al., 2003). However, a meta-analysis has shown that overall ICT did not lead to reduced evaluations of appetitive cues, such as foods and alcohol, when these were assessed with implicit, or indirect measures (Jones et al., 2016). The current study investigated whether food-specific GNG training can reduce positive evaluations for foods associated with response inhibition (no-go) compared to foods presented on go trials and food stimuli that were never included in training (cf. Chen et al.,

2016). Importantly, the study extends previous findings on explicit evaluations to assess whether training can have an effect on implicit food evaluations, when these are measured via the affective priming paradigm (APP; Fazio et al., 1986; Fazio & Olson, 2003; Hermans et al., 2001; Klauer & Musch, 2003).

There are several theoretical accounts which can explain the no-go devaluation effects in ICT studies, for which in-depth description has been provided in section 1.6.3. A prominent explanation that has received considerable support in recent studies is the Behaviour Stimulus Interaction (BSI) theory (Chen et al., 2016; Veling et al., 2008) which posits that devaluation occurs as a result of an ongoing conflict between automatic approach tendencies towards appetitive foods and the requirement for response inhibition on no-go/signal trials. The conflict can be resolved to a certain extent if the appetitive value of the no-go food stimuli is reduced during training. In a series of experiments, Chen et al. (2016) provided strong evidence for this account and showed that no-go devaluation effects may be the result of active response inhibition, regardless of whether an explicit cue is presented on no-go trials (Experiments 1 to 3), and that the proportion of no-go trials is central to observed devaluation effects (Experiments 4a and 4b). In a later study, however, Chen et al. (2018) reported findings that did not support the BSI theory. Devaluation effects were observed for both high-rated (i.e., highly appetitive) and low-rated food items, which may mean that an initial approach tendency for the foods is not needed for devaluation to occur, and the authors found that individuals with lower inhibition capacity did not show a larger devaluation effect. If the conflict between approach tendencies towards appetitive (no-go) foods and response inhibition induces negative affect (Dreisbach & Fischer, 2015; Veling et al., 2008) that later manifests as reduced explicit evaluations of these foods, it would be theoretically sound to assume that a no-go devaluation effect should also be observed for implicit evaluations. However, even in the absence of response conflict signal (BSI theory), a 'pure devaluation-by-inhibition' account would predict that response inhibition alone may have "negative affective consequences" (see Chen et al., 2018, p. 108), which could in theory be observed in APP performance. For example, negative affect could be attached to no-go food stimuli via the learned stimulus-stop associations during training if there is a hard-wired mutually excitatory connection between a 'stop' system and the Pavlovian aversive centre (Verbruggen et al., 2014a).

The meta-analysis by Jones et al. (2016) did not provide evidence for ICT devaluation effects for a range of appetitive cues, such as alcohol, tobacco and foods, but there was only a limited number of studies that examined food devaluation effects

and the authors report that there may be a methodological issue to consider, as most studies used variants of the implicit association test (Greenwald et al., 1998). For example, Adams et al. (2017) employed two unipolar, single-category IATs (SC-IATs) with chocolate images (trained vs untrained items) and found no effects of stop-signal task training on implicit food attitudes relative to double-response training (Study 1). Participants showed positive implicit attitudes for chocolate in the pleasant (positive) SC-IAT, but there was no interaction between training condition and SC-IAT measures. In IAT variants such as the SC-IATs reported in Adams et al. (2017), stimuli from a target category (e.g., chocolate) appear on the screen with two labels such as 'pleasant' vs 'neutral' (or 'unpleasant' vs 'neutral' in the negative SC-IAT) and participants have to categorise presented words as quickly and as accurately as possible, with different pairings of labels and attribute categories on subsequent blocks (e.g., 'chocolate + pleasant' vs 'neutral'; also see section 1.3.1). Although the IAT assumes automatic, or implicit, evaluations are captured due to the strict time constraints, the labels may alert participants to the aims of the task and increase the possibility of strategic responding (De Houwer et al., 2009; Fazio & Olson, 2003). Interpretations of IAT results may also be confounded by the fact that performance can be an outcome of the evaluation of category labels instead of stimulus-specific evaluations (De Houwer, 2001; as cited by Becker et al., 2015).

In contrast to the IAT, the evaluative categorisation variant of the APP requires participants to respond as quickly and as accurately as possible to the valence of the words (targets) which are not semantically relevant to the primes (e.g., food pictures) and instructions encourage participants to ignore the pictures and their content altogether. The primes are also presented for a very short duration (e.g., 233ms, as described in section 4.3.3). Evidence for the utility of the APP as an indirect measure of food evaluations, or liking, has been provided by previous studies (e.g., Lamote et al., 2004; Roefs et al., 2005; Roefs, Stapert, et al., 2005) and presented in a series of experiments for paradigm development in this thesis (see Appendix D), including a preregistered laboratory study with findings that were directly replicated in a second online cohort (Chapter 4). There is not enough evidence, however, to suggest that the APP can capture differences in the strength of the evaluations, also known as prime/attitude extremity (Herring et al., 2013), and in the food domain, it has been suggested that the strength of priming effects may not be moderated by how strongly people like the presented food primes, as long as they are positive in valence (Lamote et al., 2004). Nevertheless, Verhulst et al. (2006) indicated that the APP can successfully measure food attitudes when these had been recently acquired in a lab

setting via an evaluative conditioning procedure aimed to increase sensory liking for selected foods (i.e., cookies). Together these findings suggest that the application of the APP as an indirect measure of food devaluation effects would need to be examined further.

In order to investigate whether the no-go devaluation effect can be observed on a more automatic level of processing (i.e., implicit evaluations, or attitudes), as measured by the APP, it is crucial to test whether the GNG training paradigm leads to reduced positive evaluations of no-go foods. The GNG task design for the present study was adapted by Chen et al. (2016), in which auditory cues (signals) were paired with both go and no-go responses (see Figure 5.3.3) and food stimuli were matched on attractiveness ratings in the beginning of the study[1]. Foods with the highest evaluations were selected and the no-go devaluation effect was defined as a negative change in evaluations for no-go food items compared to both go food items and food items that were never included in training (i.e., untrained). These two baselines serve to strengthen the functional specificity of any observed effects, as devaluation of no-go foods compared only to go foods may be attributed to an increased evaluation of go foods after training, while devaluation of no-go foods relative to untrained foods alone could simply be explained by other task characteristics, such as tediousness (Chen et al., 2016).

This preregistered study aimed to investigate whether go/no-go training would lead to a robust no-go devaluation effect by measuring explicit evaluations before and after training for go, no-go and untrained food items, which would indirectly replicate previous findings (e.g., Chen et al., 2016). A novel contribution of this study was the examination of a no-go devaluation effect via the APP as an indirect measure of liking. Implicit[2] food evaluations were assessed via observed reaction time (RT) priming effects. On average, the RT priming effect for no-go foods was expected to be reduced compared to the RT priming effects for go and untrained food items.

[1]The task design was adapted from Experiment 1 of Chen et al. (2016), which also included no-cue trials to assess whether the devaluation effect would be affected by the lack of a no-go cue. In Experiments 1 and 3 authors showed that the devaluation effect is observed irrespective of a no-go cue. This element has been discarded from the GNG paradigm employed in this study.

[2]The term 'implicit' has been avoided in previous work (see section 4.1), as there is no conclusive evidence to suggest that the APP measures unconscious (implicit) affective reactions towards attitude objects, such as foods. The term is used throughout this Chapter to provide a clear distinction between food liking measures (explicit ratings vs APP) and assist in the interpretation of findings.

5.2 Hypotheses

This study tested several confirmatory hypotheses regarding the effects of go/no-go training on explicit and implicit food evaluations[3]. In line with previous literature (e.g., Chen et al., 2016; Veling et al., 2013a), go/no-go training was expected to lead to stimulus devaluation for foods associated with response inhibition during training. The devaluation effect was defined as a negative change in liking from pre-to post-training for two contrasts with different baselines, as reported in Chen et al. (2016). The mean change in explicit evaluations for no-go foods would be compared to the mean change for go foods and untrained foods. The change in explicit evaluations for different training conditions (go, no-go, untrained) was examined using difference scores (mean post-training ratings - mean pre-training ratings), whereby a negative score would indicate participants' evaluations decreased after training. Implicit food evaluations were defined based on the reaction time (RT) priming effects obtained via the APP as an implicit, or indirect, measure of food liking. Priming effect calculations are thoroughly explained in section 5.4.1.

H1. Training would have an effect on *explicit* food evaluations

H1a. The change in liking ratings from pre-to post-training would be negative for *no-go* foods and greater in magnitude compared to the change in liking ratings for *go* foods.

H1b. The change in liking ratings from pre-to post-training would be negative for *no-go* foods and greater in magnitude compared to the change in liking ratings for *untrained* foods.

A novel research question of the study was whether devaluation effects could be observed in terms of food priming effects when the affective priming paradigm was employed as an indirect measure of (food) liking. RT priming effects were calculated using median RTs on correct congruent and incongruent trials for each participant (incongruent − congruent) and then the sample means of the difference scores were

[3]**Note.** This study was used in a practical assignment for Second Year undergraduate students as part of the *Emotion & Consciousness* module in BSc Psychology at Cardiff University. The study was exclusively designed by me, but in order to allow for students' contributions they were encouraged to add a number of questionnaires from a recommended set of measures to the end of the experiment and test their own hypotheses (see section 5.3.8). The study was preregistered on the Open Science Framework (https://osf.io/c6z53).

compared across training conditions (see section 5.4.1).

H2. Training would have an effect on *implicit* food evaluations

H2a. The RT priming effect for *no-go* foods would be reduced compared to the RT priming effect for *go* foods.

H2b. The RT priming effect for *no-go* foods would be reduced compared to the RT priming effect for *untrained* foods.

The study included a manipulation check for the APP (H3), as previously employed in Chapter 4, whereby RT priming effects should be observed for positive non-food stimuli.

H3. Correct RTs on congruent trials would be on average lower compared to correct RTs on incongruent non-food prime trials.

5.3 Methods

5.3.1 Participants

A total of 150 participants were recruited via Prolific[4] (https://www.prolific.ac/) and personal communication[5]. Participants recruited via Prolific received £4.50 as reimbursement. Participants recruited outside Prolific were asked to contact the lead researcher if they wanted to enter a prize draw for a £15 Amazon voucher, which would be randomly awarded to 1 in 40 individuals. The study was approved by the local Research Ethics Committee at the School of Psychology, Cardiff University. Participants were aware of the inclusion and exclusion criteria for the study, but were also screened for eligibility via an initial short survey. Participants had to be at least 18 years old and speak English as their first or second language. They also had to report no major hearing impairments that would prevent them from hearing tones presented in the study and have normal or corrected-to-normal vision, including normal colour vision. Participants were excluded if they had a past and/or current

[4]Pre-screening criteria on Prolific specified that only individuals currently residing in the UK could participate, as the foods included in the study might not have been popular outside the UK.

[5]The data collection for this study was partially undertaken by undergraduate students from the School of Psychology, Cardiff University, who advertised the study to individuals from the general population.

history of eating disorders or reported that, at the time of the study, they were dieting with the goal to lose weight and/or taking diet pills. Fourteen drop-outs were recorded during online recruitment and twenty individuals were not eligible to participate (see section 5.5.1).

5.3.2 Sampling plan

The study employed an open-ended Sequential Bayes Factor (SBF) design (Schönbrodt et al., 2017) with a maximum sample size (*nmax*) of 130 and a minimum sample size (*nmin*) of 50. Data collection would continue until either the selected evidential threshold for preregistered hypotheses had been reached, or *nmax* had been met. The grades of evidence in terms of Bayes Factor (BF) values followed the guidelines by Lee & Wagenmakers (2013). A threshold of $BF_{10} \geq 10$ would indicate *strong* evidence for the alternative hypothesis (H1) compared to the null and a threshold of $BF_{01} \geq 10$ would reflect *strong* evidence for the null hypothesis (H0) compared to the alternative. The stopping rule for BF thresholds was applied only to preregistered hypotheses (H1, H2, H3). The data was inspected for every 20 participants, after *nmin* had been reached, and complementary frequentist statistical tests ($\alpha = 0.005$) were only conducted after data collection had been terminated. It should be noted that only the Bayesian analyses would inform the conclusions of the study. Consistent with previous work (see Chapter 4), Bayes Factor Design Analysis (BFDA; Schönbrodt & Wagenmakers, 2018) was performed to assess the probability of the proposed SBF design generating misleading evidence for the primary hypotheses (see Figure 5.1). The BFDA package from Schönbrodt & Stefan (2018) was used and the code is available at https://osf.io/s6wh5/. For BFDA simulations, the design prior was the same as the planned analysis prior ($\sqrt{2}/2$; see section 5.4.2).

5.3.3 Procedure

Participants were initially screened for eligibility, provided their consent and proceeded to adjusting the volume at which the tones (cues) for the go/no-go training task would be presented (see Figure 5.2, panel A). An initial explicit evaluation task was performed in order to select the most appetitive foods for the training paradigm (go, no-go foods; see section 5.3.4) and APP (untrained foods). Liking ratings at baseline were also used to record the change in liking from pre-to post-training (see section 5.4). Participants then rated non-food stimuli and the most liked categories were used in the non-food prime APP blocks (manipulation check; see section 5.3.6). During the

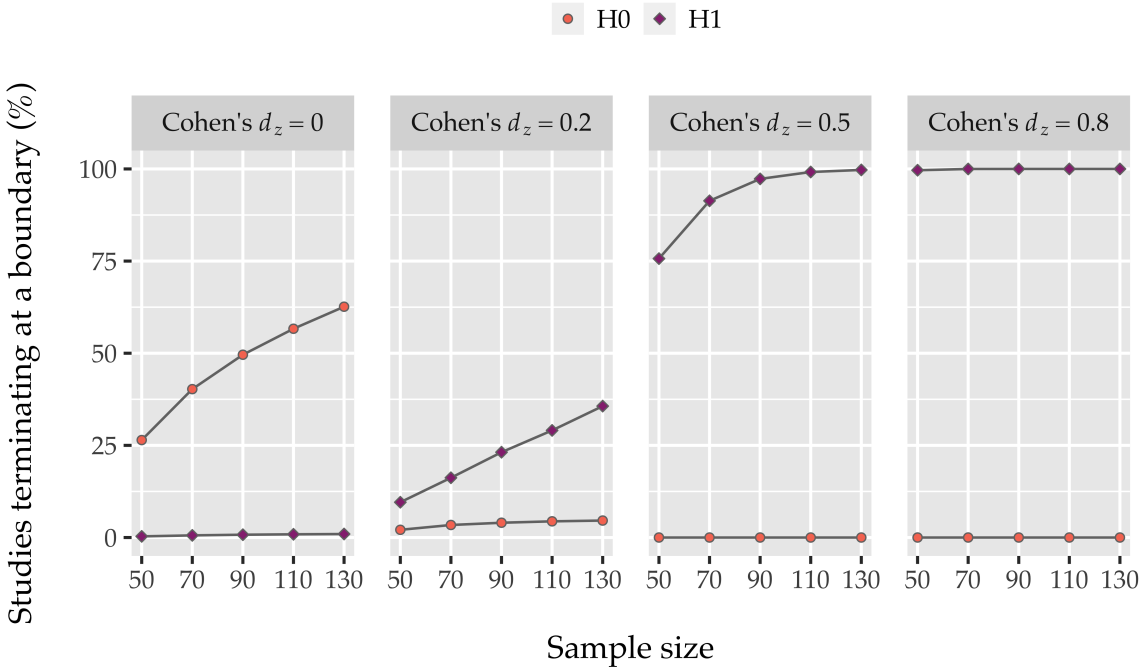


Figure 5.1: Bayes Factor Design Analysis (BFDA) results for H0 and H1 at expected sample sizes and effect sizes in a simulated sequential design. For the planned directional Bayesian paired-samples t-tests (H1-H3), we examined the probabilities of simulated studies (10000) terminating at either the H1 or H0 boundary when the specified evidential threshold is reached ($BF_{10} \geq 10$ or $BF_{01} \geq 10$). Simulations were run for the sample sizes of 50 (*nmin*), 70, 90, 110 and 130 (*nmax*) and different expected true effect sizes were incorporated in the design. As given by Cohen's *dz*, the effect sizes were either zero (i.e., H0 is true), 'small' ($dz = 0.2$), 'medium' ($dz = 0.5$) and 'large' ($dz = 0.8$). 62.62% of all simulated studies correctly terminate at the H0 boundary when *nmax* is reached and the probability of obtaining false positive evidence (FPE) is low, with only 0.95% of studies incorrectly terminating at the H1 boundary. At *nmax*, assuming a small true effect size, only 35.65% of studies correctly terminate at the H1 boundary and 4.6% of studies incorrectly stop at H0. However, for a medium effect size, results show that 99.73% of studies correctly terminate at H1 and no studies reach the H0 boundary at the specified evidential threshold (0%). For an assumed large true effect size, at a sample of 70, 99.99% of studies correctly terminate at H1.

training phase of the study, participants performed eight blocks of the GNG training task with a short practice block in the beginning (see section 5.3.5). After training completion, the APP and explicit evaluation task (i.e., food ratings) were presented in a counterbalanced order across participants. Food prime (APP_{food}) and non-food prime APP blocks ($APP_{non\text{-}food}$) were presented in a fixed order, whereby a non-food prime block was always followed by two food prime blocks. A short practice block was also provided for the APP. In the explicit evaluation task after training, participants rated all foods (go, no-go, untrained) with a total of 24 trials. At the end of the study, several questionnaire measures were completed (see section 5.3.8). The study was run via Inquisit Web and was programmed using Inquisit Lab 5 (Millisecond Software,

2017).

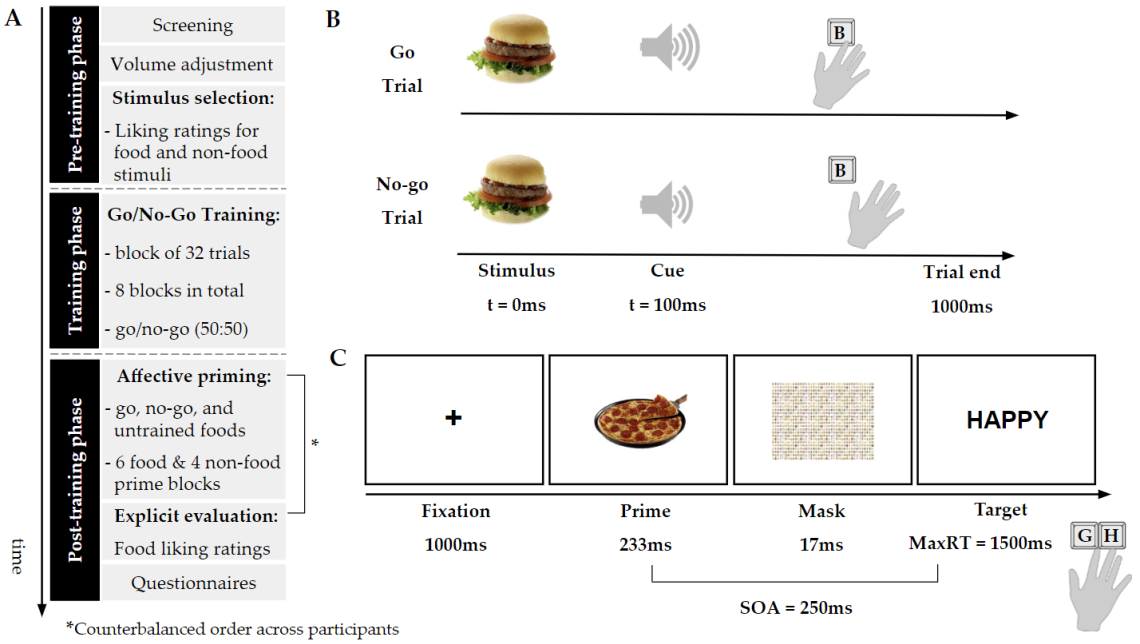


Figure 5.2: Schematic diagram of the study procedure, go/no-go training task and affective priming paradigm. A. Participants were initially screened for eligibility and adjusted the volume at which they would hear the tones (cues) during training. In the pre-training phase, they also provided liking ratings for food and non-food stimuli and stimuli were selected for training and the affective priming paradigm (go, no-go and untrained foods). Participants performed eight blocks of the go/no-go training task in total and in each block of 32 trials, go and no-go foods appeared with equal probability (50:50). In the post-training phase, the affective priming paradigm (APP) and food ratings were presented in counterbalanced order across participants. The APP consisted of both food and non-food prime blocks, presented in a fixed order (see section 5.3.6) and food prime blocks included go, no-go and untrained foods. For the explicit evaluation of foods, participants provided liking ratings and at the end of the study several questionnaires were completed. **B.** In the go/no-go training task, participants were asked to press "B" to respond on trials where a specific cue (tone) was presented (i.e., no-signal, or go trial). When another cue was heard, participants had to refrain from responding (i.e., signal, or no-go trial). The cues, which were randomly assigned to trial types across participants, were presented 100ms after stimulus onset and lasted 300ms. The trial duration was fixed to 1000ms. **C.** In the APP, participants responded to positive and negative targets by pressing the "G" and "H" keys (counterbalanced) which were preceded by food and non-food primes. The maximum reaction time (maxRT) was 1500ms and the stimulus-onset asynchrony (SOA) between primes and targets was 250ms, including the mask duration (17ms).

5.3.4 Stimulus selection

In an initial explicit evaluation task, participants were presented with 50 unhealthy foods in random order. They rated the foods according to how much they liked them at the time ("How much do you like this food right now?") on a visual analogue scale (VAS) ranging from -100 to 100, always centered at zero. The values on the VAS were not visible to the participants. The foods with the highest ratings were ranked from 1

to 24 and were assigned to three sets of eight foods, in a manner that ensures that the average explicit liking values are as matched as possible for all sets (cf. Chen et al., 2016). These sets of stimuli were then randomly selected as go, no-go or untrained foods. Each food category was represented by two exemplars.

Following the evaluation of all foods, participants were presented with 25 positive non-food stimuli (e.g., kittens) and were asked to rate how much they like them ("How much do you like this image?"). The stimuli with the maximum rating were assigned as primes in the non-food prime APP blocks (N = 12; see section 5.3.6). There were two exemplars per non-food category. Stimuli for the study have been obtained from the food-pics database (Blechert, 2019; Blechert et al., 2014) and other sources (see Appendix F.1).

5.3.5 Go/No-Go training

The ICT paradigm employed in this study was go/no-go (GNG) training using a task adapted from Chen et al. (2016). In GNG training, participants are either required to respond to (food) stimuli (i.e., go trials) or inhibit their responses (i.e., no-go trials) towards them. In this task, go and no-go trials appeared with equal probability (50% no-go) and each trial begun with the central presentation of a food stimulus, which was followed by a cue at 100ms (see Figure 5.2, panel B). The auditory cue was either a 440Hz or 1000Hz tone presented for 300ms and was randomly assigned to either go or no-go trials across participants. In order to ensure that all participants could hear the tones properly, in the beginning of the study they were asked to adjust the volume at which the tones would be played and the volume, which could be different for each tone, was changed automatically via the programmed script. Responses on each trial were determined by the assigned cue (tone). On go trials, participants needed to press the "B" key using their index finger as fast as possible after cue onset and on no-go trials, they were instructed not to respond at all. The food stimulus remained on the screen for the total trial duration (i.e., 1000ms) in order to control for visual exposure time within and across participants. The inter-trial interval (ITI) randomly varied from 800ms to 1500ms, in intervals of 100ms. This was a deviation from the task design adapted by Chen et al. (2016) aimed to slightly reduce the total duration of the GNG task for online data collection.

Each GNG training block consisted of 32 trials and participants performed eight blocks in total (256 trials). As described in section 5.3.4, randomly assigned unhealthy foods were presented on go and no-go trials, with two exemplars for each food category.

Therefore, each food category had 16 repetitions across blocks and specific exemplars were repeated eight times in total. A practice block (16 trials) was provided before the experimental blocks and accuracy feedback appeared after each trial. Foods that had been discarded during the stimulus selection process were used as stimuli in practice trials. The screen background was white and food stimuli had relative dimensions according to the participant's display resolution (40% width × 40% height). A short break was provided after four blocks of training.

5.3.6 Affective priming

The affective priming paradigm (APP) was adapted from the study presented in Chapter 4. It involved an evaluative categorisation task, in which participants had to categorise words (i.e., targets) as either positive or negative, as fast and as accurately as possible, when these were preceded by food stimuli (i.e., primes). The primes were presented supraliminally with a stimulus-onset-asynchrony (SOA) of 250 ms, as shown in Figure 5.2 (panel B). All food primes were considered positively valenced and therefore affective congruence in the APP was defined as follows; trials in which primes were paired with a positive target were congruent and trials with negative targets were incongruent. In each trial, participants were asked to focus on a central fixation point (1000ms) and the prime was presented for 233ms. The prime was masked (17ms) and the target then stayed on the screen for the maximum reaction time (maxRT) of 1500ms. The response keys "G" and "H" were randomly assigned to positive and negative categories across participants. Participants had to respond with the index and middle fingers of their preferred or dominant hand. A response was considered correct if participants categorised the target correctly before maxRT was reached. RTs were recorded from prime onset, at 1250ms, and each trial ended either when a response was registered or the total trial duration was reached (i.e., 2750ms).

Each APP block consisted of 48 trials and participants completed six blocks in total. All food categories for each training condition were included and represented by two exemplars, which were randomly assigned to interleaving blocks to be paired with either positive or negative targets. For example, in block one the first exemplar of a go food category was paired with a positive target and the second with a negative target, whereas in block two this assignment was reversed. This ensured that both exemplars of a food category were presented as primes in both congruent (positive target) and incongruent trials (negative target). There were 16 go, 16 no-go and 16 untrained food prime trials in each block. The APP include 24 positive and 24 negative targets which

had been selected based on two criteria: they had the highest valence ratings from an existing dataset (N = 84; see Appendix F.2) and they could be "unambiguously" categorised (Wentura & Degner, 2010).

In addition to the critical APP blocks (APP_{food}), a manipulation check for the task as an indirect measure of liking was employed, as already presented in Chapter 4 and the series of pilot experiments (see Appendix D). In four blocks of 24 trials, non-food stimuli that had the highest liking rating were assigned as primes and were paired with either positive (congruent) or negative targets (incongruent). All targets appeared randomly across consecutive blocks. For non-food primes, there was a total of 48 observations per design cell (i.e., affective congruence). The non-food prime blocks ($APP_{non\text{-}food}$) were presented in between two food prime APP blocks and the order was fixed across participants: one $APP_{non\text{-}food}$ block, two APP_{food} blocks, one $APP_{non\text{-}food}$ block, ..., one $APP_{non\text{-}food}$ block. The screen background for the APP was white consistent with the GNG task design and all words were capitalised. Participants completed 16 practice trials and the primes were foods that had not been assigned to an experimental set during stimulus selection. Feedback was provided for both speed and accuracy. After three APP blocks participants received a short break and were reminded of the main task instructions and response key assignments (two breaks in total).

5.3.7 Explicit evaluation

Participants rated all foods from the go, no-go and untrained conditions after training and food categories were represented by the same exemplars from the initial explicit evaluation task. Food stimuli were presented in random order. Instructions for participants highlighted that some pictures may be the same as in the first rating task, but they should indicate how much they liked them at that specific time. Instructions for both pre- and post-training ratings encouraged participants to pay attention to the specific pictures depicting each food: "For instance, you may generally like a certain type of crisps but not find this particular flavour very appealing at this specific time. Also, certain images of the food may be more appealing than others."

5.3.8 Questionnaire measures

Several trait and state variables were recorded at the end of the study, including gender, ethnicity (optional), hunger levels (VAS), hours since last meal and dietary preferences (e.g., vegetarian diet) as described in Chapter 4 (section 4.3.6 and also see Appendix

G). Body height and weight were self-reported in order to calculate the participant's body-mass index (BMI; kg/m^2). After answering the questions on demographics and trait/state variables, participants completed a follow-up study questionnaire which included questions about their performance in the APP (e.g., strategic responding), attention/instruction manipulation checks (Kees et al., 2017) and interruptions during the study (Waters & Li, 2008). The questionnaire was adapted from the previous study (see section 4.3.6 in Chapter 4) with a few additional questions. Participants were asked whether they were "aware of the study hypotheses/aims prior to completion", as for example knowing that the 'attention task' was a form of training and/or what was measured by the 'word task'. Awareness of contingencies between no-go trials and specific stimuli was examined by asking participants whether they learned that on certain occasions where they shouldn't respond there were specific food images being shown. All questions can be found in Appendix F.3.

As previously mentioned (see section 5.2), this study was conducted as part of an assignment for BSc Psychology at Cardiff University and several measures have been added for the students' hypotheses and analyses. Such measures are not described in detail in this thesis as they were only subjected to the students' exploratory analyses. All questionnaires were completed at the end of the study in random order and these included the Barratt Impulsiveness Scale (BIS-15; Spinella, 2007), Food Cravings Questionnaire - Trait - reduced (FCQ-T-reduced; Meule et al., 2014), Perceived Stress Scale (PSS; Cohen et al., 1983), Big-Five Inventory ("Neuroticism" dimension only; Goldberg, 1993; John & Srivastava, 1999) and the *weight control*, *health*, and *mood* factors from the Food Choice Questionnaire (FCQ; Steptoe, Pollard, & Wardle, 1995).

5.4 Analyses

5.4.1 Measures & Indices

For APP performance and calculated priming effects, median RTs were obtained, from correct trials only, for each participant and each design cell (e.g., congruent go food trials). Medians were preferred instead of means as they are less sensitive to outliers and would indicate central tendency more accurately in the expected positively-skewed RT distributions. Priming effects were calculated as the change in median RTs from incongruent to congruent trials ($\text{median}RT_{inc} - \text{median}RT_{con}$) for each training condition (go, no-go, untrained). The sample means were then compared across conditions and are referred to as ΔRT. For explicit evaluations pre-

and post-training, mean ratings for each training condition were calculated (eight go, eight no-go, and eight untrained foods). Difference scores of these means were finally calculated for each training condition (i.e., $\Delta\text{Liking}_{\text{go}}$, $\Delta\text{Liking}_{\text{nogo}}$, $\Delta\text{Liking}_{\text{untrained}}$). Negative difference scores (post - pre) would reflect a reduction in liking from pre-to post-training. Other descriptive measures of APP and GNG task performance were also recorded for data exclusions (see section 5.4.3) and exploratory analyses, such as the inspection of potential speed-accuracy trade offs in the APP (see section 5.5.3).

5.4.2 Preregistered analyses

Data pre-processing and analyses were conducted in R (R Core Team, 2017) using RStudio (RStudio Team, 2016) and scripts were shared on the OSF project, available at https://osf.io/6bsnv/. All confirmatory hypotheses were tested using directional Bayesian paired-samples t-tests (Rouder et al., 2009), as listed below. The prior with the $\sqrt{2}/2$ scale parameter for the half-Cauchy distribution was used for all t-tests. Shapiro-Wilk tests were performed to check for potential violations of the normality assumption and in case of violation ($p < 0.005$) additional analyses based on log-transformed RTs (logRTs) for H2 and H3 would be reported in a supplementary manner (see section 5.5.3). Alternative analyses for normality violations under H1 were not preregistered and are therefore reported in supplementary exploratory analyses as well.

H1a. $\Delta\text{Liking}_{\text{nogo}} < \Delta\text{Liking}_{\text{go}}$
H1b. $\Delta\text{Liking}_{\text{nogo}} < \Delta\text{Liking}_{\text{untrained}}$

H2a. $\Delta\text{RT}_{\text{nogo}} < \Delta\text{RT}_{\text{go}}$
H2b. $\Delta\text{RT}_{\text{nogo}} < \Delta\text{RT}_{\text{untrained}}$

H3. $\text{RT}_{\text{con}} < \text{RT}_{\text{inc}}$ (non-food prime trials)

5.4.3 Data exclusions

Error rates were inspected for both the GNG and APP tasks. Participants with error rates greater or equal to 0.4 from within either the set of critical food prime or non-food prime trials were excluded from all respective analyses. For the GNG training, participants who had a proportion of successful inhibitions (i.e., correct no-go responses) lower than 0.65 would be excluded, as it has been shown that this

is an important moderator for training effects (see Jones et al., 2016, Section 3.3). Participants who did not complete all the tasks/measures of the study critical to confirmatory hypotheses (GNG, APP, explicit evaluation task) were not included in preregistered analyses. However, participants who did not complete the questionnaires at the study were not excluded. Further data exclusions were implemented based on the timing of events in APP trials. In online data collection settings, certain timing delays could be observed due to varying technical specifications (e.g., screen refresh rate). APP trials in which the duration of the prime (233ms) and mask (17ms) was delayed by two or more refresh rates (at 17ms) were discarded. Participants with more than 25% discarded trials would be excluded from all analyses. All data exclusion criteria outlined here were preregistered prior to data collection.

5.5 Results

5.5.1 Sample characteristics

From the recruited sample of 140 participants, not taking into account recorded drop-outs, 20 individuals running the study via Prolific did not meet the eligibility criteria during screening. Eight users reported not having normal or corrected-to-normal vision, five users were not native or bilingual English speakers and seven individuals indicated that they were on a diet and/or taking diet pills at the time of the study. A total of 120 participants successfully completed the study. 74 participants were recruited via Prolific and 46 were contacted via personal communication. The data were inspected for exclusions according to the above-mentioned preregistered criteria (section 5.4.3) and the final sample consisted of 113 participants. Four participants were first excluded because their mean error rates in either food or non-food APP blocks were greater or equal to 0.4 and another three participants were not included in the data for analysis due to the proportion of correct responses on no-go trials (i.e., successful inhibitions) being lower than 0.65. Data were also inspected for timing delays in the APP and there were no participant exclusions for more than 25% of discarded trials, with only a trivial number of trials removed for four participants (1-4 trials).

Overall, the average liking ratings for the food items in each training condition were matched. The majority of participants found the foods appetitive and rated positively go items ($M = 52.64$, $SD = 25.08$), untrained items ($M = 52.20$, $SD = 25.10$) as well as no-go items ($M = 52.38$, $SD = 25.01$). The proportion of successful inhibitions, that

is correct responses on no-go trials, was very high across participants (M = 96.70, SD = 3.48), which may be an important determinant of training effects (Jones et al., 2016). Descriptive statistics of sample demographics and trait/state variables were recorded for 112 participants (one incomplete dataset). Although the data were collected online the sample was not diverse in terms of ethnicity (% White; M = 87.50, SD = 33.22) and age (years; M = 26.91, SD = 10.66). The sample was, however, relatively matched in terms of gender (% female; M = 57.14, SD = 49.71). Participants were on average not very hungry at the time of the study (1-9; M = 4.78, SD = 2.57). The hours since last food intake were not indicative of elevated appetite, as 49.11% of participants reported having a meal 1-3 hours before the study and 23.21% had a meal less than one hour before. The total scores on the FCQ-T-r were inspected (M = 44.73, SD = 12.64) and there was no apparent clinically-relevant 'pathology' related to eating behaviours (Meule, 2018). Several questionnaire measures were added for exploratory analyses that fall outside the scope of this thesis chapter (see section 5.3.8) and are therefore not presented in this section as sample characteristics.

5.5.2 Findings from confirmatory analyses

All results from Bayesian and supplementary frequentist statistical tests can be found in Table 5.1. There was *extreme* evidence that go/no-go training had an *explicit* devaluation effect on the selected unhealthy foods when both baselines were examined (i.e., go and untrained foods). Differences between training conditions for changes in liking ratings (ΔLiking) can be seen in Figure 5.3 (panel A) and distributions for individual data points pre- and post-training have been visualised in the raincloud plot (Allen et al., 2019, 2018) shown in Figure 5.4. ΔLiking difference scores were expected to be negative for no-go foods and that compared to go and untrained foods the change would be greater (see 5.4.1 for calculation details). As stated in H1a, the change in explicit liking ratings, from pre-to post training was negative for no-go foods ($\Delta Liking_{nogo}$; M = -18.94, SD = 21.89) and greater compared to the change for go foods[6] ($\Delta Liking_{go}$; M = -11.29, SD = 18.27). Similarly, there was conclusive support for H1b, as the negative change in liking ratings was greater for no-go foods after training relative to untrained foods ($\Delta Liking_{untrained}$; M = -11.53, SD = 15.64). The RT priming effects for each training condition were also examined and there was *very*

[6]The 'go valuation effect', whereby positive evaluations of go foods are increased after training compared to untrained foods (e.g., Chen, Veling, et al., 2018; Chen et al., 2016), was not examined in this study, but in case of interest, both descriptively and statistically there was no difference between the difference scores; BF_{01} = 9.49, $t(112)$ = 0.14, p = 0.889.

strong evidence for an *implicit* no-go devaluation effect, as demonstrated in Figure 5.3 (panel B). H2a was supported and the RT priming effect for no-go foods (ΔRT_{nogo}; $M = 0.29$, $SD = 38.58$) was lower compared to the RT priming effect for go foods (ΔRT_{go}; $M = 14.78$, $SD = 40.68$). H2b also received conclusive support, as the overall RT priming effect for no-go foods was lower than the RT priming effect for untrained foods ($\Delta RT_{untrained}$; $M = 12.23$, $SD = 36.96$). The distributions of RT priming effects for all training conditions can be seen in Figure 5.5. The manipulation check for the APP (H3) was successful, as there was *extreme* evidence that participants were on average faster to respond on congruent ($M = 561.01$, $SD = 77.75$) rather than incongruent non-food prime trials (correct RTs only; $M = 573.14$, $SD = 73.04$).

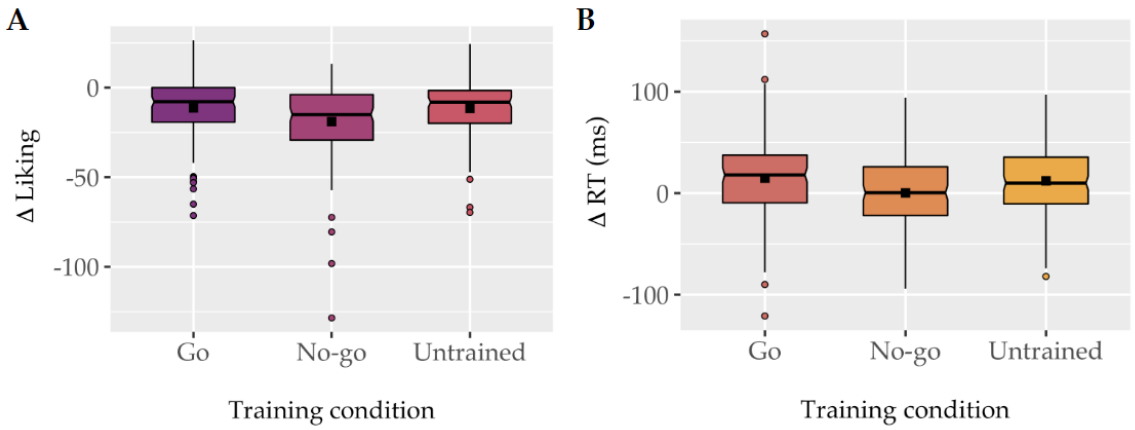


Figure 5.3: Boxplots showing the *explicit* and *implicit* no-go devaluation effects. A. The difference scores for the changes in explicit liking ratings from pre-to post-training (ΔLiking) have been plotted for each training condition. The boxplots show that the change in explicit evaluations for no-go foods was negative and greater in magnitude compared to both go and untrained foods (*explicit* no-go devaluation effect). **B.** ΔRT refers to the differences between correct median reaction times (RTs) on congruent and incongruent food prime trials, as calculated and plotted for each training condition. The RT priming effect (ms) for no-go foods was lower than the RT priming effects for go and untrained foods (*implicit* no-go devaluation effect). *Note.* Coloured dots represent the outliers that fall outside the Interquartile Range. The black squares depict the sample means of the difference scores.

Table 5.1: Statistical test results for confirmatory hypotheses H1, H2 and H3 (N = 113)

	BF_{10}	$t(112)$	p	d_{av}	95% CI for d_{av} Lower	95% CI for d_{av} Upper	Evidence interpretation
H1a	109.42	-3.68	$< .001$	-0.38	-0.59	-0.17	*Extreme* evidence for H1
H1b	678.73	-4.22	$< .001$	-0.39	-0.58	-0.20	*Extreme* evidence for H1
H2a	44.30	-3.39	$< .001$	-0.37	-0.58	-0.15	*Very strong* evidence for H1
H2b	30.06	-3.26	0.001	-0.32	-0.51	-0.12	*Very strong* evidence for H1
H3	158.99	-3.80	$< .001$	-0.16	-0.25	-0.07	*Extreme* evidence for H1

Note. Evidence is interpreted for the alternative hypothesis (H1) compared to the null (H0) and vice versa. The effect size is given by Cohen's d_{av}. Hypotheses are descriptively and statistically defined in sections 5.2 and 5.4.2 respectively.

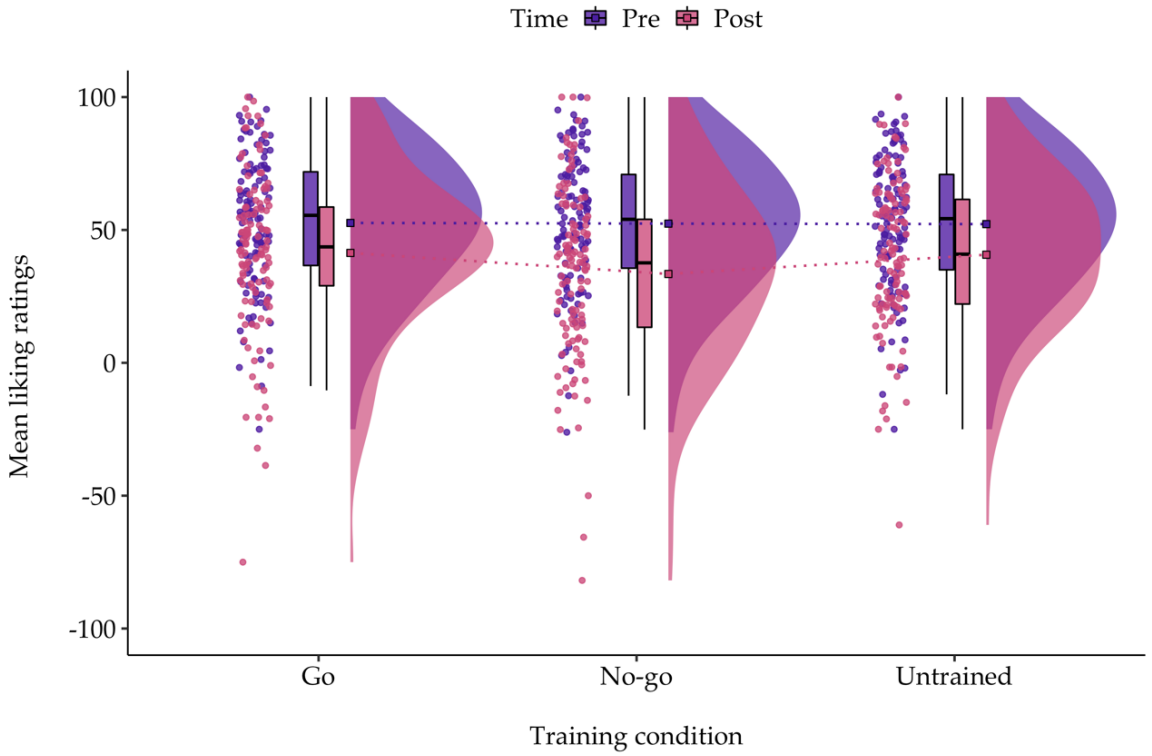


Figure 5.4: Raincloud plot of the explicit liking ratings pre- and post- training across training conditions. The distributions of explicit liking ratings indicate that on average all foods were rated less positively after training relative to baseline, which may be attributed to regression to the mean. As stated in the preregistered hypotheses, this negative change in explicit evaluations was considerably larger for no-go foods compared to both go (H1a) and untrained foods (H1b). *Note.* The 'split-half violin' elements in the plot show smoothed distributions and boxplot vertical lines represent the range, excluding outliers based on the Interquartile Range. Square boxes depict the sample means and the dashed lines show the differences across training conditions.

5.5.3 Findings from exploratory analyses

Priming effects across training conditions

Although the difference scores for RT priming effects in each training condition were compared directly in planned paired comparisons, additional exploratory analyses were conducted to examine whether positive effects would be obtained for the two baselines (go and untrained foods). There was *extreme* evidence that participants were on average faster to respond on congruent (M = 560.44, SD = 77.71) compared to incongruent go food prime trials (M = 575.22, SD = 72.13) [BF_{10} = 195.25; $t(112)$ = -3.86, p = < .001, d_{av} = -0.200, 95% CI for d_{av} = -0.300, -0.090]. There was also *very strong* evidence for a positive RT priming effect for congruent (M = 562.49, SD = 76.69) and incongruent untrained food prime trials (M = 574.72, SD = 73.39) [BF_{10} = 64.58; $t(112)$ = -3.52, p = < .001, d_{av} = -0.160, 95% CI for d_{av} = -0.260, -0.070]. However, there was *moderate* evidence for the absence of a positive RT priming effect when no-go foods were examined. Participants were not faster to respond on congruent (M = 569.53, SD = 78.18) compared to incongruent no-go food prime trials (M = 569.82, SD = 69.40) [BF_{01} = 8.99; $t(112)$ = -0.08, p = 0.468, d_{av} < 0.001, 95% CI for d_{av} = -0.100, 0.090].

Table 5.2: Statistical test results for reaction time differences in the affective priming paradigm

					95% CI for d_{av}	
	BF_{10}	$t(112)$	p	d_{av}	Lower	Upper
No-go RT_{con} > Go RT_{con}	19.56	3.11	0.001	0.12	0.04	0.19
No-go RT_{con} > Untrained RT_{con}	7.35	2.75	0.004	0.09	0.02	0.16
No-go RT_{inc} < Go RT_{inc}	1.89	-2.15	0.017	-0.08	-0.15	-0.01
No-go RT_{inc} < Untrained RT_{inc}	1.76	-2.12	0.018	-0.07	-0.13	0.00

Note. The effect size is given by Cohen's d_{av}. RT_{con}: Sample mean of median reaction times on congruent trials; RT_{inc}: Sample mean of median reaction times on incongruent trials

RTs towards no-go foods could be affected by a general slowing effect induced during go/no-go training (see section 5.6.2 for discussion). *Moderate* evidence for the absence of an RT priming effect on no-go food prime trials indicates that this was not the case in this study. Distributions of individual median RTs (see Figure 5.5) hinted at the possibility of slowing occurring only on congruent trials. To strengthen the findings presented here, the RTs on congruent and incongruent trials were statistically compared for no-go food prime trials and the two baselines; go and untrained food

prime trials. Results from the directional paired samples t-tests can be found in Table 5.2. There was *strong* evidence that RTs on congruent trials were slower when no-go foods were presented compared to go foods and *moderate* evidence that RTs were slower for no-go foods relative to untrained foods. However, the effect sizes for these differences were negligible. Evidence for RTs on incongruent trials being faster for no-go foods relative to go and untrained foods was only *anecdotal*. Together these results indicate that there was no general slowing effects on RTs for no-go foods. Instead, the study offers preliminary evidence that participants may be slower on congruent non-food prime trials.

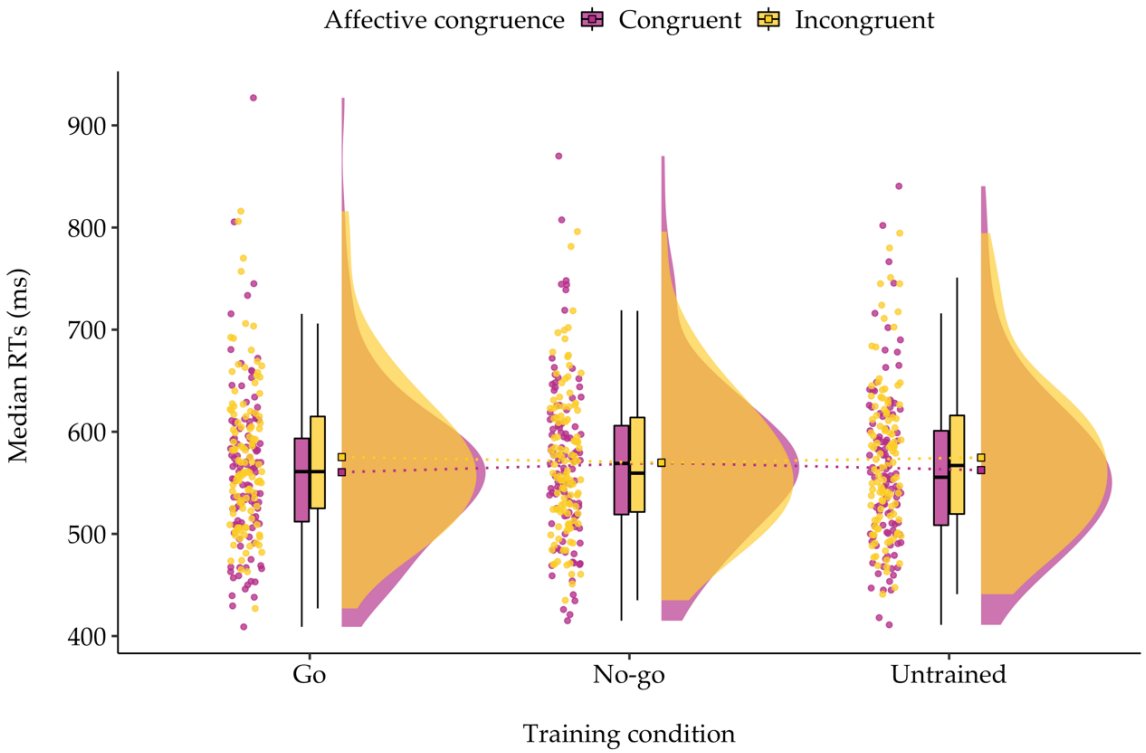


Figure 5.5: Raincloud plot of the median reaction times on congruent and incongruent trials across training conditions. The distributions of individual median reaction times (RTs) from congruent and incongruent trials of the affective priming paradigm (APP) show that positive priming effects were observed for both go and untrained foods (also see section 5.5.3). A positive priming effect for foods that have been rated highly on liking was expected and this effect is not observed for no-go foods. The boxplots and split-half violin elements show that participants were not faster to respond on congruent compared to incongruent no-go food prime trials. The sample means, as depicted by the square boxes, are overlapping and appear identical. Interestingly, the sample median RTs actually show that RTs were slightly slower in congruent compared to incongruent trials, which may indicate that no-go foods were associated with negative affective reactions, facilitating performance when negative targets had to be categorised (but see Table 5.2). *Note.* The 'split-half violin' elements in the plot show smoothed distributions and boxplot vertical lines represent the range, excluding outliers based on the Interquartile Range. The dashed lines show the differences across training conditions.

Inspection for speed-accuracy trade-offs

Error rates on congruent and incongruent trials across training conditions were inspected for the potential occurrence of speed-accuracy trade-offs (SATs), where participants strategically choose between accuracy and speed (e.g., slowing down to be more accurate, or responding consistently fast ignoring any errors). Error rates would need to be either greater on incongruent compared to congruent trials or statistically no difference should be observed. Bayesian and frequentist paired samples t-tests were not directional (or two-tailed). There was *moderate* evidence that average error rates did not differ between congruent (M = 0.07, SD = 0.07) and incongruent go food prime trials (M = 0.08, SD = 0.07) [BF_{01} = 4.75; $t(112)$ = -1.20, p = 0.232, d_{av} = -0.11, 95% CI for d_{av} = -0.29, 0.07]. On no-go food prime trials, there was *moderate* evidence for no differences in error rates between congruent (M = 0.07, SD = 0.07) and incongruent trials (M = 0.07, SD = 0.07) [BF_{01} = 6.65; $t(112)$ = 0.87, p = 0.388, d_{av} = 0.07, 95% CI for d_{av} = -0.09, 0.23]. *Moderate* evidence for the null compared to the alternative was also obtained for error rate differences on congruent (M = 0.07, SD = 0.07) and incongruent untrained food prime trials (M = 0.07, SD = 0.07) [BF_{01} = 6.85; $t(112)$ = -0.83, p = 0.408, d_{av} = -0.06, 95% CI for d_{av} = -0.22, 0.09].

Supplementary analyses for normality violations

As described in section 5.4.2, data were inspected for potential violations of the normality assumption in paired comparisons. Shapiro-Wilk tests revealed that all contrasts (i.e., difference scores of the sample means) under H2 did not follow a normal distribution and as planned, the median RTs were log-transformed and RT priming effects were re-computed for supplementary analyses. Consistent with the results from confirmatory analyses, there was *very strong* evidence for both H2a and H2b. The overall logRT priming effect for no-go foods was lower relative to the observed effect for go foods [H2a; BF_{10} = 67.43; $t(112)$ = -3.53, $p < .001$, d_{av} = -0.37, 95% CI for d_{av} = -0.58, -0.16]. The logRT priming effect for no-go foods was also lower compared to the effect for untrained foods [H2b; BF_{10} = 33.00; $t(112)$ = -3.30, p = 0.001, d_{av} = -0.31, 95% CI for d_{av} = -0.50, -0.12].

The difference scores for changes in liking ratings from pre-to post-training could not be log-transformed, but supplementary analyses were conducted in order to examine whether the devaluation effect was robust after the removal of extreme values in the data. Participants were excluded from these analyses if based on the Interquartile Range Rule (IQR Rule) their difference scores were above or below the

acceptable maximum and minimum values[7], respectively. The sample size after the removal of outliers was 103 and there was still *extreme* evidence that participants rated no-go foods more negatively after training relative to both go foods [H1a; BF_{10} = 1126.94; $t(102)$ = -4.37, $p < .001$, d_{av} = -0.50, 95% CI for d_{av} = -0.73, -0.26] and untrained foods [H1b; BF_{10} = 162.36; $t(102)$ = -3.81, $p < .001$, d_{av} = -0.36, 95% CI for d_{av} = -0.56, -0.17].

Relationship between explicit and implicit devaluation

The *explicit* and *implicit* devaluation effects were defined as distinct difference scores for the two baselines (no-go − go and no-go − untrained). Bayesian correlation pairs were tested with the default prior settings to examine whether the devaluation effects would be positively correlated. There was *anecdotal* evidence that the change in RT priming effects from no-go foods relative to go foods did *not* positively correlate with the change in explicit evaluations (BF_{01} = 1.76; r = 0.13, p = 0.080, 95% CI for r = -0.02, 1.00). Similarly, there was *moderate* evidence that the change in RT priming effects for no-go foods relative to untrained foods did *not* positively correlate with the change in explicit ratings (BF_{01} = 6.21; r = 0.04, p = 0.358, 95% CI for r = -0.12, 1.00). These findings indicate that there is no apparent correlation between the *explicit* and *implicit* no-go devaluation effects and the relationship between affective evaluations that are assessed using direct and indirect measures should be explored further.

Follow-up study questionnaire results

Data quality assurance measures were set in place for online testing settings, consistent with the procedure in Chapter 4. First, participants should have read the questionnaire instructions properly to provide a correct answer on Q1, which was an instructional manipulation check (Kees et al., 2017). As shown in Table 5.3, there was a proportion of participants who did not pay attention the questionnaire instructions and proceeded straight to answering the questions, but more than half of participants answered correctly. However, participants paid attention to the questions as evidenced by the percentage of participants who gave the correct answer on the attention check question (Q6). As expected for testing settings outside the controlled laboratory environment, several participants self-reported being interrupted at least once during the GNG and APP tasks. Recruitment was partially conducted via personal communication and an

[7]Any values greater than the third quartile (75%) plus the IQR × 1.5 were removed and any values lower than the first quartile (25%) minus the IQR × 1.5 were also discarded.

assurance measure was added for this reason in order to check whether participants had any prior knowledge of the study aims and/or hypotheses, such as the fact that the 'attention task' was a form of training. This would also be a possibility if students from the BSc Psychology programme were recruited. Only two participants reported being aware of the aims and/or hypotheses of the study.

Participants' awareness about APP and GNG training manipulations was also measured via the follow-up study questionnaire. The responses on Q2 related to the awareness of RT differences in the APP were varied, with only 36.61% of participants reporting that no differences were observed. Participants were on average consciously aware of prime content, but not on every trial (Q3; 5="Somewhat frequently"). This was to be expected as the primes were presented supraliminally. More than half of all participants were aware of the effects of affective congruence on their performance, identifying differences in their reaction times for both positive prime - positive target and positive prime - negative target pairs. The majority of participants found the targets clearly positive or negative and target ambivalence was not a prevalent issue in the employed task design. Consistent with the results from the exploratory analyses on APP error rates (see section 5.5.3), the majority of participants reported that they did not purposefully use any kind of strategy to make their responses faster and/or more accurate. Contrary to prior expectations, most participants were generally not aware of stimulus-response contingencies, specifically referring to stimuli associated with no-go responses (Q11). The validity of answers on all checkbox questions (Q2, Q4, Q7) was inspected and no participants were excluded based on inconsistent responses, such as indicating that their responses were not influenced by the content of the pictures while also selecting any of the other options for observed RT differences on Q4. For all exploratory measures presented in this section the sample size was 112, as one participant did not complete the questionnaire. All questionnaire questions can be found in Appendix F.3.

Table 5.3: Standardized results from the follow-up study questionnaire

	M	*SD*
Q1. Instruction manipulation check question (% correct)	53.57	50.10
Q2. Awareness of RT differences (% selected)		
Faster to categorise positive words	23.21	42.41
Faster to categorise negative words	11.61	32.18
Faster to categorise words towards the end	16.96	37.70
Slower to categorise positive words	15.18	36.04
Slower to categorise negative words	20.54	40.58
No differences observed	36.61	48.39
Q3. Awareness of prime content (1-7)	5.31	1.47
1="Never", 4="Occasionally", 7="Always"		
Q4. Awareness of affective congruence (% selected)		
Faster with positive prime - positive target pairs	35.71	48.13
Slower with positive prime - negative target pairs	33.04	47.25
Responses were not influenced by prime content	42.86	49.71
Q5. Ambivalence of targets (% Yes)	75.89	42.97
Yes- all words clearly positive or negative		
Q6. Attention check question (% correct)	94.64	22.62
Q7. Response strategies (% selected)		
Slowed down to be more accurate	15.18	36.04
Responded consistently fast, ignoring errors	25.89	44.00
No strategy used	61.61	48.85
Q8. Interruptions during the GNG (% one or more)	37.50	48.63
Q9. Interruptions during the APP (% one or more)	41.07	49.42
Q10. Prior knowledge of study aims/hypotheses (% No)	98.21	13.30
Q11. Awareness of stimulus-response contingencies (% Yes)	36.61	48.39

Note. Cumulative percentages do not add up to 100% on checkbox questions (Q2, Q4, Q7) as participants could select more than one option that applied. Stimulus-response contingencies were only examined for no-go trials, by asking participants whether they learned that on occasions where they shouldn't respond there were specific food images being shown (Q11). RT: reaction time; GNG: go/no-go training; APP: affective priming paradigm; *M*: Mean; *SD*: Standard deviation

5.6 Discussion

This preregistered study employed a go/no-go (GNG) training paradigm with cued go and no-go trials that occurred with equal probability and unhealthy foods that were matched in explicit liking in the beginning of the study. The task design was adapted by Chen et al. (2016) and it was expected that GNG would lead to a reduction in positive evaluations of food stimuli that were associated with response inhibition on no-go trials compared to both food stimuli presented on go trials and stimuli that did not appear during training. This no-go devaluation effect was measured using explicit ratings consistent with previous literature (Chen et al., 2016, 2018; Veling et al., 2013a)[8], but implicit food evaluations were also assessed via the affective priming paradigm (APP). In line with the definition of the no-go devaluation effect provided by Chen et al. (2016), confirmatory hypotheses for the reduction in *explicit* and *implicit* evaluations of no-go foods were tested using two baselines, that is relative to the change in evaluations for go and untrained foods.

5.6.1 Did food-specific go/no-go training lead to an *explicit* no-go devaluation effect?

Confirmatory analyses showed that the change in liking ratings from pre-to post-training was negative for no-go foods and greater in magnitude compared to the change in liking ratings for both go foods and untrained foods. These results confirmed that the go/no-go training task employed in this study had an *explicit* no-go devaluation effect. There was a general decrease in explicit evaluations from pre-to post-training across conditions (see Figure 5.4), but this was not explored further due to potential regression to the mean, consistent with the results reported by Chen et al. (2016). The results presented in this study indirectly replicate the robust devaluation effects observed in other preregistered studies (Chen et al., 2016, 2018). Specifically, as the GNG task design was adapted by Chen et al. (2016), it is worth noting that the effect size for a reduction in explicit evaluations for no-go foods compared to go foods (see Table 5.1) was small-to-medium consistent with the results reported by Chen et al. (2016) in Experiment 1[9]. The authors reported a medium effect size

[8]Please note that in this study the ratings refer to food liking, while in other studies the rating scales measure attractiveness. Liking was preferred based on previous work that provided evidence for the utility of the APP as an indirect measure of food liking (see Chapter 4).

[9]For the direct comparison of effect sizes, Hedge's correction was applied to H1a and H1b Cohen's d_{av} values to obtain the unbiased effect size estimates (Lakens, 2013) as reported by the authors (Cohen's d_{unb}).

for change in evaluations for no-go foods relative to untrained foods, while in this study there was only a small-to-medium effect similar to the go foods baseline. In line with previous literature, these results support the BSI theory (Chen et al., 2016; Veling et al., 2008) as an explanatory account of no-go devaluation because effects were obtained for most liked (i.e., 'highly appetitive') foods, but further investigation of mechanisms behind these effects was not possible with the current design, as it is further discussed below (*Implications & future directions*). However, this study contributes to our understanding of the GNG devaluation effect by examining changes in food evaluations using an indirect, or implicit, measure of liking.

5.6.2 Did the affective priming paradigm capture an *implicit* no-go devaluation effect?

The APP was successfully applied as an outcome measure for stimulus devaluation effects after training. The reaction time (RT) priming effects were calculated as the difference in RTs between congruent and incongruent trials, whereby a positive score indicates participants were faster to respond on trials where the valence of the categorised targets matched the valence of the food primes. It was hypothesised that the expected positive RT priming effects for foods would differ between training conditions, so that the RT priming effect for no-go food primes would be reduced compared to the observed effects for both go and untrained food primes. Although there is not enough evidence to infer whether the magnitude of the APP priming effects can be influenced by the strength of the primes, such as how much participants like the food items (Herring et al., 2013; Lamote et al., 2004), there was *very strong* evidence for the expected differences between RT priming effects for no-go compared to go and untrained foods.

This *implicit* devaluation effect was explored further in terms of RT differences on congruent and incongruent trials and response inhibition on no-go trials appears to have led to reduced response facilitation on trials where no-go food primes preceded positive targets. Exploratory analyses were conducted to test whether RTs on congruent trials were reduced for no-go foods compared to go and untrained foods and there was conclusive support for the observed RT differences[10]. Chen et al. (2016) correctly identified the methodological challenge of measuring implicit food evaluations using reaction time tasks, such as the APP, as previous studies have shown that response speed towards no-go stimuli can be reduced after training via learned stimulus-stop

[10]However, the effect sizes for these differences were negligible, as discussed in section 5.5.3.

associations (Best et al., 2016, also see 2019; Bowditch et al., 2016). In the evaluative categorisation task variant of the APP, any general slowing of RTs would affect performance in both congruent and incongruent trials, which would not significantly change the strength of observed priming effects. In this study we show that slowing of RTs was specific to congruent no-go food prime trials in the APP, which implies that the positive affective reactions towards no-go foods were reduced after training and in turn the degree of response facilitation in congruent trials was also decreased (see Herring et al., 2013; Wentura & Degner, 2010). I recommend that these novel findings from exploratory analyses are interpreted with caution, as the replicability of these observed RT differences has not yet been assessed.

Performance in the APP was inspected further in order to provide further support for the robustness of the observed RT priming effect differences between training conditions. First, there was *extreme* evidence for a positive RT priming effect for non-food stimuli, which was a manipulation check for the employed APP task design (confirmatory hypothesis). In exploratory analyses, conclusive evidence is provided for the presence of positive RT priming effects for go and untrained foods. As explained above, the slowing of RTs for congruent no-go food prime trials led to the absence of an overall positive RT priming effect for no-go foods. Error rates in the APP were examined to test whether speed-accuracy trade-offs (SATs) occurred on food prime trials of each training condition. Although participants could be expected to respond more accurately on congruent compared to incongruent trials, in line with previous findings (e.g., Lamote et al., 2004) and as reported in Chapter 4, in this study there were no differences between error rates on congruent and incongruent trials. This finding supports the assumption that SATs could not explain observed RT priming effects. Overall, the APP was successfully used as an indirect measure of food liking, thus allowing inferences to be made on an implicit no-go devaluation effect. Nonetheless, it is strongly advocated that this study is replicated in order to establish the robustness of the APP as an indirect measure of liking in the context of stimulus devaluation.

5.6.3 Implications & future directions

The novel findings presented in this study regarding the effects of food-specific go/no-go training on implicit food evaluations for foods associated with response inhibition should be assessed for replicability in different contexts, as for example other ICT paradigms or GNG training protocols with different parameters. The findings should

also be extended to more representative samples for research into unhealthy eating behaviours, such as obese individuals (e.g., see Chen, Veling, et al., 2018). Findings presented here provide additional evidence for potential theoretical explanations of no-go devaluation effects, whereby negative affect is induced for no-go foods during training (e.g., BSI theory). To elaborate, the measurement of explicit food attitudes, or evaluations, can be confounded by demand characteristics and other response bias (see Podsakoff et al., 2003 for review). By showing that the no-go devaluation effect can be captured by the APP, stronger conclusions can be drawn about the effects of food-specific response inhibition in the GNG task on affective reactions towards appetitive, most liked, unhealthy foods. However, the employed task design could not disambiguate potential devaluation mechanisms, as for example the role of response conflict and existing approach tendencies for appetitive foods could not directly be measured to provide support exclusively for the BSI theory. Future research should utilise the APP to measure implicit devaluation effects for both high-rated and low-rated food items and further investigate the relationship of inhibitory control capacity (general and/or food-specific) and observed training effects (see Chen et al., 2018).

Chapter 6

General Discussion

In this thesis I have reviewed the literature for behavioural measures and interventions that target food-related affective, motivational and cognitive processing and attempted to answer four major research questions that can inform the methodological development of these behavioural paradigms: 1) Does food-specific inhibitory control training (ICT) have an effect on automatic action tendencies?; 2) Can a novel ICT protocol influence food cravings and evaluations?; 3) Can the affective priming paradigm (APP) indirectly measure food attitudes and predict food choice behaviour?; and 4) Does food-specific ICT have an effect on implicit food evaluations?. Following a dual-process framework of eating behaviours and theoretical accounts of inhibitory control training mechanisms, the relationship between affect and motivation was examined in terms of training outcomes. In Chapter 2, a preregistered study tested whether food-specific go/no-go training would influence individuals' automatic action tendencies towards unhealthy foods that were consistently associated with response inhibition. In Chapter 3, I presented a novel ICT paradigm that trains participants to inhibit their responses towards unhealthy foods and execute alternative action plans by responding to healthy foods. Participants were randomly allocated to either a stop, stop-change, or go (control) training group and the feasibility and effectiveness of the novel paradigm was tested in relation to explicitly measured evaluations and cravings.

Although there is evidence to suggest that food-specific ICT can reduce the evaluations of foods that are paired with response inhibition when these are directly measured (e.g., visual analogue scales), an important question for theoretical accounts of the no-go devaluation effect is whether training can reduce the strength of automatic affective reactions towards foods, which may be paramount for the maintenance of unhealthy eating behaviours, such as overeating. In order to capture affective food evaluations at an automatic level of processing indirect, or implicit, measures can be

employed. Previous research has shown that the IAT may not be a very sensitive measure in this context and thus the APP was preferred as an alternative indirect measure. Therefore, a series of pilot experiments (see Appendix D) led to the development of a study protocol that tested the utility of the APP as an indirect measure of food attitudes and potential cognitive influences on behaviour, such as the healthiness of the foods. In Chapter 4, food priming effects were tested in the laboratory via the APP that was developed in the pilot experiments and findings were replicated in a second cohort of participants who were recruited online. Finally, in Chapter 5 the effects of go/no-go training were examined for food evaluations that were assessed via the APP (implicit). The findings from all research studies are discussed for their methodological and potentially theoretical significance in section 6.1, while general limitations and directions for future research are outlined in section 6.2.

6.1 Evaluation & synthesis of findings

1) Does food-specific ICT have an effect on automatic action tendencies?

No. The food-specific ICT did not have an effect on automatic action tendencies, but did influence participants' impulsive food choices. In Chapter 2, a GNG training task was employed and included unhealthy foods that were pre-selected by the researchers as appetitive. The stimulus-response (S-R) mapping was consistent for go and no-go foods and inconsistent for filler foods that appeared with equal probability on go and no-go trials (50:50). Automatic action tendencies were indirectly measured via an AAT pre- and post- training and secondary training outcomes consisted of explicit food evaluations and impulsive food choices. GNG training did not lead to a reduction in approach bias towards no-go foods compared to filler (control) foods after training and there was only *anecdotal* evidence for a no-go devaluation effect. However, GNG training influenced participant's choices for no-go foods and there was evidence for acquired stimulus-response associations during training. The proportion of successful response inhibition was on average greater for no-go foods compared to control foods that appeared on no-go trials. This may indicate that the consistent S-R mapping for no-go foods led to the development of automatic inhibition which would facilitate performance (Verbruggen & Logan, 2008a). Mean reaction times on correct go trials (GoRTs) were also compared for go foods and control foods that were paired with go responses. Evidence for faster GoRTs for

go compared to $control_{go}$ can support the idea that stimulus-go associations were formed, but learning of stimulus-stop associations was not tested. Support for the development of automatic inhibition rather than improved top-down inhibitory control could not be provided by the design of the study in Chapter 2, as GoRTs towards no-go foods should be examined on separate trials (e.g,. go trials after training) where the S-R mapping is reversed. It should be noted that GNG training often includes go and no-go trials that occur with equal probability, but the percentage of trials where response inhibition towards no-go foods was 33.33% due to the addition of filler foods. The proportion of no-go / stop-signal trials may be an important moderator of training effects (Veling et al., 2017), but this issue was not investigated further.

A question that could not be resolved without further testing (e.g., subsequent replication or follow-up experiments) was how GNG training led to reduced choices of no-go foods when there was no conclusive evidence that no-go food evaluations were less positive after training. However, since directly measured affective evaluations can be subject to response bias, such as demand characteristics (see Podsakoff et al., 2003), a plausible explanation is that the no-go devaluation effect occurred at a more automatic, or implicit, level which in turn affected participants' impulsive food choices. This study only provided preliminary evidence regarding the effects of food-specific ICT and exploratory analyses indicated that there are various methodological parameters in the AAT that could potentially influence the outcomes. While such parameters can be formally examined (e.g., implicit vs explicit task instructions; Phaf et al., 2014), other measures could also be employed to assess participants automatic action tendencies after training such as the SRC manikin task (see 1.4.1). In addition to approach bias towards unhealthy foods, future research could address the influence of attentional bias for food cues in the environment and their expected relationship with approach motivation in eating behaviours (see review by Field et al., 2016).

2) Can a novel ICT protocol influence food cravings and evaluations?

Yes. The novel ICT protocol led to the reduction of unhealthy food evaluations and cravings, but only when these were selected by the participants, and had no effect on ratings for healthy foods. A potentially important limitation of the study reported in Chapter 2 was that the appetitiveness of the foods was predetermined and the sets of food stimuli were not tailored to the participants' evaluations. In Chapter 3, participants selected healthy and unhealthy foods that they liked the most and rank-ordered them according to how much they would like to eat

them at that time. The foods with the highest ranking were assigned to signal trials in the training tasks. The ICT tasks did not follow the go/no-go paradigm which has been shown to produce larger effects on health behaviour change compared to the stop-signal paradigm (Allom et al., 2016; Aulbach et al., 2019; Jones et al., 2016; Turton et al., 2016). Instead, the ICT protocol included a stop-signal task (SST) and a stop-change task (SCT) that, contrary to previous literature (Lawrence et al., 2015), involved consistent S-R mappings (i.e., signal-associated responses always paired with unhealthy target stimuli). Each food exemplar was presented eight times across blocks in total and unhealthy targets stimuli on signal trials (33.33% of trials in each block) were either selected or non-selected by the participants.

Stop and stop-change training groups showed comparable reductions (small-to-medium effects) in unhealthy food evaluations and cravings relative to the control group but only when the food stimuli were selected by the participants. This suggests that the devaluation of selected unhealthy foods could be explained by the BSI theory (Chen et al., 2016; Veling et al., 2008) which postulates that highly appetitive stimuli trigger an approach tendency that is incompatible with the situational constraints (i.e., required response inhibition) and that this induced response conflict can be resolved through the attachment of negative affect (i.e., stimuli are devalued). Veling et al. (2008) have provided evidence for the BSI theory and found that the no-go devaluation effect is observed for positive stimuli, but not negative or neutral stimuli. Changes in cravings could be attributed to the reduced food evaluations, as there is a direct link between affect and motivation in the dual-process framework of (eating) behaviour. Exploratory analyses confirmed the existing positive correlations between evaluations and cravings for selected unhealthy foods.

Stimulus-stop associations were investigated via go test blocks that were administered before and after training. Participants in all groups were required to respond to food stimuli that were presented on signal trials during training. The pre-post training difference scores for GoRTs were not influenced by training and upon further inspection, the velocity profiles of participants' mouse movements during the go trials were approximately the same across groups. At a first glance, the lack of evidence for learned stimulus-stop associations would provide further support for the BSI theory, but due to the novel nature of the ICT tasks (e.g., computer mouse movements, stimulus presentation outside the central visual field), effects of training and potential mechanisms of action should be examined further. In future experiments, the stop-change paradigm could be integrated with a standard classification task where participants respond with key presses (e.g., instead of the left

arrow key press the right arrow key) and instructions encourage the focus of attention on the presented stimuli. Taken together, these findings suggest that the stop-change paradigm is worth developing as an ICT intervention due to the higher ecological validity of the trained responses, which not only require response inhibition but the updating of action plans and re-engagement in alternative actions (Boecker et al., 2013), such as choosing a healthier snack when inhibiting the behavioural tendency to consume an unhealthy food.

3) Can the APP indirectly measure food attitudes and predict food choice behaviour?

Yes. The APP was shown to be a reliable indirect measure of food liking with cognitive components of attitudes (i.e., healthiness) having no observed influence on priming effects. However, it did not predict food choice behaviour. Stimulus devaluation is an important training outcome in ICT studies because it is a potential mechanism of action behind training effects on health-related behaviours, such as food intake and choice behaviour (see Veling et al., 2017 for review). The meta-analysis by Jones et al. (2016) reported an absence of evidence for stimulus devaluation effects of ICT (food and alcohol cues), but the majority of included studies had employed an IAT, which is often criticised for category-level processing that does not reflect automatic affective evaluations of the presented (food) stimuli (see section 1.3.1). The APP has been previously used as an indirect measure of food liking (e.g., Lamote et al., 2004). In a series of pilot experiments (see Appendix D) an evaluative categorisation task variant of the APP was tested and developed further in laboratory settings and key methodological parameters (e.g., number of targets) were identified for the study presented in Chapter 4. We investigated whether the APP can reliably capture food liking and whether it is sensitive to both affective and cognitive components of attitudes (i.e., healthiness). The relationship between observed RT priming effects and impulsive food choices in a binary food choice task were also examined.

Confirmatory findings from two separate cohorts (laboratory and online) showed that the RT and ER priming effects were reliably observed for both healthy and unhealthy foods, but they were not associated with food choice behaviour. The priming effects did not differ between healthy and unhealthy foods, but it would be essential to reexamine the sensitivity of the APP to cognitive influences in a target population of overweight and obese participants who may show stronger affective

reactions towards unhealthy rather than healthy foods. If participants' performance indicated stronger liking for healthy foods (e.g., see Roefs, Stapert, et al., 2005), it could be assumed that affective evaluations are determined by health concerns. However, disentangling the potential explanations for priming effect differences is not a trivial issue. Before any conclusions can be drawn, more research would need to be conducted to examine to what extent RT and/or ER priming effects can be confounded by explicit response bias, such as social desirability, especially when the primes are presented supraliminally and the content of the pictures can be consciously perceived (see section 4.5.4). Overall, the study in Chapter 4 provided conclusive evidence for the utility of the APP as an indirect measure of food liking and it established our confidence to employ it in an ICT study to examine whether training can reduce participants' implicit evaluations of unhealthy foods.

In future research, different measures (e.g., IAT and APP) and related reliability metrics (e.g., test-retest, internal) could be directly compared in the context of food liking to assess which task can better capture automatic affective reactions. The convergence between direct and indirect measures should also be explored further. The factors and/or context in which direct and indirect measures diverge are not clearly established (e.g., see Fazio & Olson, 2003; Carruthers, 2018; Ellis et al., 2014). The predictive validity of indirect measures, such as the APP, in relation to food choice behaviour requires further investigation in order to account for the potential interaction between automatic and controlled processing, such as examining whether food choices can be better predicted when individuals have lower inhibitory control (e.g., see section 1.5.3).

4) Does food-specific ICT have an effect on implicit food evaluations?

Yes. The food-specific ICT had the expected devaluation effect for both explicit and implicit food evaluations. In the last ICT study presented in Chapter 5, the training protocol was adapted from previous research on the no-go devaluation effect (Chen et al., 2016). In contrast to the previous studies, the GNG task had auditory cues on both go and no-go trials that were randomly assigned across participants and the percentage of no-go trials was 50% with consistent S-R mapping. The stimulus selection procedure was improved relative to previous studies, as food stimuli with the highest liking ratings were randomly assigned as go, no-go and untrained foods and liking was matched for all stimulus sets. Untrained food items served as a second baseline and provided stronger support for the no-go devaluation

effect. It is possible that reduced evaluations for no-go foods compared to go foods could be observed if go foods were rated more positively after training (i.e., go valuation effect; Chen et al., 2016).

There was *extreme* evidence that the change in explicit liking ratings, from pre-to post training was negative for no-go foods and greater compared to the change for go and untrained foods. Liking was measured indirectly after training via an APP variant that required evaluative categorisations of target words (positive or negative). All food primes in the APP were considered positive and therefore affective congruence was only defined in relation to the targets, that is, trials were congruent when the target was positive and incongruent when the target was negative. The RT priming effect was calculated for each participant from the correct median RTs on congruent and incongruent trials. In line with the *a priori* hypotheses, there was *very strong* evidence that the RT priming effect for no-go foods was on average lower compared to the RT priming effect for go and untrained foods. This study had promising findings as it indicates that stimulus devaluation, which is primarily evidenced by changes explicit ratings that can be affected by response bias, may actually occur at an implicit level as suggested by the BSI theory. If negative affect is automatically attached to no-go food stimuli during training to resolve the response conflict triggered by the behavioural tendency to approach the food stimuli when response inhibition is required, this should be observed in participants' automatic affective reactions towards these foods after training.

Interestingly, exploratory analyses revealed that the average RT priming effect for no-go foods was almost diminished and RTs were slightly slower in congruent relative to incongruent trials, which may reflect negative affective reactions towards no-go foods as performance was facilitated when negative targets were paired with the food primes. These findings are very significant for understanding the underlying mechanisms of training and related devaluation effects. Nevertheless, it is paramount that these observations from exploratory analyses are examined on a confirmatory basis in future studies and that all findings are replicated in different cohorts and extended to account for potential deviations due to variation in the methodological parameters of the ICT protocols (e.g., time delay between cue/signal and stimulus, proportion of no-go/stop-signal trials, total repetitions of food-specific exemplars).

6.2 General limitations & future directions

6.2.1 Defining food healthiness

The healthy-unhealthy dichotomy in food-related research studies can prove very useful for the examination of implicit attitudes towards foods and effects on inhibitory control training on behaviour change, such as impulsive food choices. The definition of food healthiness can vary across studies and researchers can often focus on one type of nutritional content, such as fat or sugar. Outside the laboratory, the healthy-unhealthy dichotomy can become problematic when taking into account that foods that have a high fat content, such as raw almonds and avocados, can be classified as 'unhealthy' using conventional guidelines (e.g., NHS food labelling system) even when total fat (per 100g) may refer to healthy fats (monounsaturated or polyunsaturated) rather than unhealthy fats (saturated or trans). Dietary guidelines focus on a balanced diet based on recommended daily intake of calories and nutrients. For example, daily reference intakes for adults include no more than 70g of total fat and 90g of total sugars, although energy requirements can vary depending on an individual's energy requirements (see NHS, 2017). It has recently been suggested that this issue should be clearly communicated to consumers, who should focus on the overall healthiness of their dietary patterns by consuming healthy fats (e.g., nuts, vegetable oils) and not limit their intake based on total dietary fat (Liu et al., 2017).

Research studies that investigate automatic affective reactions and/or approach bias to foods could assess the influence of specific nutritional characteristics (e.g., added sugars, saturated fat) that are commonly found in palatable, potentially processed, foods for which over-consumption can contribute to increased weight gain and development of overweight or obesity (World Health Organization, 2018). Affective evaluations of foods can be determined by several nutritional characteristics and this has not yet been elucidated (Woodward & Treat, 2015). There may be underlying individual and cross-cultural differences in perceived food healthiness (e.g., young women with disordered eating symptoms relying more on fat content; Rizk & Treat, 2014) as well as associations between tastiness and healthiness (e.g., "healthy = tasty" in a French sample vs "unhealthy = tasty" in a US sample; Werle, Trendel, & Ardito, 2013; Raghunathan et al., 2006).

'Objective' classification of healthiness in the laboratory can be subject to researchers degrees of freedom and additional variability may be introduced when participants' perceptions of healthiness is not compatible with this classification. For this reason, it is highly recommended that future studies report all the food categories

utilised in behavioural tasks and measures along with nutritional information to allow for potential exploratory analyses of nutrition-specific influences on behaviour and the assessment of perceived healthiness, which can easily be conducted via self-report, as implemented in the experiments reported in Chapter 4.

6.2.2 Ecological validity

The accumulation of evidence for the effects of ICT paradigms on health behaviour change will not lead to the formulation of clinically-relevant interventions if the ecological validity of these effects is not established. Moving from the laboratory to the various real-world contexts where individuals can be vulnerable to unhealthy eating behaviours (e.g., unhealthy food choices during shopping, emotional eating or binge eating at home), training may show weak or no transfer effects. In this thesis, all research studies measured food-related affect, motivation and food choices in a controlled context and training was limited to a single session with outcomes being examined shortly after training administration. The studies in Chapters 2 and 3 were predominantly conducted in the laboratory and the ICT protocols consisted of a single training session. Only the ICT protocol in Chapter 5 was exclusively administered online, but we did not examine health-related training outcomes.

Even in research studies where actual eating behaviours were assessed, such as *ad libitum* food intake, the generalisability of ICT effects may be questionable (see Adams, 2014). It should be noted, however, that the promising potential of ICT interventions for facilitating weight loss has been documented in studies that administered a training program online (i.e., outside of the controlled laboratory environment) with multiple sessions (e.g., Lawrence, O'Sullivan, et al., 2015; Veling et al., 2014). Future research should therefore shift from single-session training protocols in the laboratory to Ecological Momentary Intervention strategies, which have higher ecologically validity due to the administration of the interventions in individuals' natural environments and during their daily lives (e.g,. at home or at work) via mobile technologies (Heron & Smyth, 2010). The assessment of ICT effectiveness in different contexts may be complemented by direct and indirect measures that can help disentangle the factors that might have contributed to weight and/or food intake outcomes, such as affective evaluations, approach bias, strength and frequency of cravings, daily/weekly snacking frequency, food choice behaviour in the supermarket (e.g., less unhealthy foods purchased) and levels of physical activity (also see Ecological Momentary Assessment techniques in Heron & Smyth, 2010).

6.2.3 Target processes & populations

The research studies conducted as part of this thesis were primarily methodological in nature and did not examine the potential effects of ICT paradigms or application of behavioural measures in representative populations for the targeted eating behaviours (e.g., overeating). Participants were on average healthy-weight and there was a lack of diversity in terms of age, gender, and ethnicity in both laboratory and online samples. The development of behavioural measures and interventions for clinically-relevant settings will depend on proof-of-concept and proof-of-mechanism studies that recruit overweight and obese participants, while influential state and trait moderators (e.g., appetite, dietary restraint) should be examined to account for individual differences (also see A. Jones, Robinson, et al., 2018) . For example, indirect behavioural measures for individuals' automatic affective reactions and approach bias could be used to identify specific food categories or nutritional characteristics that contribute to unhealthy eating patterns, which can then inform tailored behaviour change interventions. This is consistent with the suggestions by A. Jones, Robinson, et al. (2018) in a recent critical review of cognitive training interventions. The authors emphasise that a "one-treatment-fits-all" approach (cf. Franken & van de Wetering, 2015) can undermine the therapeutic potential of cognitive training interventions, as for example individuals who do not have existing approach bias towards unhealthy foods will not benefit from approach-avoidance training.

This form of pre-screening, or tailoring, should be examined in the target populations as the predictions of the RIM for behaviour may not be evidenced in healthy-weight individuals. Specifically, unhealthy eating behaviours such as overeating are presumably determined by a strong impulsive system (e.g., strong attentional and/or approach bias) and a weak reflective system (e.g., lower inhibitory control). Even methodological, proof-of-concept, laboratory studies with healthy-weight samples do not investigate all these impulsive and reflective precursors (or sometimes none). For example, in Chapter 2, we showed that participants did not have initial approach bias towards unhealthy foods and GNG training did not influence participants' automatic action tendencies, but other impulsive and reflective precursors were not examined. This is a general limitation that can characterise all the research studies included in this thesis. This is a challenging task for future studies, however, as increasing the number of confirmatory hypotheses about interactive effects (e.g., moderation analyses) may require very large sample sizes to achieve adequate statistical power and reduce the possibility of false positive, or false negative, findings.

Moving beyond the targeted processes in ICT interventions that should be examined

systematically at baseline, the majority of research studies in the literature do not include post-training assessments of general or cue-specific inhibitory control (e.g., see Stroop interference task in Allom & Mullan, 2015) and thus inferences about the exact mechanisms of cue-specific or generalised ICT cannot be made. As highlighted in a recent review (Veling et al., 2017), examining the improvement of inhibitory control over the course of training does not represent an accurate representation of enhanced inhibitory control ability, as lower error rates are consistent with the development of automatic, bottom-up, inhibition from formed stimulus-stop associations, as previously discussed in section 1.6.3. Food-specific inhibitory control can be measured in separate blocks of trials where stimulus-response mappings are reversed and participants do not anticipate the presentation of a no-go cue or stop-signal, as it was implemented in the Chapter 3 study (i.e., pre- and post-training go tests). In the current state of the literature, we cannot assume that ICT paradigms strengthen top-down inhibitory control (Veling et al., 2017) and in what context, such as in the presence of appetitive food cues or a general state irrespective of cue-specific demands.

The importance of context is also apparent in studies that examine inhibitory control as part of an assumed weak controlled processing system and have found that eating behaviour may be predicted by differences in food-specific rather than general cognitive control resources as discussed in section 1.5.2 (also see Bartholdy et al., 2016b). Returning to the issue of sampling, the effects of ICT paradigms on top-down inhibitory control may also differ between healthy-weight and overweight/obese populations. If these effects are dose-dependent, future research should identify how many blocks of training and stimulus-stop repetitions are needed per session to yield robust effects in the population for which ICT protocols can have therapeutic potential.

6.2.4 Online testing settings

The prevalence of research studies with small samples sizes, as defined by the statistical power to detect true effects especially when the effects are expected to be small, can undermine the reliability of research findings and contribute to the lack of reproducibility in scientific fields (Button et al., 2013). There is thus an emerging need for larger sample sizes in psychology and neuroscience that can require extensive data collection time and resources. One potential solution for this challenge is conducting collaborative research, as for example through consortia that bring together several universities, as reported in Chapter 2, and collaborative networks, such as the Psychological Science Accelerator (Moshontz et al., 2018). Another affordable and

easily-to-implement approach that does not require external collaborations is online testing via crowd-sourcing platforms, such as Amazon's Mechanical Turk (MTurk) or Prolific. Although such platforms have received considerable attention in the past decade for social and consumer psychology fields that primarily depend on self-report measures (e.g., questionnaires), online testing can also been successfully implemented for experimental reaction time tasks (e.g., see Peer, Brandimarte, Samat, & Acquisti, 2017).

In this thesis a recently developed crowd-sourcing platform was used (i.e., Prolific) as an alternative to MTurk, which has been criticised for being prone to lack of naivety among respondents and dishonest behaviour (Palan & Schitter, 2018). Prolific has been reported to have low rates of failure on attention check questions and dishonest behaviour[1], while all expected effects from four judgment and decision-making tasks were replicated in the recruited sample (Peer et al., 2017). Prolific incorporates pre-screening of users to accommodate several inclusion/exclusion criteria in research studies with great specificity as researchers can select sample characteristics based on demographics, geographic and socioeconomic variables, hobbies/interest (e.g., video games) as well as political, religious and personal beliefs. This can aid in the recruitment of potentially hard-to-reach populations (also see Heron & Smyth, 2010 for delivering behaviour change interventions via mobile technologies) but more importantly, it can increase the diversity in study samples which are often limited to undergraduate students from local Universities.

Online testing was employed in all the research studies reported in this thesis to varying degrees and there were a number of advantages that should be communicated here along with potential pitfalls for future studies that aim to recruit participants via crowd-sourcing platforms. In Chapter 2, online testing was minimal and therefore any issues could not be identified, but in Chapter 3 online data collection was terminated due to several technical difficulties and high drop-out rates or exclusions due to poor performance during training practice. The lack of controlled laboratory settings also had implications for data analyses of reaction time measures. The training tasks involved continuous motor responses with a computer mouse, which can be constrained by external factors that cannot be controlled by the researcher(s), such as the adequacy of desk space, the use or absence of a mouse-pad to reduce friction during movements, and other technical specifications that can insert variability in RT measures including

[1]This was estimated via a die-rolling task where a randomly rolled die indicated a bonus for study completion. Participants were expected to claim a bonus of 35 cents on average based on a uniform distribution (die roll $\times$ 10 cents) and over-reporting was examined against this benchmark in all samples (i.e., crowd-sourcing platforms being examined).

the speed of the mouse and acceleration settings (e.g., default option in Windows OS). In my opinion, when there are a number of variables about the experimental setup that should be carefully controlled, online experiments should be avoided.

Another potential pitfall of online experiments is that participants cannot contact the researcher to ask questions about the task(s) and that they would not pay attention or adhere to the instructions (e.g., high error rates, random responding). It is highly recommended that researchers include instructional manipulation checks and attention check questions in the study to assess data quality (see Kees et al., 2017), as implemented in the experiments reported in Chapters 4 and 5. In order to facilitate participants' understanding of the task instructions, performance requirements for task performance should be clearly explained with added visual aids where appropriate, and adequate practice should be provided. In online testing settings participants could easily be distracted or interrupted during the study (e.g., by phone ringing, or computer notifications appearing) and thus instructions for minimising instructions should also be provided. Participants could be asked to self-report the number of times where distractions or interruptions occurred (Waters & Li, 2008) and researchers could accommodate the participants' needs to respond to such distractions by including several self-timed breaks during the study.

These recommendations are derived from the experiments reported in Chapters 4 and 5, where there was no indication that potential pitfalls with online testing affected task performance and adherence to instructions. In Chapter 4, I provided preliminary evidence for the advantages of online testing beyond the size of the recruited sample (N = 202), such as higher success in the instructional manipulation check and less (self-reported) strategic responding in the online sample compared to the laboratory sample. Importantly, priming effects from the APP were reliably obtained in the online sample (and directly replicated) of the study in Chapter 4 and in the experiment reported in Chapter 5.

6.2.5 Neuromodulation for eating behaviours

Neuromodulation research for obesity and related unhealthy eating habits is becoming increasingly important and has the potential to guide promising interventions for clinical settings (Forcano, Mata, de la Torre, & Verdejo-Garcia, 2018). For example, non-invasive brain stimulation (NIBS) studies can contribute to the formulation of standardized protocols for clinical settings that aim to reduce food cravings and consumption. There is a growing interest in the efficacy of such protocols in both

healthy-weight and clinical samples (for reviews see Grall-Bronnec & Sauvaget, 2014; Hall, Vincent, & Burhan, 2018; Lowe, Vincent, & Hall, 2017; Val-laillet et al., 2015). Transcranial direct current stimulation (tDCS) and transcranial magnetic stimulation studies (TMS) have provided mixed evidence that the up-regulation of the left dorsolateral prefrontal cortex (dlPFC) via excitatory protocols can result in the reduction of cravings towards high-calorie foods (Jauch-Chara et al., 2014; Uher et al., 2005). The left dlPFC is a common target in NIBS studies, but the theoretical basis of that choice is not always justified. There is a general consensus that the dlPFC plays a crucial role in cognitive control of food intake and effects of NIBS could be attributed to reward-valuation mechanisms, inhibitory control, attentional biases, or other executive functions (Val-laillet et al., 2015).

Interestingly, the possible mechanisms of action behind the effects of facilitatory dlPFC stimulation on food cravings and consumption may better be understood when considering the functional magnetic resonance imaging (fMRI) literature. Many studies have investigated the neural underpinnings of dietary self-control, including inhibitory control and value modulation processes (see Han, Boachie, Garcia-Garcia, Michaud, & Dagher, 2018). These processes are often operationalised using craving regulation and dietary decision-making (i.e., choice) tasks, respectively. In line with fMRI research about dietary self-control at the neural level (e.g., Hare et al., 2011; Dietrich, Hollmann, Mathar, Villringer, & Horstmann, 2016; Harris, Hare, & Rangel, 2013), it could be assumed that left dlPFC high-frequency repetitive TMS (HF-rTMS) can enhance inhibitory control and/or value modulation when self-control is required. This is consistent with the dual-process framework and evidence for an interplay between automatic and controlled processes discussed in sections 1.2 and 1.5.3.

Two key directions for future research are thus elucidating the mechanisms by which dlPFC stimulation influences food-related behaviour and examining whether neuromodulation techniques can be used to enhance the effects of ICT interventions on health behaviour change. Strengthening inhibitory control both at a behavioural and neural level may have promising clinical applications and should be explored further first at a proof-of-concept stage in laboratory environments and then in randomised clinical trials to establish the effectiveness of tailored treatment protocols in target populations.

6.2.6 Open science challenges

As discussed in Chapter 1 (section 1.7), open science practices such as preregistration and sharing of study materials, code and data, can aid in the efforts to reduce the lack of reproducibility in psychological science and specific research areas. The methodological rigour and robustness of research studies is also paramount as the literature is often dominated by experiments with small sample sizes that can yield false positive findings and observed effects that cannot be replicated (Button et al., 2013; Open Science Collaboration, 2015). The preregistration of study protocols that were included in this thesis was fundamental to the reproducibility and transparency of the research. However, there are certain challenges that encompass the adoption of open science practices at a PhD level that should be discussed further (Maizey & Tzavella, 2019). A core aspect of study preregistration is the perspective from which researchers view confirmatory and exploratory research. Publication of empirical studies may not often require a clear-cut distinction between confirmation and exploration due to the tendency to create attractive narratives (i.e., stories) for the reader, as for example presenting exploratory findings as *a priori* hypotheses and manipulating the data to yield significant findings (e.g,. trying different criteria for the removal outliers), which are questionable research practices and undermine the replicability of findings (Huber, Potter, & Huszar, 2019; Munafò et al., 2017). The development of a robust preregistered study can be more demanding because a number of considerations and decisions need to be made before the data are inspected, while hypotheses and respective statistical tests should achieve the highest level of specificity and consistency.

In the first protocol for Chapter 3, prior expectations about the outcomes of training were phrased as confirmatory hypotheses and directional tests were planned but not explicitly stated. The protocol was focused on the reproducibility of methods but the sections on hypotheses and planned statistical analyses were overall inadequate and this can open the possibility for deviations and risk of confirmation bias. The first preregistration also involved a between-subjects design with a sequential sampling plan based on BF thresholds for *strong* evidence. Importantly, the proposed study involved a novel ICT protocol that had not been properly tested before preregistration. Together all these factors contributed to a very long period for data collection, possibly high rates of participant exclusions, and challenging reformulation of hypotheses and analyses that reduces the risk of bias as much as possible. In the second preregistration for the study presented in Chapter 2, a within-subjects design was employed and the sample size was determined according to a power analysis, but with feasible criteria for data collection. Small deviations in the preregistration were still required, but there

was an overall improvement. The preparation of robust preregistered protocols and accompanying materials (e.g., open code) can be more successful and less challenging for PhD students who are limited by time (and resource) constraints if proper training is provided and our understanding of the scientific method is correctly established at an undergraduate or postgraduate level (e.g., manipulation and quality checks, positive controls, statistical power).

The preregistration of research studies at an early career level may be avoided due to time constraints when there is a pressing need to "publish or perish" (e.g., see Everett & Earp, 2015). A promising alternative is offered by the Registered Reports article format in eligible journals, where an accepted peer-reviewed study protocol is published irrespective of the results. The study presented in Chapter 4 was accepted as a Stage 1 Registered Report (S1 RR) and required data collection both in laboratory and online settings to directly replicate confirmatory findings in a second cohort of participants. The development of the S1 RR protocol had a prolonged duration compared to other study preregistrations and was increasingly demanding due to very high standards for reproducibility set by the specific journal. Additionally, extensive piloting was conducted in order to establish the robustness of the manipulation check to be included in the S1 RR protocol, with sample sizes that may often characterise complete research studies. As a PhD researcher, a key challenge in adopting the RR format was that data collection could not be initiated until IPA was received, which meant that a maximum sample size of 200 in the laboratory was not achieved on time for thesis completion. It should be formally recognised that (robust) open science is slower science and more attention should be given to the quality rather than the quantity of publications at an early career level. Although there are several challenges for early career researchers (e.g., see Maizey & Tzavella, 2019), engagement in open science practices has had a considerable impact on my personal development and the formulation of the S1 RR protocol has enhanced and redefined my perspective on the scientific method. The implementation of various open science practices during the PhD stage can help shape the future generation of researchers at an academic or industrial level and should be encouraged. However, we should not ignore the lack of systemic support that can constitute an important barrier for PhD students, as for example insufficient training when requested or course requirements that favour novelty over reproducibility (e.g., replications; Everett & Earp, 2015).

Conclusion

The methodological validity of behavioural measures and interventions for food-related cognition, motivation and affect was investigated using reproducible, transparent methods that allow for direct replication and extension of findings. We provided preliminary evidence that inhibitory control training may not affect individuals' automatic action tendencies when these are assessed by an approach-avoidance task, while training participants to withhold their responses when presented with specific unhealthy foods can lead to reduced impulsive choices for these foods. Results regarding participants' approach bias should be interpreted with caution, however, because the AAT may not constitute a sensitive and reliable measure of automatic action tendencies in all contexts. In a second study, participants were trained to avoid target unhealthy foods and instead execute responses towards healthy foods and the novel training task led to reduced food evaluations and cravings only when the food stimuli were selected by the participants in the beginning of the study. This novel task had comparable effects to a training task adapted from the stop-signal paradigm where participants only inhibited their responses towards unhealthy foods. These results suggest that the stop-change training task should be developed further in laboratory settings to explore whether it can be more effective compared to standard go/no-go and stop-signal tasks.

A very important study in this thesis provided evidence for the utility of the affective priming paradigm as an indirect measure of liking, which also included a direct replication of findings. I strongly recommend that this paradigm should be employed in future research, while the use of standardised self-report questionnaires can inform the potential influences of response bias and awareness in observed priming effects. The predictive validity of the measure and its sensitivity to cognitive components of attitudes (e.g,. food healthiness) should be examined in future studies with target populations (e.g,. overweight/obese participants, restrained eaters). The final training study employed the affective priming paradigm to investigate whether go/no-go training can lead to the devaluation of foods associated with response inhibition at

an automatic, or implicit, level. To our knowledge, this is the first study to date that supports the idea of an *implicit* no-go devaluation effect (as measured via the affective priming paradigm) and both confirmatory and exploratory analyses should be repeated in future replication attempts to establish the robustness of this effect and examine under what conditions (e.g,. different training protocol specification) it can be reliably observed. On a final note, all the research studies included in this thesis have yielded very rich datasets that include a number of potential moderators of training effects (e.g., hunger, BMI, trait cravings) and priming effects (e.g., target valence and arousal ratings, nutritional characteristics of the food primes) that were not explored further and will be subjected to further analyses for publication purposes.

Appendix A

Interpretation of Bayes factors

Table A.1: Evidence categories for the Bayes factor adapted from Lee and Wagenmakers (2013)

	BF_{10}			$\text{Log}(BF_{10})$		Interpretation
	$>$	100		$>$	4.61	*Extreme* evidence for H1 relative to H0
30	-	100	3.40	-	4.61	*Very strong* evidence for H1 relative to H0
10	-	30	2.30	-	3.40	*Strong* evidence for H1 relative to H0
3	-	10	1.10	-	2.30	*Moderate* evidence for H1 relative to H0
1	-	3	0	-	1.10	*Anecdotal* evidence for H1 relative to H0
	1			0		No evidence for H1
1/3	-	1	-1.10	-	0	*Anecdotal* evidence for H0 relative to H1
1/10	-	1/3	-2.30	-	-1.10	*Moderate* evidence for H0 relative to H1
1/30	-	1/10	-3.40	-	-2.30	*Strong* evidence for H0 relative to H1
1/100	-	1/30	-4.61	-	-3.40	*Very strong* evidence for H0 relative to H1
	$<$	1/100		$<$	-4.61	*Extreme* evidence for H0 relative to H1

Note. Evidence categories have been adapted from Table 7.1 in Lee & Wagenmakers (2013). The natural logarithm of the BF is denoted by $\text{Log}(BF_{10})$ and is often used in this thesis when the BF values are too large to be reported in their decimal form.

Appendix B

Supplementary information for Chapter 2

B.1 Sample characteristics & questionnaire measures

All sample characteristics, apart from gender and hours since last meal, are presented in the Table B.2 together with total scores from relevant questionnaire measures, as described in the *Survey & Questionnaires* section. Descriptive statistics of the questionnaire scores can be found in Table B.1. Pearson's r coefficients were conventionally interpreted as small, medium and large at 0.10, 0.30 and 0.50. As it would be expected for the Food Cravings Questionnaire Trait- reduced (FCQ-T-r) measure, there was a positive correlation, although small, with BMI as well as medium-to-large positive correlations with total scores on the Barratt Impulsivity Scale (BIS) and Perceived Stress Scale (PSS). Trait food cravings negatively correlated with stop control, as measured by the Stop Control Scale (SCS) and the food subscale of the Delaying Gratification Inventory (DGI).

Table B.1: Descriptive statistics of questionnaire scores from the final sample

	FCQ-T-r total	BIS total	PSS total	SCS total	DGI - food
Mean	45.362	32.773	19.896	40.951	22.245
Median	45.000	32.000	19.000	41.000	22.000
Standard Deviation	9.997	5.751	6.298	7.665	4.677
Minimum	20.000	21.000	4.000	20.000	10.000
Maximum	70.000	51.000	38.000	57.000	34.000

Note. For descriptions and abbreviations, please see the *Survey & Questionnaires* section.

Table B.2: Correlation matrix for sample characteristics and questionnaire measures

		1.	2.	3.	4.	5.	6.	7.
1. Age	r	–						
	$\log(BF_{10})$	–						
	p	–						
2. Hunger	r	-0.064	–					
	$\log(BF_{10})$	0.352	-2.322	–				
	p	0.420	–					
3. BMI	r	0.182	0.001	–				
	$\log(BF_{10})$	0.352	-2.322	–				
	p	0.020	0.987	–				
4. FCQ-T-r	r	-0.098	0.203	0.246*	–			
	$\log(BF_{10})$	-1.554	1.034	2.655	–			
	p	0.213	0.009	0.002	–			
5. BIS	r	-0.089	0.129	0.161	0.491*	–		
	$\log(BF_{10})$	-1.690	-0.991	-0.245	19.572	–		
	p	0.259	0.101	0.041	$< .001$	–		
6. PSS	r	-0.138	0.040	0.125	0.462*	0.316*	–	
	$\log(BF_{10})$	-0.782	-2.195	-1.067	16.754	6.043	–	
	p	0.078	0.611	0.111	$< .001$	$< .001$	–	
7. SCS	r	0.176	-0.085	-0.122	-0.374*	-0.721*	-0.260*	–
	$\log(BF_{10})$	0.181	-1.747	-1.133	9.630	56.042	3.247	–
	p	0.025	0.281	0.121	$< .001$	$< .001$	$< .001$	–
8. DGI-food	r	0.075	-0.161	-0.189	-0.612*	-0.433*	-0.226	0.376*
	$\log(BF_{10})$	-1.878	-0.237	0.577	35.070	14.168	1.849	9.777
	p	0.343	0.040	0.016	$< .001$	$< .001$	0.004	$< .001$

Note. Age was self-reported in years and hunger ratings ranged from 1="Not at all" to 9="Very". Body-mass index (BMI; kg/m^2); * Supported correlations at $BF_{10} > 10$

B.2 Recruitment & data exclusions

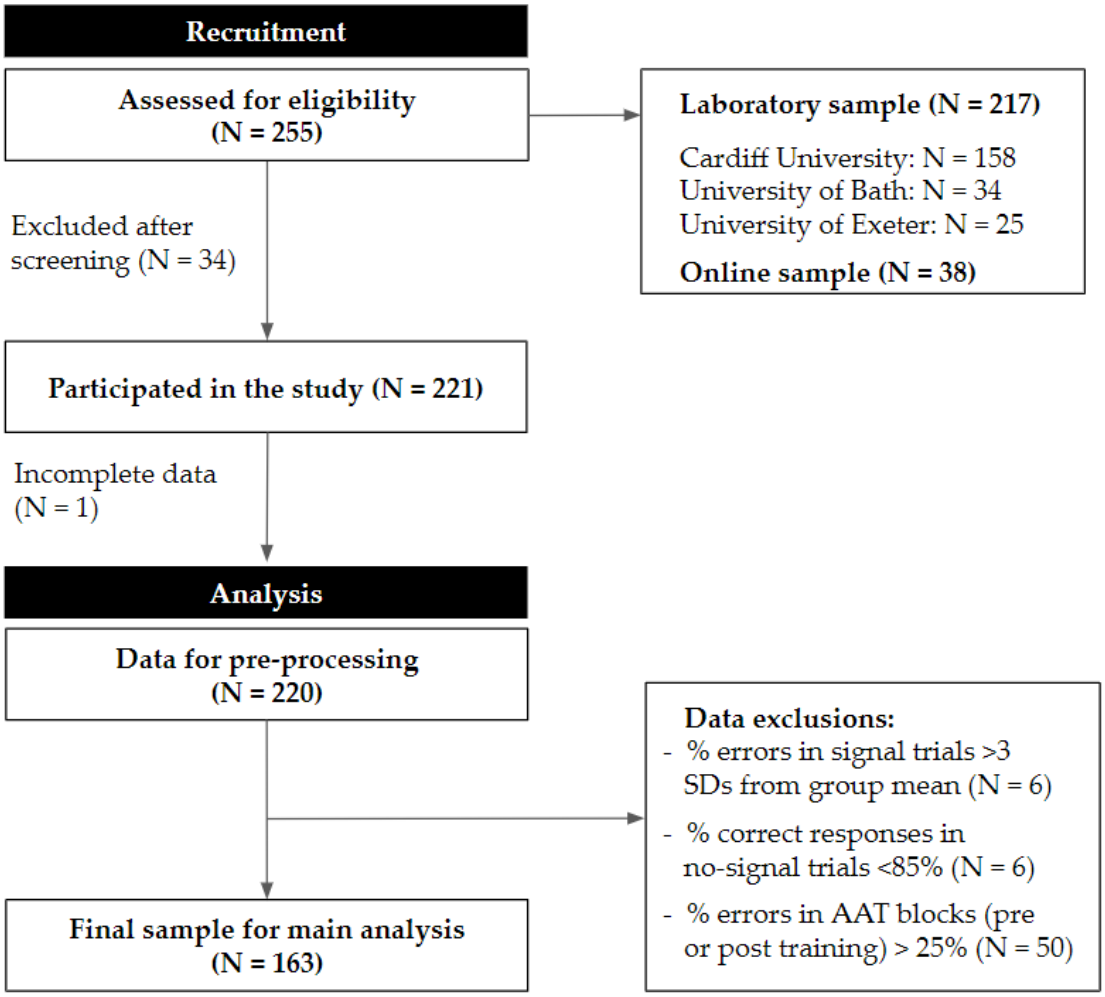


Figure B.1: Flow diagram of recruitment and participant-level data exclusions. There were 255 individuals recruited and assessed for eligibility across laboratory sites and online via personal communication. 34 participants were excluded after screening for not meeting the advertised inclusion/exclusion criteria and datasets were obtained from 221 participants. The online sample was recruited by the University of Bath and University of Exeter. One participant was excluded for providing incomplete data and 220 datasets were submitted for pre-processing and inspection. There were no participants with a mean reaction time on no-signal trials (GoRT) greater than three standard deviations (SDs) from the group mean and there were no cases of consistently missed (i.e., default option of 50) responses on food rating trials. Six participants had a percentage of errors in signal trials was greater than three SDs from the group mean and six participants also had a percentage of correct responses in no-signal trials lower than 85%. Please note that some participants met more than one exclusion criterion. 50 participants were excluded as their percentage of errors in either the pre- or post-training approach-avoidance task (AAT) blocks was greater than 25%. The final sample consisted of 163 participants.

Appendix C

Supplementary information for Chapter 3

C.1 Food selection task

In the food selection task, there was always a text reminder of the instructions on the top centre of the screen and additional instructions when participants had reached their selection count (i.e., "You have selected 12 items. Review your selections and/or proceed to checkout. To change an item, click on it again to unselect it"). The visual setup of the task can be seen in Figure C.1. On the top left of the screen there was a box called "Basket count" which indicated the number of selections participants had made. On the top right of the screen there was a box called "Checkout", which appeared in red colour and was not interactive so that no responses could occur before the selection count had been reached. The box changed into a light green colour when selection was finished. A black rectangle appeared around the images when a mouse-click was registered to visually confirm that a selection had been made.

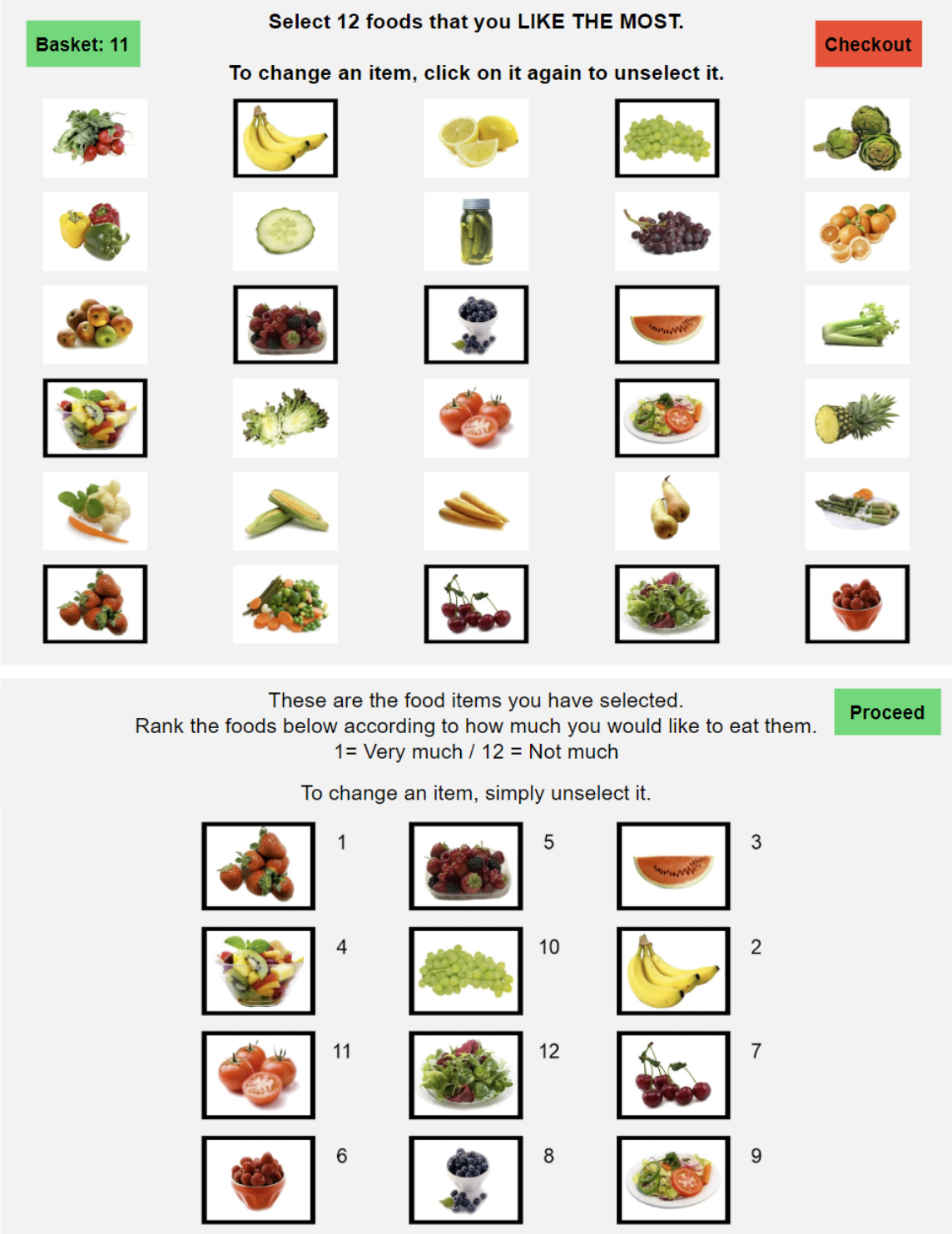


Figure C.1: Example selection and sorting pages from the food selection task.

C.2 Food stimuli

All food stimuli were obtained from the 'food-pics' online database (Blechert et al., 2014) and pictures were compressed to have a resolution of 300 × 225 pixels. All stimuli had a white background. Food categories were selected based on the number of available exemplars in the database, as three were needed for each category. Healthiness was considered using the colour-coded nutritional guidelines provided by NHS (see https://www.nhs.uk/live-well/eat-well/how-to-read-food-labels/). Information on saturates and salt (per 100g) was not available in the database and these guidelines were therefore disregarded. It should be noted that some unhealthy food categories did not meet the NHS guidelines for being high in fat and/or sugars, but these are most commonly considered unhealthy (e.g., pizza, burger) in terms of over-consumption. Also, nutritional information may vary according to the brands of these foods. All healthy foods met the conditions for low fat and low sugars. In the unhealthy category, there were 18 sweet and 12 savoury foods in total and the healthy category included 14 fruits and 16 vegetables.

For the unhealthy foods, the average fat per 100g was 17.26 (SD = 11.00), the average carbohydrates per 100g were 33.88 (SD = 18.48) and there were on average 323.04 calories per 100g (SD = 129.88). For the healthy foods, there was an average fat content of 0.33 per 100g (SD = 0.35) and the carbohydrates per 100g were 7.21 (SD = 7.23). There we on average 38.88 calories per 100g (SD = 33.09). All food categories and the corresponding stimulus IDs from the database have been provided on the preregistered study protocol (https://osf.io/y7fsk/). Although the 'food-pics' database at the time had been extended to include a variety of new food pictures, the nutritional information for these was not available. In those cases, the macro-nutrients for a picture of the same food category were used. All pictures were matched as much as possible in terms of characteristics and normative ratings, as shown in Table C.1. These included recognisability, familiarity, valence, arousal, palatability, and cravings (see Blechert et al., 2014).

The exemplars presented in the food selection task were not selected randomly, but instead the following criteria were applied. If there was diversity of food items and/or ingredients in the three exemplars, the picture with the most mood items and/or ingredients was presented. If there was no diversity but there was more than one item of the same category displayed, the picture with the highest number of displayed items was selected. Lastly, if none of those criteria applied and all images were the same in terms of content, the picture with the highest complexity rating (as reported in the

database) was selected for inclusion in the food selection task.

Table C.1: Descriptive statistics for characteristics and normative ratings of food stimuli

Mean (SD)	Recognisability	Familiarity	Valence	Arousal	Palatability	Cravings
Healthy	98.74	98.98	62.70	63.17	64.41	40.30
foods	(2.18)	(1.99)	(7.65)	(8.50)	(11.07)	(12.84)
Unhealthy	95.89	96.68	52.09	34.31	57.88	35.22
foods	(5.77)	(5.00)	(6.24)	(5.46)	(7.53)	(6.11)

Note. Descriptive statistics, that is means and standard deviations (SDs) were retrieved from the information available in the 'food-pics' database (Blechert et al., 2014).

C.3 Linear mixed-effects models

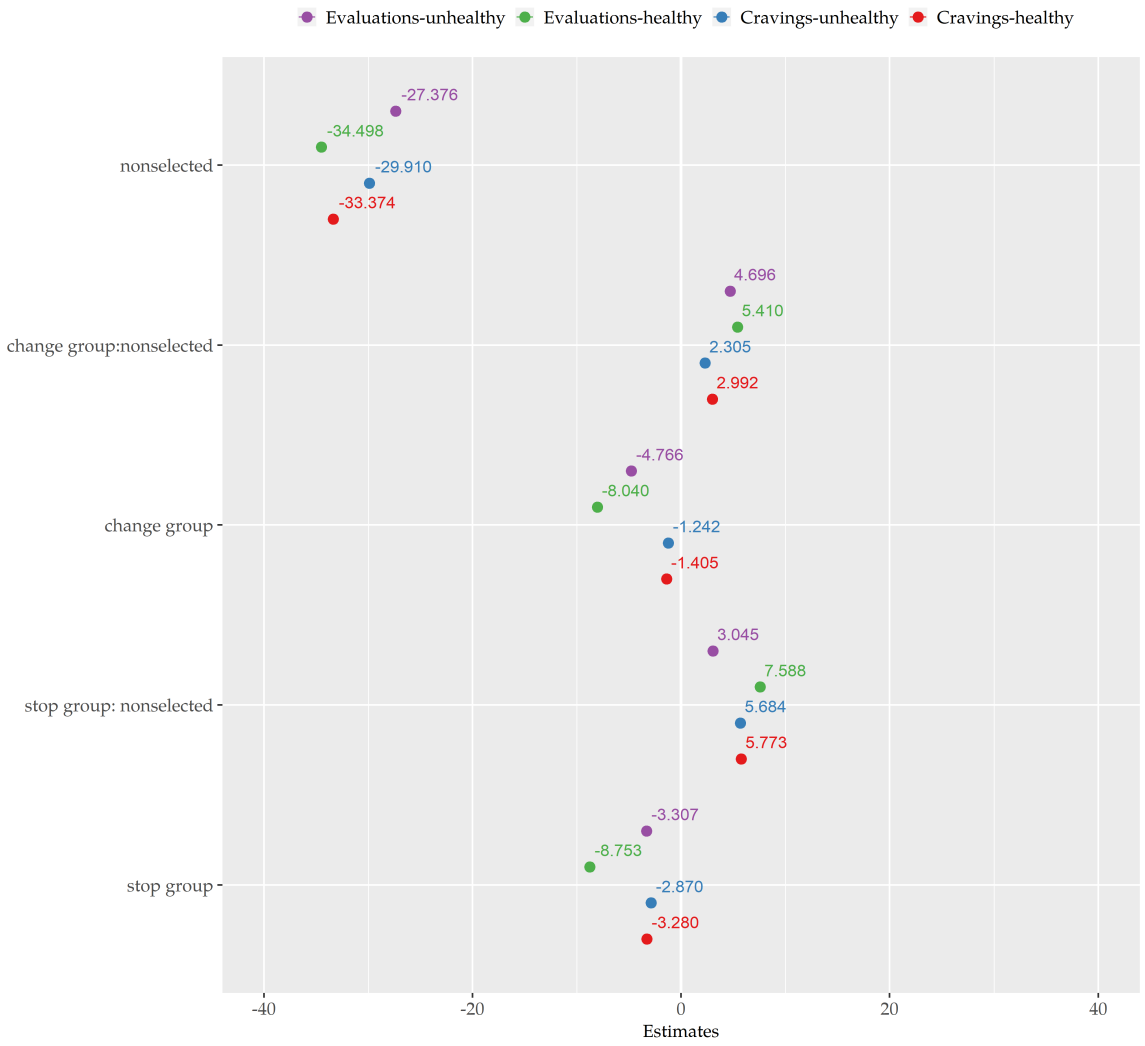


Figure C.2: Estimates of fixed effects for linear-mixed effect models This plot shows The fixed effect parameter estimates for the linear mixed-effect models fitted using the 'lme4' package that included a two-way interaction between training group and selection condition. Due to potential assumption violations, confidence intervals and p-values for these estimates were not computed. Models for all training outcomes are depicted, that is, evaluations of healthy and unhealthy foods as well as cravings for healthy and unhealthy foods. Estimates are interpreted in relation to the reference design cells (go group and selected foods). For example, evaluations for unhealthy foods are reduced by 4.766 in the stop-change group compared to the control group (go) and by -3.307 in the stop group compared to the control. When the foods were non-selected the estimates indicate that the changes from the experimental training groups to the control are no longer negative (see change group:nonselected and stop group:nonselected).

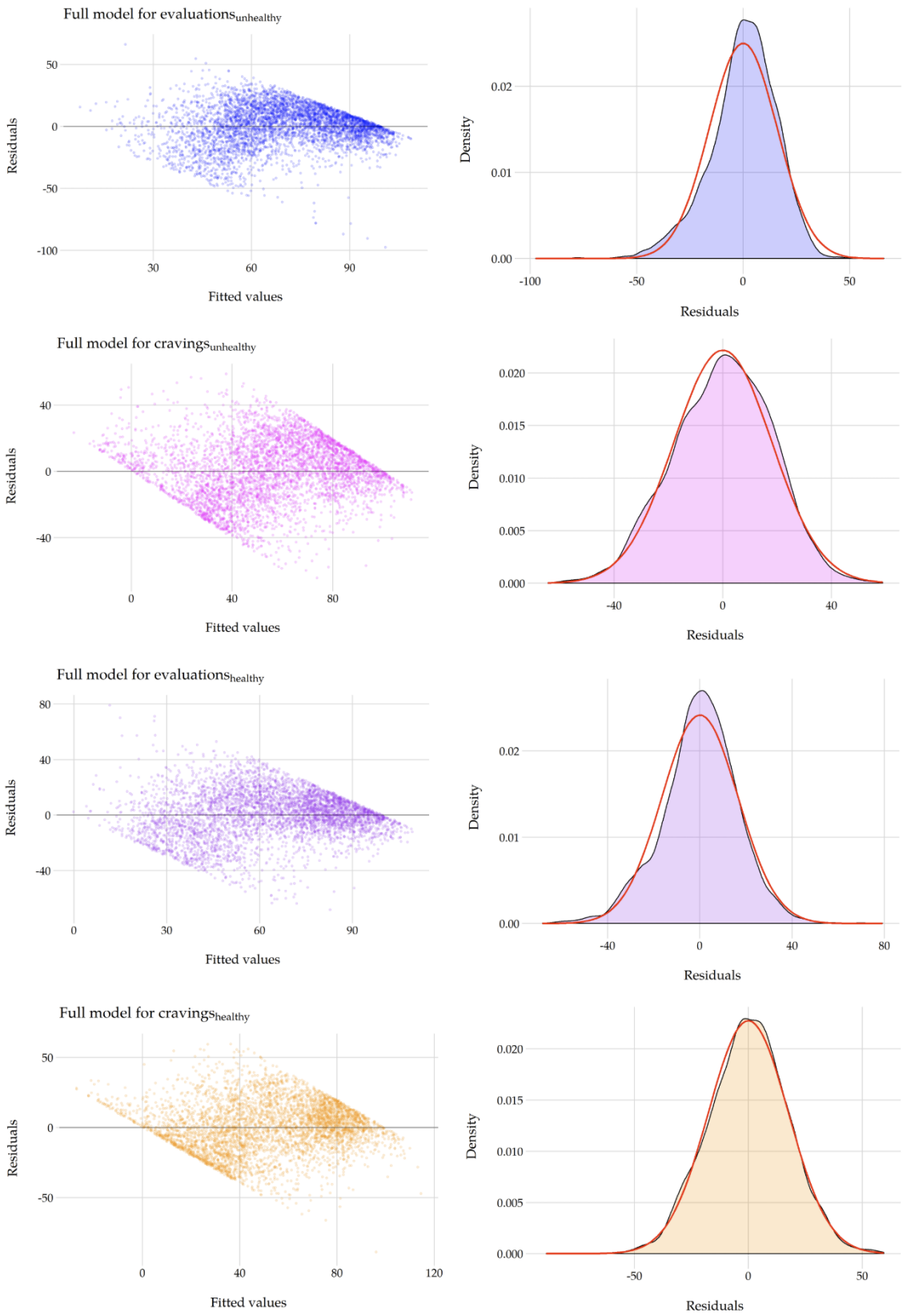


Figure C.3: Diagnostic plots for linear mixed-effects models.

The scatterplots were inspected for potential violation of the assumption of homoskedasticity in the linear mixed-effects models (LMMs) fitted to the ratings data for tastiness (evaluations) and desire to eat (cravings). Plots were created for the full models including a three-way interaction for training condition, selection condition and stimulus novelty and the added random effect for participants. The spread of the residuals is not constant across the range of fitted values (heteroscedasticity), as it can clearly be observed by the clustering of plotted points in the top-left plot of the full model for the evaluations of unhealthy foods. The density plots of the residuals do not indicate that the normality assumption was violated for any of the full models.

Appendix D

Pilot experiments for Chapter 4

D.1 Background & rationale

The empirical study presented in Chapter 4 was developed through a series of pilot experiments which assessed the feasibility of the affective priming paradigm (APP) as an indirect measure of food attitudes. The proposed study would be submitted as a Registered Report in an eligible scientific journal and it was of paramount importance to obtain evidence for the robustness of the APP design before submission. Not only did the pilot experiments led to the development of a robust paradigm, but also provided conclusive evidence for the proposed manipulation check of the study. As described in section 4.2, in order to infer that the employed APP task would be effective when applied to food stimuli, priming effects would need to observed for non-food stimuli as a manipulation check.

D.2 Pilot Experiment 1

D.2.1 Pilot objectives

The first pilot experiment was conducted to assess the feasibility of the task design for the APP to be employed in the proposed study. An additional sub-experiment was conducted in parallel for the development of an independent study examining whether priming effects could also be observed for subliminally presented food primes (for a review see De Houwer et al., 2009). Experiment 1a (supraliminal stimuli only) was consistent with the design of the proposed study, and we also report the relevant findings from Experiment 1b (involving supra- and subliminal primes) as it provided additional data for analysis. The manipulation check was an observed priming effect

for positive non-food primes, corroborating the internal validity of the affective priming paradigm. In particular, the ability to demonstrate a positive priming effect for non-food stimuli would enable the absence of priming for food stimuli to be interpreted informatively, over and above generic failure of the current task to induce priming in general.

D.2.2 Pilot 1: Methods

Participants

Participants (Experiment 1a- N = 44; Experiment 1b- N = 26) were recruited through the experimental management system (EMS) at Cardiff University. All participants completed the study online using Inquisit 4 (Millisecond Software, 2015) and were reimbursed via course credits. Sample sizes for the pilot experiments were determined on an ad-hoc basis. Inclusion criteria for participation were being at least 18 years of age, having normal or corrected-to-normal vision, including normal colour vision, being able to read and understand English well and not being on a diet and/or taking diet pills at the time of the study. All eligible participants provided informed consent for participating and were debriefed at the end of the study. All pilot experiments were approved by the Research Ethics Committee at the School of Psychology, Cardiff University.

Primes & targets

Food primes were chosen by the participants in the beginning of the study using a selection task, as shown in Figure D.1. Participants selected four foods as 'most liked' and four foods as 'least liked' from two sets of healthy and unhealthy foods. Control (non-food) primes were not selected by the participants[1]. A fixed set of stimuli was used as they were considered to have positive valence (i.e., animals and flowers). Targets consisted of 16 positive and 16 negative words which were selected based on expected valence, word familiarity ratings (i.e., ≥ 500), as included in the MRC Psycholinguistic Database (Coltheart, 1981 retrieved from https://goo.gl/M3dFWH) and number of syllables (1-2).

[1]Non-food primes are referred to as control primes in these pilot experiments, but this term was not included in the final study.

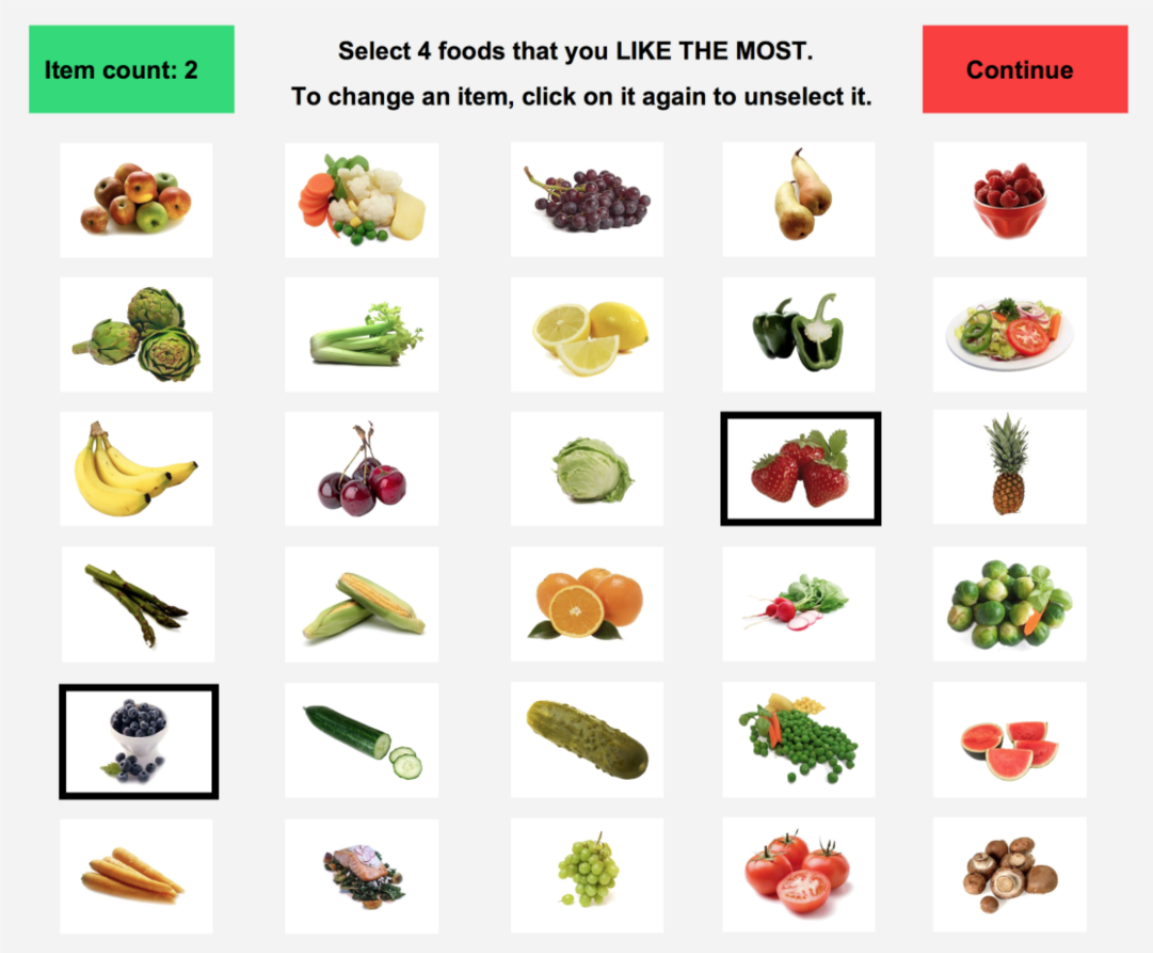


Figure D.1: Example section from the prime selection task. In this section, two healthy foods have been selected as most liked, as it can be seen in the *Item count* box. Participants could not proceed to the next section until the colour of the *Continue* box changed from red to green.

Task design

Each block in the APP employed in Experiment 1a consisted of 32 food prime trials and 16 control (non-food) prime trials (supraliminal). Food prime trials had an equal number of congruent and incongruent prime-target pairs for which either a healthy or unhealthy food was paired with either a positive or negative target. For each set of prime-target pairs, there was an equal probability for either a most liked or least liked food prime to appear. Control prime trials had eight congruent and eight incongruent prime-target pairs. The order of presentation for the targets and primes was random and all targets appeared with equal probability across blocks.

Participants categorised targets as positive or negative using the "G" and "H" keys on a standard keyboard using their dominant hand. Participants were instructed to place their middle and index fingers on the keys accordingly; that is, right-handed

participants placed their index finger on the "G" key and middle finger on the "H" key. Response key assignments (e.g., "G" for positive) were counterbalanced across participants. Each trial begun with a fixation cross in the centre of the screen, which was followed by the prime at 975 milliseconds (ms). Primes stayed on the screen for 233ms. A mask was presented after the prime for 17 ms and the target appeared at 1225ms. The stimulus-onset asynchrony (SOA) was 250ms and the maximum reaction time (maxRT) was set to 1500 ms (i.e., total trial duration = 2725ms). All text stimuli were presented in white bold Arial fonts on a black background. Target words were presented in upper-case letters.

Experiment 1b included trials with either supraliminal or subliminal primes, but details on the subliminal trials go beyond the scope of this investigation and are not discussed further. In each block of the APP (supraliminal primes only), there were 16 food prime trials and 8 control prime trials. The resulting number of food prime trials for 8 blocks was 96 for each affective congruence level. Most liked and least liked primes appeared with equal probability. One methodological parameter that could potentially influence the design of the affective priming paradigm was the additional responses participants had to make after they had categorised the targets as either positive or negative. They were asked to indicate whether they had seen the picture or not by pressing the "G" (Yes) and "H" (No) keys, which were not counterbalanced. All stimuli durations were exactly the same as in Experiment 1a apart from the fixation duration (i.e., 983 ms), which shifted all trial events by 8 ms (e.g., primes were presented at 1216 ms instead of 1208 ms).

D.2.3 Pilot 1: Results & Discussion

Median reaction times from correct responses were used in the main response speed analyses, while data from participants with mean error rates greater than or equal to 0.5 in the control and food prime trials were excluded. In Experiment 1b, five participants were excluded based on their error rates on food and control prime trials. Data from the APP were analysed using Bayesian paired samples t-tests and complementary frequentist statistics are reported. All Bayesian paired samples t-tests conducted for the pilot experiments used the default scale parameter $\sqrt{2}/2$ (r=0.707) for the half-Cauchy distribution. All comparisons were directional (i.e., measurement one less than measurement two). Please note that only results which were considered to be crucial for the development of the proposed protocol are reported here. Specifically, we were interested in whether an affective priming effect can be obtained for healthy

and unhealthy foods and whether a positive priming effect for reaction times could be reliably induced with non-food primes (i.e., manipulation check). However, all pilot results are available at https://osf.io/c95av/.

Priming effects for foods

Both Experiment 1a and 1b showed that an affective priming effect can be obtained for healthy and unhealthy foods on the basis of reaction time (RT) and error rate (ER) differences. In Experiment 1a, there was *extreme* evidence that participants responded faster in congruent (M = 547.81; SD = 67.18) than incongruent food prime trials (M = 571.11; SD = 60.58); $t(43)$ = -5.55, $p < .001$, Cohen's d = -0.84; BF_{10} = 20894.35. Participants also had lower error rates in congruent (M = 0.09; SD = 0.07) than incongruent trials (M = 0.13; SD = 0.10); $t(43)$ = -3.82, $p < .001$, Cohen's d = -0.58; BF_{10} = 126.35. Similarly in Experiment 1b, there was *very strong* evidence for RTs being lower in congruent (M = 689.50; SD = 100.17) than incongruent food prime trials (M = 726.52; SD = 103.12); $t(20)$ = -4.01, $p < .001$, Cohen's d = -0.87; BF_{10} = 99.46. Consistent with Experiment 1a, there was also *moderate* evidence for ERs being lower in congruent (M = 0.13; SD = 0.12) than incongruent food prime trials (M = 0.17; SD = 0.14) in Experiment 1b; $t(20)$ = -2.73, p = 0.006, Cohen's d = -0.60; BF_{10} = 8.11).

Manipulation checks

There was *anecdotal* evidence for the absence of an affective priming effect for control primes (manipulation check) in Experiment 1a. Participants did not respond considerably faster on congruent (M = 560.67; SD = 67.35) than incongruent trials (M = 567.68; SD = 66.76); $t(43)$ = -1.50, p = 0.071, Cohen's d = -0.23; BF_{10} = 0.85. Contrary to this result, in Experiment 1b RTs were faster for congruent (M = 664.67; SD = 117.37) than incongruent (M = 737.98; SD = 107.10) control prime trials; $t(20)$ = -2.85, p = 0.005, Cohen's d = -0.62; BF_{10} = 10.07. The distributions of RTs from control prime trials in both experiments can be seen in Figure D.2. Consistent with the discrepancies in RT results, there was *anecdotal* evidence for an affective priming effect for error rates in Experiment 1B ($t(20)$ = -1.89, p = 0.037, Cohen's d = -0.41; BF_{10} = 1.93), but *strong* evidence for the absence of an effect in Experiment 1a ($t(43)$ = 1.28, p = 0.896, Cohen's d = 0.19; BF_{10} = 0.08). These discrepancies between Experiment 1a and Experiment 1b led to the re-evaluation of certain APP design parameters, which are further discussed below.

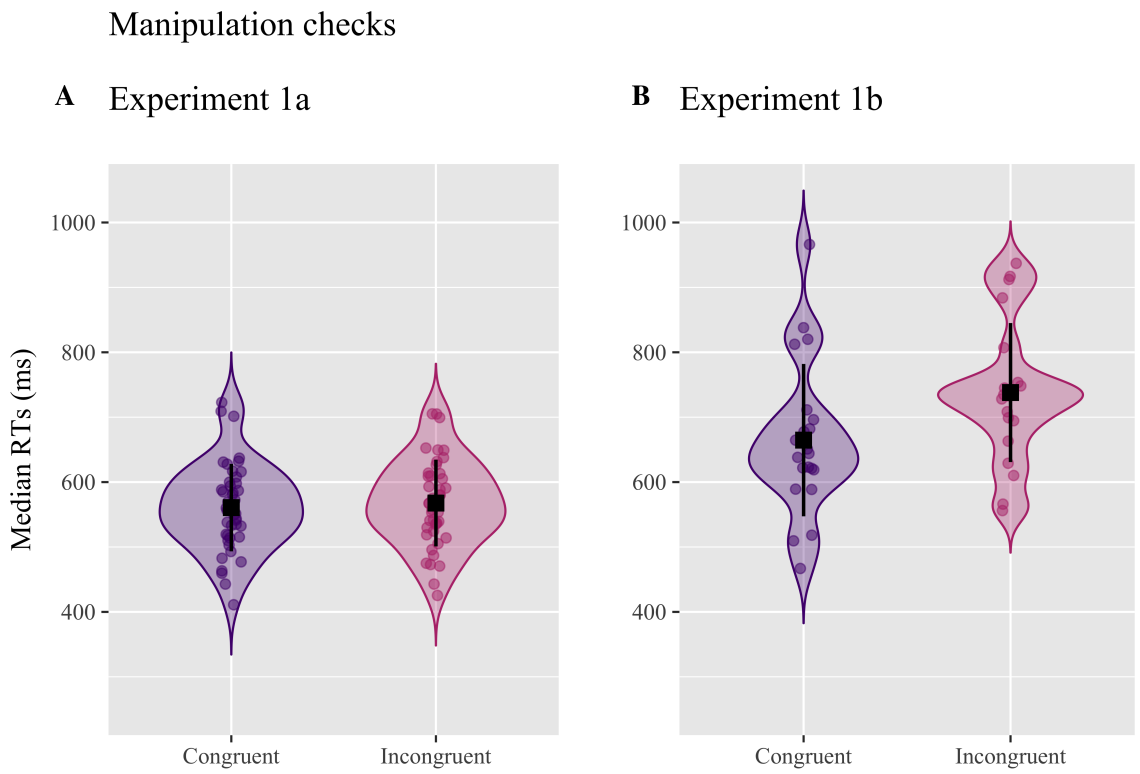


Figure D.2: Median reaction time distributions from control prime trials in Experiments 1a and 1b. The violin plots show the distributions of individual median reaction times (correct responses only) from control prime trials (manipulation check) in Experiment 1a and 1b. **A.** There was no apparent difference between the means in Experiment 1a, suggesting the absence of a priming effect. The distributions of RTs in Experiment 1a were approximately symmetrical and showed an even spread of data points around the means. **B.** The distributions of RTs in Experiment 1b showed a number of asymmetries. However, participants in Experiment 1b responded considerably faster on congruent than incongruent trials, indicating the success of the priming manipulation. *Note.* Error bars denote 1±SD from the sample mean, as depicted by the black squares.

D.3 Pilot Experiment 2

D.3.1 Pilot objectives

Due to the discrepancies in findings for the control prime trials in Pilot Experiment 1, the manipulation check was tested again in Experiment 2 using control (non-food) primes that were tailored to individual evaluations, thus aligning the stimulus selection procedure for food and non-food primes. A secondary purpose of Experiment 2 was to develop a greater understanding of potential methodological limitations from the participants' perspectives using follow-up survey questions (e.g., response strategies). The survey had similar content with the one developed for the proposed study (see Appendix E.4).

D.3.2 Pilot 2: Methods

Participants (N = 37) were recruited using EMS and written correspondence at Cardiff University. The same inclusion criteria as in Experiment 1 were applied and participants were reimbursed with £5. The experiment was conducted in a laboratory group setting. In addition to the selection of the food primes, participants were asked to choose four non-food stimuli from a set of pictures. Specifically, participants selected four categories that they found the most pleasant and were instructed to select the specific images that were the most positive to them. Categories included animals, babies, landscapes, flowers and more. Taking into account individual differences, we considered the possibility that the selection task alone may not be enough to gather data on explicit food liking. Therefore, all primes were explicitly evaluated by the participants in a rating task after all stimuli have been selected. In the preliminary version of the task, participants only evaluated primes on pleasantness (i.e., "How pleasant is this image to you?").

Each block of the APP was consistent with the design in Experiment 1a, except for the number of control prime trials, which was reduced to eight. This modification was implemented to reduce the total number of trials and thus total duration of the experiment (i.e., 20-25 minutes) to include new elements to the experimental procedure, such as the selection of non-food primes and explicit evaluation of all primes. We also considered it important to minimise the duration of the experiment to facilitate data collection for future application in online settings (i.e., preregistered study). In Experiment 2, the fixation duration was 1000 ms and the primes were followed by the mask at 1233 ms. The targets appeared at 1250 ms, therefore keeping the SOA consistent with Experiment 1.

D.3.3 Pilot 2: Results & Discussion

Priming effects for foods

One participant was excluded based on error rates on control prime and food prime trials, as described previously. The findings for food prime trials from Experiment 1 were replicated with the employed design. Participants were faster to respond on congruent (M = 533.10; SD = 58.85) than incongruent food prime trials (M = 555.86 ms; SD = 57.81); $t(35)$ = -8.65, p< .001, Cohen's d = -1.44; $BF_{10} = 6.62 \times 10^7$. Participants also exhibited lower ERs on congruent (M = 0.06; SD = 0.03) than incongruent trials (M = 0.09; SD = 0.06); $t(35)$ = -4.20, p < .001, Cohen's d = -0.70; BF_{10} = 300.16.

Manipulation checks

Experiment 2 also provided *extreme* evidence for the affective priming effect in control prime trials, supporting the improved design for the suggested manipulation check. RTs were reduced for congruent (M = 522.72; SD = 65.90) compared to incongruent trials (M = 553.57; SD = 57.83); $t(35)$ = -4.16, $p < .001$, Cohen's d = -0.69; BF_{10} = 268.60. Similarly, ERs were lower on congruent (M = 0.05; SD = 0.04) than incongruent trials (M = 0.10; SD = 0.08); $t(35)$ = -4.76, $p < .001$, Cohen's d = -0.79; BF_{10} = 1369.50. RT differences on food and control prime trials can be seen in Figure D.3.

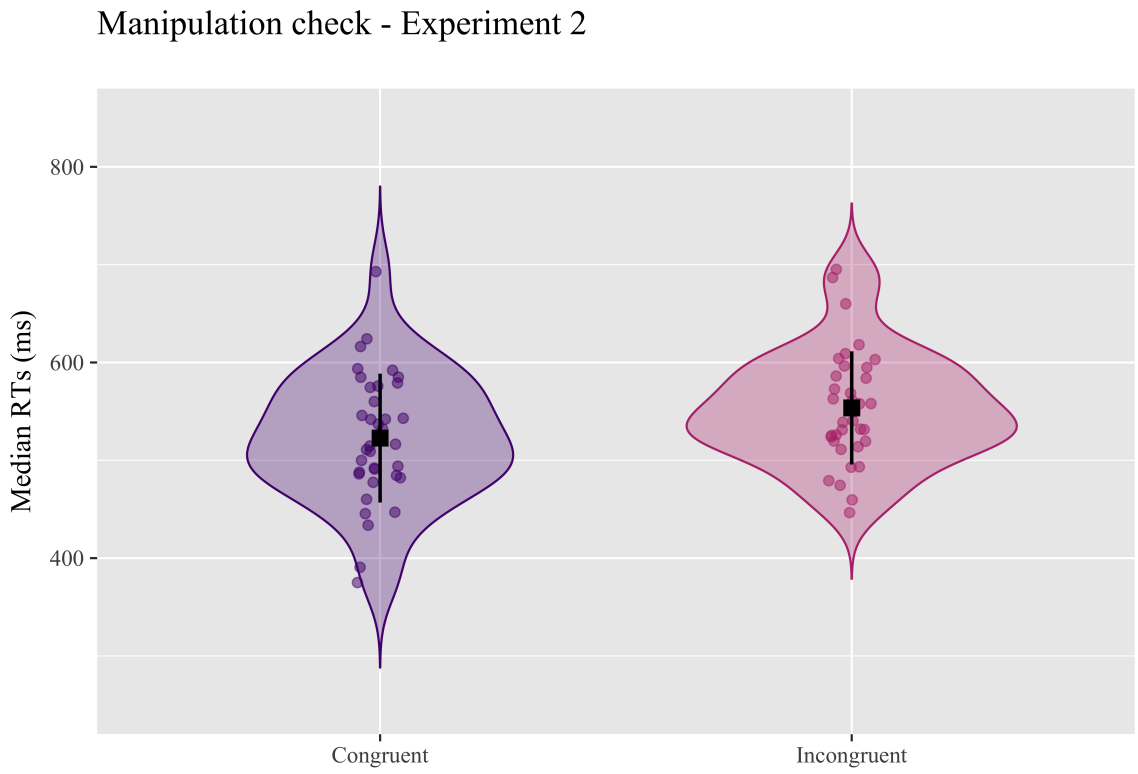


Figure D.3: Median reaction time distributions from control prime trials in Experiment 2 (manipulation check). The violin plots show the distributions of individual median reaction times (correct responses only) from control prime trials in Experiment 2 (i.e., manipulation check). As in Experiment 1b, results indicate success of the priming manipulation. It should be noted that a number of outliers can be detected in congruent control prime trials and the spread of RTs is larger for congruent compared to incongruent trials. *Note.* Error bars denote 1±SD from the mean. Means are depicted by the black squares.

Follow-up survey

The follow-up survey administered in Experiment 2 yielded a number of findings and consequently led to several methodological improvements for the proposed study. Prior assumptions about potential confounds for performance in the APP informed the original design of this open-ended survey. For qualitative data (open-ended responses and comments), an approach similar to thematic analysis (Braun & Clarke, 2006) was employed, whereby emerging themes were coded for frequency and then formally categorised into standardised questions for the development of questionnaire to be used in the proposed study (see sections 4.3.6 and 4.5.4). The final set of questionnaire items can be found in Appendix E.4.

The original survey administered to participants in Experiment 2 had four main sets of questions, First, participants were asked if the task was easy to complete and whether they noticed "any differences about their responses on separate occations (e.g., faster to categorize a type of word)". An explanation was required in an open-ended format. The phrasing of the question did not reveal anything about possible effects of affective congruence on performance specifically, as the purpose was to examine to what extent the participants were aware of such effects. Overall, 47.22% of participants (N = 17) had a level of awareness and clearly understood one or more trial types in which congruence was manipulated (e.g., positive prime-positive target, positive prime-negative target). There were therefore different aspects of affective congruence that needed to be categorised for the final questionnaire (i.e., checkboxes for multiple options that apply). Selected verbatim statements from participants are shown in Table D.1. Awareness of congruence effects on performance would depend on participants seeing the content of the primes preceding the targets. Survey responses on the question "How often did you see the content of the image that was presented before the target?" confirmed this, as 42.86% of particants reported seeing the content "Most of the time", 42.86% reported "always" seeing the primes, and only 14.29% of participants indicated they "rarely" saw the content of the picture.

Two participants recognised that their performance was different for specific words and three participants answered that they felt they became faster at categorising the targets over time (e.g. "Faster after I got to know the words and saw the same ones again and again"). It is possible that if the question probed participants to think about potential practice effects, there would be more responses to corroborate this theme. Indeed, several participants informally reported this during verbal feedback after debriefing. This was considered an important methodological issue, as it would be theoretically sound to assume that target words could be retrieved from memory

Table D.1: Selected verbatim statements related to the 'awareness of affective congruence' theme

Trial type	Verbatim statements
Positive prime - positive target	"Easy when the picture was positive and the word was also positive"
	"I felt my responses were faster when pleasant words were anticipated by pleasant images"
Positive prime - Negative target	"I found it difficult to respond negatively when a bad word came up with a picture that pleased me"
	"Found it very difficult to categorise words as negative if they followed a picture I liked (i.e. pizza or cats!)"
Negative prime - Negative target	"Faster to categorise words when they followed the corresponding category of picture; i.e. positive word following pleasant picture and negative words following unpleasant image"
	"...when negative image was followed by negative word my reaction time should have been faster" *

Note. Many participants were aware of the effects of affective congruence on their performance. Within this theme, different sub-themes were identified for specific trial types. ∗Several statements indicated that often participants were aware of more than one aspect of affective congruence.

after repeated exposure, possibly reducing or diminishing observed priming effects due to the absence of evaluative judgments (i.e., categorisation based on target valence) . A ceiling effect in performance could also be induced by repeated practice, whereby participants would not be able to respond any faster or more accurately for either conruent or incongruent trials. This finding was incorporated into an 'awareness of reaction time differences' theme in the final study questionnaire.

Participants were also asked whether they purposefully used any kind of strategy to make their responses faster and/or more accurate, such as slowing down in order to get a correct response ('Response strategies' theme). Although 69.44% (N = 25) of participants responded "Yes" on this question, their statements revealed that the majority of 'strategies' referred to trying to ignore the content of the prime and concentrating more on the words. As this question aimed to capture strategic responding with regards to speed-accuracy trade offs, it was clear that such strategies would need to be stated explicitly in the final questionnaire. Six participants explained that they slowed down their responses in order to avoid making errors. It should be noted that the instructions for the task already prioritised response speed over accuracy. This finding reaffirmed our prospective interpretation strategy for reaction

time and accuracy outcomes and examination of speed-accuracy trade-offs (see section 4.2).

The possibility of stimulus (target) confounds (Wentura & Degner, 2010) was taken into account when designing the survey for Experiment 2 and for reliable priming effects to be obtained participants should be able to categorise the targets as clearly positive or negative. Participants were asked whether they found all the words clearly positive or negative and 36.11% (N = 13) answered "No". Several participants indicated that the word *alone*, for example, is ambivalent as it can be either positive or negative depending on the specific context. This is an important theme that was also included in the final questionnaire (i.e., 'Ambivalence of targets'). Stimulus confounds were also examined for food and non-food primes. When asked whether they found a sufficient number of foods that they liked the most and the least in the prime selection task, 61.54% of participants (N = 16) suggested that there was a lack of variety for foods that could be selected as 'least liked'. Several suggestions for the types of foods that should be included in the selection task were received and these were taken into account for the planned study. The list of non-food stimuli was also updated to include more pictures of sceneries and cues of pleasant activities (e.g., football, video-games).

D.4 Pilot experiment 3

D.4.1 Pilot objectives

The primary aim of Experiment 3 was to directly replicate the findings of the previous pilot for the control prime trials via online data collection. The follow-up survey introduced in Experiment 2 also informed two alterations to the experimental procedure and APP. As discussed above, certain targets in the APP could be considered ambivalent by the participants and that would have implications for task performance. Therefore, an important development for Experiment 3 was to select the targets based on normative ratings of valence and ask participants to evaluate them before the task. We also considered the possibility of a ceiling effect in performance due to the repetition of targets during the task. Therefore, in Experiment 3 the number of targets was increased. Additionally, some foods on the selection task were replaced in order to introduce more variety for items that could potentially be chosen as 'least liked'.

D.4.2 Pilot 3: Methods

Participants (N=41) were recruited via *Prolific* (https://www.prolific.ac/) and completed the tasks online. Reimbursement involved monetary payment following the procedures set in place for *Prolific*. Inclusion criteria were consistent with the previous pilot experiments. Certain items in the food section of the prime selection task were replaced. In an effort to reduce practice effects associated with the number of word repetitions across blocks, the number of targets was increased to 32 positive and 32 negative words . All targets were rated by the participants on valence (i.e., "How positive or negative is this word to you?") before the APP. The APP employed in Experiment 3 included 32 food and 8 non-food prime trials in each block and all targets appeared with equal probability across blocks. The screen background was changed from black to light grey, as it was observed during Experiment 2 that the high contrast between the primes and the screen may induce visual after-effects. The fonts were changed to black. All timings were exactly the same as in Experiment 2 and the proposed protocol.

D.4.3 Pilot 3: Results & Discussion

One participant was excluded from analyses of the food prime trials, based on error rates (i.e., ER $\geq$ 0.5). Experiment 3 directly replicated the results of Experiment 2 for the affective priming effect on food and control prime trials (see Figure D.4). Participants were faster to respond in congruent (M = 589.74; SD = 67.37) than incongruent food prime trials (M = 602.20 ms; SD = 68.05); $t(39)$ = -4.02, $p < .001$, Cohen's d = -0.64; BF_{10} = 206.42. There was also *anecdotal* evidence for a priming effect in relation to error rates ($t(39)$ = -2.32, p = 0.013, d = -0.37; BF_{10} = 3.64). The manipulation check was considered robust following the replication of findings from Experiment 2. On control prime trials, participants were faster to respond in congruent (M = 580.94; SD = 69.62) than incongruent trials (M = 602.94; SD = 77.08); $t(40)$ = -3.04, p = 0.002, Cohen's d = -0.48; BF_{10} = 17.36.

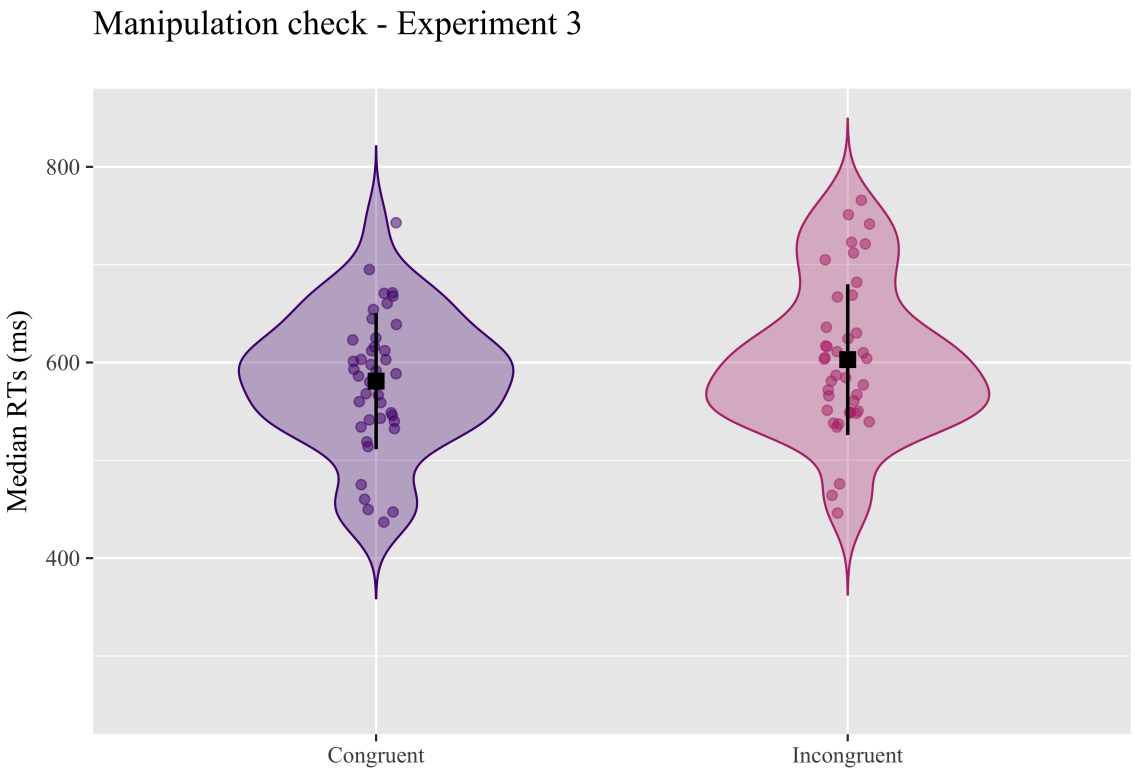


Figure D.4: Median reaction time distributions from control prime trials in Experiment 3 (manipulation check). The violin plots show the distributions of individual median reaction times (correct responses only) from control prime trials in Experiment 3 (i.e., manipulation check). As in Experiment 1b and Experiment 2, results confirm the success of the priming manipulation. *Note.* Error bars denote 1±SD from the mean. Means are depicted by the black squares.

Appendix E

Supplementary information for Chapter 4

E.1 Food stimuli & food choice task setup

Descriptive & nutritional information of food stimuli

Stimuli were obtained from the food-pics online database (Blechert, 2019; Blechert et al., 2014) and Pixabay (https://pixabay.com/). Many food stimuli (i.e., branded foods) have been photographed and all stimuli were edited to have the same dimensions and a white background. The healthiness of the foods was considered based on what constitutes a healthy eating pattern, whereby the consumption of vegetables, fruits, grains and protein foods is encouraged, whereas added sugars, saturated fats and sodium intake should be limited (see https://bit.ly/2nDQnMg). Nutritional information of all healthy and unhealthy foods included in the prime selection task can be found in Tables E.1 and E.2, respectively. Non-food stimuli consisted of several positive categories, such as animals, flowers, sceneries and babies. Pictures with a CC0 license have been retrieved from Pixabay and have also been edited. Materials and stimulus IDs for stimuli obtained from the food-pics database, which could not be shared openly, have been made available at https://osf.io/sjcx7/ to ensure reproducibility of methods.

Food choice task items and constraints for selection by the researcher(s)

Foods were selected under certain constraints for their inclusion in the food choice task. In laboratory settings, participants were offered a food item at the end of the

experiment (see section 4.3.4). However, several healthy and unhealthy foods cannot be safely stored in the laboratory due to decay (e.g., fresh fruit, cooked meals). Tables E.1 and E.2 show whether foods are suitable for laboratory storage or not. Similarly, due to health and safety regulations, we have chosen to provide participants with 'cupboard' items which can be bought in small packets (i.e., serving size). Participants were instructed that the food they would receive would be selected by the researcher(s). It was considered that participants should not be offered foods that they had rated negatively (i.e., 'least liked') and therefore this additional constraint was placed on the selection process. At the end of the experiment, participants were shown the foods they have chosen and were asked to wait for the researcher to select the food. With a total maximum of 16 foods being chosen, a $4 \times 4 \times 4 \times 4$ grid of food names appeared on the screen and 'most liked' foods were programmed to appear on the left side of the screen (see Figure E.1). This procedure would ensure that the selection of 'least liked' foods was avoided.

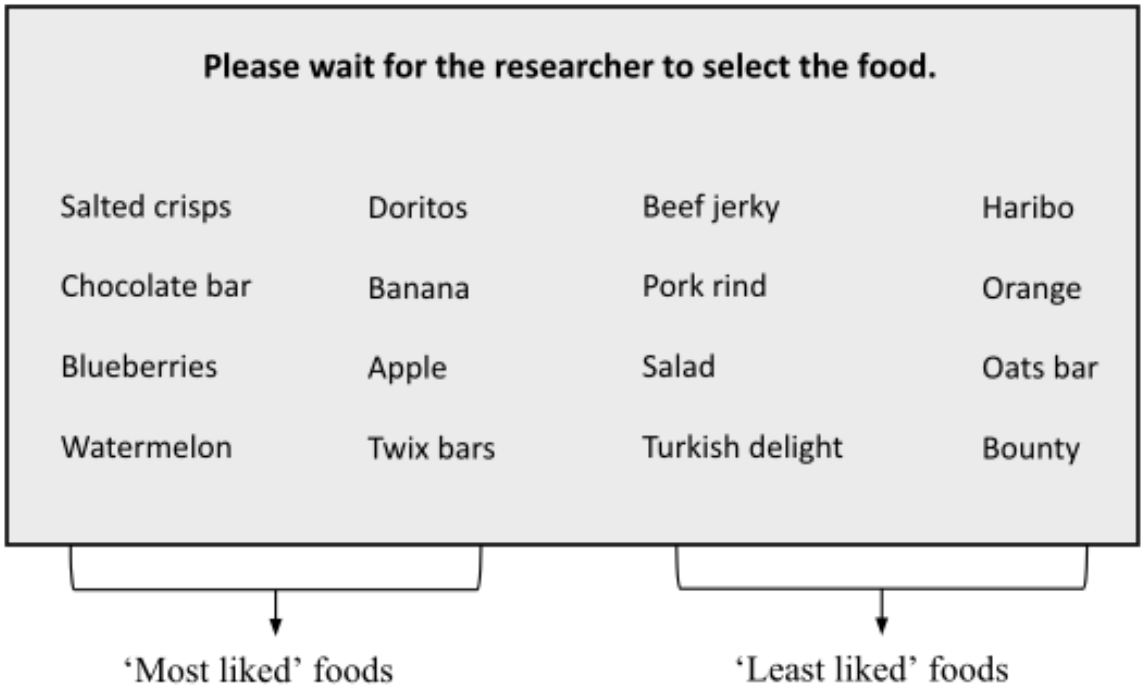


Figure E.1: Schematic of food selection page for participants in laboratory settings. There was a variable number of chosen foods being presented at the end of the experiment in laboratory settings, with a maximum of 16. The names of the foods were shown in a grid as shown above. Foods presented on the left columns were 'most liked' and foods shown on the right columns were 'least liked'. The researcher(s) then selected a 'most liked' food to offer for consumption.

Table E.1: Descriptive and nutritional information of healthy foods in the prime selection task

Food description		Nutritional information per 100g						Serving
Item	Lab∗	KCals	Fat	Sats	Carbs	Sugar	Salt	g
Raw almonds	Yes	587	49.00	3.70	9.50	3.90	0.00	25.0
Oats & honey bar	Yes	456	17.20	72.40	64.50	28.30	0.80	42.0
Summer berries bar	Yes	332	4.20	2.00	55.00	16.00	0.06	19.0
Chocolate & orange bar	Yes	339	5.90	2.40	52.00	18.00	0.01	19.0
Nutri-grain raisin bake	Yes	377	8.80	1.20	69.00	41.00	0.45	45.0
Beetroot & parsnip crisps	Yes	325	2.50	0.50	54.00	47.00	2.00	18.0
Pineapple crisps	Yes	344	0.00	0.00	81.00	70.00	0.00	20.0
Greek salad	No	116	9.40	2.60	4.60	3.30	0.72	185.0
Gherkin	No	20	0.20	0.08	2.60	2.60	1.23	100.0
Asparagus	No	29	0.60	0.10	2.00	1.90	0.01	62.0
Brussel sprouts	No	51	1.40	0.30	4.10	3.10	0.02	80.0
Radish	No	14	0.20	0.10	1.90	1.90	0.10	80.0
Carrots	No	42	0.30	0.10	7.90	7.40	0.00	100.0
Celery	No	10	0.20	0.10	0.90	0.90	0.15	90.0
Peppers	No	23	0.23	0.10	3.83	3.66	0.01	125.0
Beetroot	No	42	0.35	0.20	7.05	7.01	0.18	100.0
Strawberry	No	30	0.10	0.01	6.00	6.00	0.01	100.0
Orange	No	41	0.20	0.00	8.20	8.20	0.00	100.0
Grapes	No	66	0.10	0.10	15.40	15.40	0.01	100.0
Banana	No	103	0.30	0.10	23.20	20.90	0.00	150.0
Watermelon	No	33	0.30	0.10	6.90	6.90	0.01	90.0
Blueberries	No	68	0.30	0.03	14.50	10.00	0.00	100.0
Apple	No	53	0.10	0.01	11.80	11.80	0.00	133.0
Cherries	No	52	0.10	0.10	11.50	11.50	0.01	100.0
Raspberries	No	32	0.30	0.10	4.60	4.60	0.00	100.0

Note. Lab∗- suitability of foods for storage in the laboratory and offer to participants after the food choice task. Carbs: Carbohydrates; KCals: Energy in kilocalories; Fat: Total fat; Sats: Saturates; g: grams

Table E.2: Descriptive and nutritional information of unhealthy foods in the prime selection task

Food description		Nutritional information per 100g						Serving
Item	Lab∗	KCals	Fat	Sats	Carbs	Sugar	Salt	g
Crisps- salted	Yes	526	31.90	2.60	51.50	0.40	1.40	25.0
Crisps- salt & vinegar	Yes	519	30.80	2.50	52.60	1.00	1.62	25.0
Crisps- cheese & onion	Yes	520	30.60	2.50	52.60	3.30	1.23	25.0
Quavers- cheese	Yes	536	30.80	2.70	62.10	2.70	2.14	16.0
Frazzles	Yes	483	22.70	1.70	62.50	2.40	2.76	18.0
Doritos- cheese	Yes	499	26.30	2.40	55.40	2.60	1.27	30.0
Cheese puffs	Yes	546	33.00	4.00	56.10	6.60	1.96	16.5
Crisps- chicken	Yes	525	30.00	2.80	54.00	2.20	1.50	27.0
Crisps- steak	Yes	526	31.00	2.80	53.00	2.30	1.50	27.0
Crisps- bacon	Yes	524	30.00	2.70	54.00	2.90	1.50	27.0
Mini cheddars	Yes	512	29.20	11.60	50.10	5.10	2.50	25.0
Corn snack- roast beef	Yes	492	25.00	2.20	59.00	3.00	1.73	22.0
Corn snack- onion	Yes	492	25.00	2.10	60.00	3.00	1.55	22.0
Beef jerky	Yes	315	3.50	1.50	32.40	20.60	3.60	40.0
Pork rind	Yes	626	46.50	17.00	1.60	0.10	2.90	22.5
Twirl bar	Yes	535	30.00	18.00	57.00	56.00	0.22	21.5
Crunchy bar	Yes	466	17.00	10.00	73.00	65.00	0.71	32.0
Chocolate bar	Yes	534	30.00	18.00	57.00	56.00	0.24	45.0
Chocolate caramel bar	Yes	484	23.00	14.00	63.00	53.00	0.37	45.0
Bounty coconut bar	Yes	487	25.70	21.20	58.90	48.20	0.25	28.5
Milk chocolate buttons	Yes	535	30.00	18.00	57.00	56.00	0.24	40.0
Aero peppermint	Yes	531	28.90	17.10	61.60	60.80	0.25	36.0
Twix bars	Yes	495	24.00	13.90	64.60	48.80	0.44	25.0
Turkish delight	Yes	363	6.70	3.80	74.00	64.00	0.36	51.0
Haribo starmix	Yes	342	0.50	0.10	7.00	47.00	0.03	50.0

Note. Lab∗- suitability of foods for storage in the laboratory and offer to participants after the food choice task. Carbs: Carbohydrates; KCals: Energy in kilocalories; Fat: Total fat; Sats: Saturates; g: grams

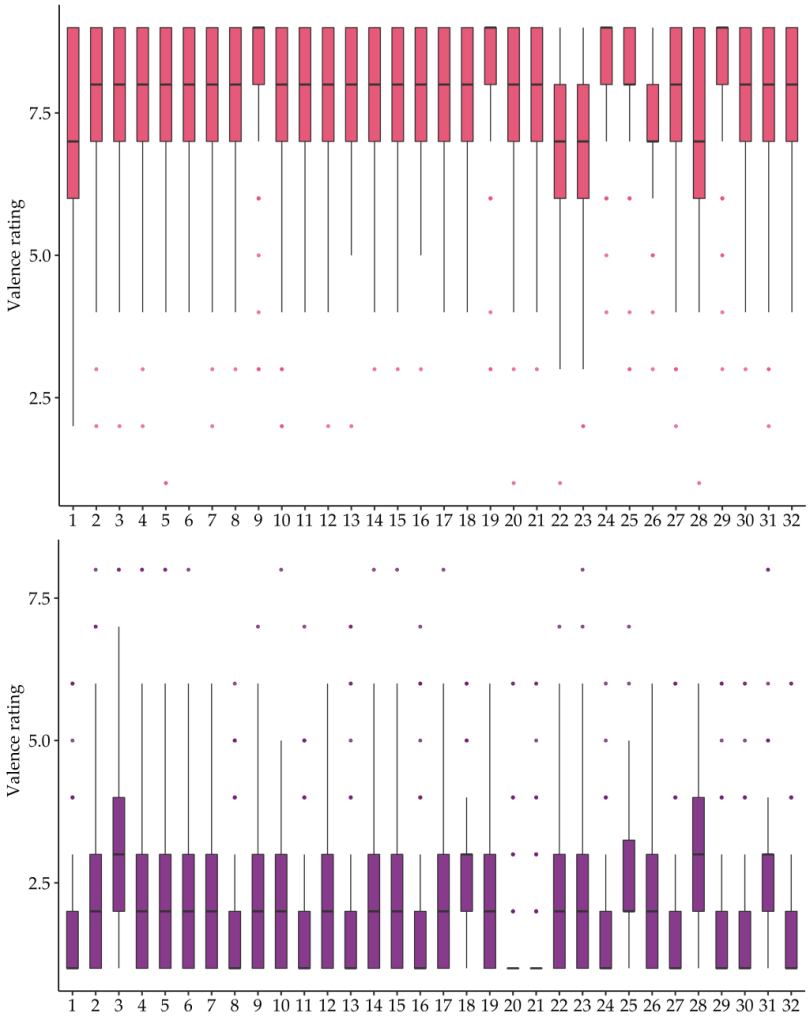
E.2 Targets in the affective priming paradigm

Word characteristics and ratings were obtained from the *EMOTE* database (Grühn, 2016). The sets of positive and negative words are matched as much as possible on emotionality, imagery, concreteness and familiarity, as shown below in Table E.3. Negative targets are on average higher on arousal compared to positive targets and there is also a discrepancy for word frequency between the two sets of words.

Table E.3: Means (M) and standard deviations (SD) on word characteristics for positive and negative targets in the affective priming paradigm

	Positive targets		Negative targets	
	M	*SD*	*M*	*SD*
Frequency (BNC)	79.17	91.09	48.03	62.93
Valence	6.00	0.38	1.79	0.35
Arousal	2.28	0.57	4.65	1.58
Emotionality	4.63	0.98	5.00	0.86
Imagery	5.61	0.70	5.30	0.86
Concreteness	4.24	0.99	4.52	1.00
Familiarity	4.91	0.69	4.82	0.82

Note. BNC: British National Corpus; All word characteristics are scored on a scale from 1 to 7, apart from frequency (BNC).



Positive targets

1.	HAPPY	17.	CUTE
2.	SMILE	18.	RAINBOW
3.	DREAM	19.	PARTY
4.	BEAUTY	20.	SUNSET
5.	FRIEND	21.	ANGEL
6.	LOVE	22.	KISS
7.	PEACE	23.	LOYAL
8.	HEAVEN	24.	LUCKY
9.	PLEASURE	25.	LAUGHTER
10.	NICE	26.	BRAVE
11.	KIND	27.	INSPIRED
12.	JOY	28.	PROUD
13.	FREE	29.	WIN
14.	CHEER	30.	TRAVEL
15.	HUMOUR	31.	PRETTY
16.	HUG	32.	HOPE

Negative targets

1.	AFRAID	17.	TRAUMA
2.	HATE	18.	STINK
3.	KILL	19.	BULLY
4.	SICK	20.	NASTY
5.	EVIL	21.	RUDE
6.	BAD	22.	CORPSE
7.	POISON	23.	INSULT
8.	MURDER	24.	SLAUGHTER
9.	JAIL	25.	GRIEF
10.	HURT	26.	UPSET
11.	PAIN	27.	CRUEL
12.	ANGRY	28.	AWFUL
13.	DEATH	29.	ABUSE
14.	ALONE	30.	DESPAIR
15.	FEAR	31.	TERROR
16.	CORRUPT	32.	WAR

Figure E.2: Valence ratings for positive and negative targets from the laboratory and online cohorts (Total N = 310) Boxplot vertical lines show the range in the data excluding outliers, which are shown in the plot separately as coloured dots. Please note that some outliers overlap.

E.3 Prime & target rating scales

Food and non-food primes

- How positive or negative is the feeling elicited by this image? (9-point Likert scale)
  1= Very negative, 9= Very positive

- How relaxed or tensed is the feeling elicited by this image? (9-point Likert scale)
  1= Very relaxed, 9= Very tensed

Food primes only

- How healthy do you perceive this food to be? (9-point Likert scale)
  1= Very unhealthy, 9= Very healthy

- Over the past month, how often have you experienced a craving for this food?
  1= Never, 2= Almost never, 3= Sometimes, 4= Often, 5= Very often, 6= Almost always, 7= Always

Targets

- How positive or negative is the feeling elicited by this word? (9-point Likert scale)
  1= Very negative, 9= Very positive

- How relaxed or tensed is the feeling elicited by this word? (9-point Likert scale)
  1= Very relaxed, 9= Very tensed

E.4 Follow-up study questionnaire

Please answer the following questions about the main word task you completed. Please try to respond honestly. Research shows that people, when answering questions, prefer not to pay attention and minimise their effort as much as possible. If you are reading this, please select "none of the above" on the next question.

Q1. What was this study about?

☐ Food adverts ☐ Body weight ☐ Healthy diets ☐ None of the above

Q2. Did you notice any differences about your responses on separate occasions? Please select all that apply.

☐ Faster to categorise positive words
☐ Faster to categorise negative words
☐ Faster to categorise words towards the end of the task
☐ Slower to categorise positive words
☐ Slower to categorise negative words
☐ No differences observed

Q3. How frequently did you see the content of the picture that was presented before the word?

1=Never; 2=Very infrequently; 3=Somewhat infrequently; 4=Occasionally; 5=Somewhat frequently; 6=Very frequently; 7=Always

Q4. Please indicate whether you believe that the picture content influenced your responses in any way by selecting all statements below that apply to your performance in the word task.

☐ Faster to categorise positive words when the picture was positive (i.e., picture you liked the most)
☐ Faster to categorise negative words when the picture was negative (i.e., picture you liked the least)
☐ Slower to categorise positive words when the picture was negative

☐ Slower to categorise negative words when the picture was positive
☐ Responses were not influenced by the content of the pictures

Q5. Did you find all the words in the task clearly positive or negative? Certain words may be considered unclear or ambivalent. These may be words that have both positive and negative meaning for you depending on the context. If not, please type in any words in the text box
- Yes
- No [open-ended response]

Q6. Obama was the first American president.
7-point Likert scale (1=strongly disagree to 7=strongly agree)

Q7. Did you purposefully use any kind of strategy to make your responses faster and/or more accurate? Please select all that apply.

☐ Slowed down to be more accurate
☐ Responded fast most of the time and ignored any errors
☐ No strategy used
☐ Other [open-ended response]

Q8. How many times were you interrupted during the word task (e.g., by the phone ringing or by somebody trying to talk to you)?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ Other [numerical input up to two digits]

Explanation of attention and instruction manipulation checks

As described in Kees et al. (2017), we have added one question in the survey to serve as an attention check (Q6). For this question, participants should respond with 1=strongly disagree if they are paying attention. We have also included a modified instructional manipulation check (IMC) that fits the research context of the study, whereby participants should read the survey instructions carefully to correctly answer Q1. The survey also includes an adapted question from (Waters & Li, 2008), that is Q8, which aims to capture how many times participants were interrupted during the affective priming paradigm ("word task").

E.5 Robustness checks

Table E.4: Robustness checks for preregistered hypotheses in the laboratory cohort under different reaction time reduction criteria

	RT reduction criterion 1		RT reduction criterion 2	
	Log(BF_{10})	Evidence interpretation	Log(BF_{10})	Evidence interpretation
H1a	12.61	*Extreme* evidence for H_1	12.25	*Extreme* evidence for H_1
H2a	34.40	*Extreme* evidence for H_1	30.82	*Extreme* evidence for H_1
H2b	27.63	*Extreme* evidence for H_1	21.60	*Extreme* evidence for H_1
H2c	15.99	*Extreme* evidence for H_1	17.56	*Extreme* evidence for H_1
H2d	-2.87	*Strong* evidence for H_0	-2.45	*Strong* evidence for H_0
H4a	-2.14	*Moderate* evidence for H_0	-2.55	*Strong* evidence for H_0
H4b	-2.42	*Strong* evidence for H_0	-2.54	*Strong* evidence for H_0
H4c	-2.54	*Strong* evidence for H_0	-2.40	*Strong* evidence for H_0

Note. Evidence is interpreted for the alternative hypothesis (H_1) compared to the null (H_0) and vice versa. All hypotheses are statistically defined in section 4.4. Both criteria refer to using mean instead of median RTs to aggregate data per participant. Criterion 1 excludes RTs smaller than 250ms for each participant and criterion 2 refers to the exclusion of trial-level RTs based on the standard deviation from the mean of each design cell. The reaction time (RT) reduction criteria are discussed in detail in section 4.5.3. Log(BF10): Natural logarithm of BF_{10}

Table E.5: Robustness checks for preregistered hypotheses in the online cohort under different reaction time reduction criteria

	RT reduction criterion 1		RT reduction criterion 2	
	Log(BF_{10})	Evidence interpretation	Log(BF_{10})	Evidence interpretation
H1a	18.96	*Extreme* evidence for H_1	23.67	*Extreme* evidence for H_1
H2a	22.59	*Extreme* evidence for H_1	20.99	*Extreme* evidence for H_1
H2b	16.93	*Extreme* evidence for H_1	13.50	*Extreme* evidence for H_1
H2c	13.12	*Extreme* evidence for H_1	13.22	*Extreme* evidence for H_1
H2d	-2.81	*Strong* evidence for H_0	-2.33	*Strong* evidence for H_0
H4a	-1.03	*Anecdotal* evidence for H_0	-1.19	*Moderate* evidence for H_0
H4b	-0.78	*Anecdotal* evidence for H_0	-1.30	*Moderate* evidence for H_0
H4c	-2.79	*Strong* evidence for H_0	-2.99	*Strong* evidence for H_0

Note. Evidence is interpreted for the alternative hypothesis (H_1) compared to the null (H_0) and vice versa. All hypotheses are statistically defined in section 4.4. Evidence is interpreted for the alternative hypothesis (H_1) compared to the null (H_0) and vice versa. All hypotheses are statistically defined in section 4.4. Both criteria refer to using mean instead of median RTs to aggregate data per participant. Criterion 1 excludes RTs smaller than 250ms for each participant and criterion 2 refers to the exclusion of trial-level RTs based on the standard deviation from the mean of each design cell. The reaction time (RT) reduction criteria are discussed in detail in section 4.5.3. Log(BF10): Natural logarithm of BF_{10}

Appendix F

Supplementary information for Chapter 5

F.1 Food and non-food stimuli characteristics

The set of non-food stimuli used for stimulus selection was adopted from previous work and all information has already been described in Appendix E.1. Similarly, a proportion of the unhealthy food stimuli were re-used for the study presented in Chapter 5. Due to the additional number of food categories required, additional stimuli were obtained via Pixabay (https://pixabay.com/) and the food-pics online database (Blechert, 2019; Blechert et al., 2014). All stimuli that could be shared openly in the public domain are available at https://osf.io/u36nd/ and stimulus IDs from the food-pics database are also provided for copyright-protected pictures. The nutritional information of the foods has not been recorded in detail for this study as the task design only included unhealthy food categories and food choice behaviour was not investigated (e.g., see Appendix E.1).

F.2 Targets in the affective priming paradigm

Targets were selected based on ratings from 84 individuals recruited as part of ongoing data collection for the study presented in Chapter 4. Valence and arousal ratings were recorded and participants were also asked to indicate which targets they considered ambivalent and if any, such words were excluded from consideration (e.g., "alone"). The descriptive statistics for positive and negative target word ratings can be found in Tables F.1 and F.2 respectively. The sets of positive and negative targets were originally selected from the EMOTE database (Grühn, 2016) and were matched as much possible on imagery, concreteness, familiarity, and emotionality, as described in Appendix E.2.

Table F.1: Descriptive statistics for positive target word ratings (N = 84)

	Valence		Arousal	
	Mean	Standard deviation	Mean	Standard deviation
BRAVE	7.69	1.15	3.70	1.74
CHEER	7.67	1.16	2.67	1.38
CUTE	7.57	1.58	2.60	1.64
DREAM	7.70	1.12	2.54	1.52
FREE	7.86	1.42	2.36	1.64
FRIEND	8.02	1.20	2.55	1.67
HAPPY	8.16	1.49	2.18	1.59
HOPE	7.87	1.16	2.63	1.35
HUG	7.99	1.15	2.30	1.44
HUMOUR	8.00	1.15	2.18	1.34
INSPIRED	7.82	1.17	2.94	1.60
JOY	7.90	1.26	2.43	1.48
KIND	7.83	1.14	2.36	1.43
KISS	7.72	1.13	2.87	1.62
LAUGHTER	8.01	1.16	2.20	1.35
LOVE	8.42	0.94	2.45	1.88
LOYAL	7.80	1.15	2.73	1.59
LUCKY	7.52	1.29	3.00	1.59
PEACE	8.34	1.05	2.02	1.65
PLEASURE	8.25	1.00	2.25	1.51
PROUD	7.71	1.28	2.93	1.60
SMILE	8.17	1.48	2.36	1.85
SUNSET	7.72	1.17	2.28	1.67
WIN	7.83	1.16	3.33	1.89

Table F.2: Descriptive statistics for negative target word ratings (N = 84)

	Valence		Arousal	
	Mean	Standard deviation	Mean	Standard deviation
ABUSE	1.49	0.86	8.11	1.22
AFRAID	2.20	1.37	7.42	1.54
BAD	2.27	1.18	6.86	1.71
BULLY	1.96	1.14	7.40	1.35
CORPSE	1.82	1.12	7.99	1.31
CORRUPT	1.99	1.18	7.30	1.48
CRUEL	1.92	0.99	7.55	1.22
DEATH	1.52	1.05	8.00	1.48
DESPAIR	1.95	1.06	7.63	1.23
EVIL	1.67	1.49	7.83	1.58
FEAR	2.08	1.15	7.66	1.29
GRIEF	1.98	1.31	7.70	1.32
HATE	1.58	1.29	7.67	1.50
HURT	2.12	1.12	7.48	1.36
JAIL	1.92	1.10	7.58	1.53
KILL	1.30	0.87	8.18	1.39
MURDER	1.46	1.24	8.33	1.09
PAIN	2.12	1.31	7.59	1.51
POISON	1.86	1.28	7.66	1.26
SICK	2.11	1.20	7.06	1.65
SLAUGHTER	1.58	0.90	8.00	1.17
TERROR	1.76	1.16	8.11	1.27
TRAUMA	1.82	1.00	7.83	1.23
WAR	1.64	1.08	8.00	1.29

F.3 Follow-up study questionnaire

Please answer the following questions about the main word task you completed. Please try to respond honestly. Research shows that people, when answering questions, prefer not to pay attention and minimise their effort as much as possible. If you are reading this, please select "none of the above" on the next question.

Q1. What was this study about?

☐ Food preferences ☐ Attention ☐ Decision-making ☐ None of the above

Q2. Did you notice any differences about your responses on separate occasions? Please select all that apply.

☐ Faster to categorise positive words
☐ Faster to categorise negative words
☐ Faster to categorise words towards the end of the task
☐ Slower to categorise positive words
☐ Slower to categorise negative words
☐ No differences observed

Q3. How frequently did you see the content of the picture that was presented before the word?

1=Never; 2=Very infrequently; 3=Somewhat infrequently; 4=Occasionally; 5=Somewhat frequently; 6=Very frequently; 7=Always

Q4. Please indicate whether you believe that the picture content influenced your responses in any way by selecting all statements below that apply to your performance in the word task.

☐ Faster to categorise positive words when the picture was positive (i.e., picture you liked the most)
☐ Faster to categorise negative words when the picture was negative (i.e., picture you liked the least)
☐ Slower to categorise positive words when the picture was negative

☐ Slower to categorise negative words when the picture was positive
☐ Responses were not influenced by the content of the pictures

Q5. Did you find all the words in the task clearly positive or negative? Certain words may be considered unclear or ambivalent. These may be words that have both positive and negative meaning for you depending on the context. If not, please type in any words in the text box
- Yes
- No [open-ended response]

Q6. Obama was the first American president.
7-point Likert scale (1=strongly disagree to 7=strongly agree)

Q7. Did you purposefully use any kind of strategy to make your responses faster and/or more accurate? Please select all that apply.

☐ Slowed down to be more accurate
☐ Responded fast most of the time and ignored any errors
☐ No strategy used
☐ Other [open-ended response]

Q8. How many times were you interrupted during the ATTENTION task (e.g., by the phone ringing or by somebody trying to talk to you)?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ Other [numerical input up to two digits]

Q9. How many times were you interrupted during the WORD task (e.g., by the phone ringing or by somebody trying to talk to you)?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ Other [numerical input up to two digits]

Q10. Were you aware of the study hypotheses/aims prior to completion? If yes, please explain. For example, did you know that the attention task is a form of training and/or what is measured by the word task?
- No
- Yes [open-ended response]

Q11. During the attention task, did you learn that on occasions where you

shouldn't respond there were specific food images being shown?
- No
- Yes

Appendix G

Screening & other survey questions

G.1 Questions for screening participants

English language

Are you fluent in written and spoken English? [version 1 - Chapter 2]
Yes / No

How well can you read and understand English? [version 2 - Chapter 3]
Well / Not well

Which option would best describe your ability to read and understand English? [version 3 - Chapters 4 and 5]

- Native English speaker
- Bilingual
- I can read and understand well
- I cannot read and/or understand well

Vision

Do you have normal or corrected-to-normal vision (e.g., wearing glasses)?
This includes normal colour vision
Yes / No

Dieting and diet pills

Are you currently on a diet and/or have recently been taking diet pills? [version 1 - Chapters 3 and 4]
Yes / No

Are you currently dieting, with a weight goal and time-frame in mind? [version 2 - Chapter 2]
Yes / No

Are you currently on a diet with the goal to lose weight and/or have recently been taking diet pills? [version 3 - Chapter 5]
Yes / No

Allergies and/or intolerances

Do you have any food allergies and/or intolerances? [version 1 - Chapter 4]
Yes / No

Do you have any major food allergies and/or intolerances to the following ingredients? [version 2 - Chapter 3]

- Milk
- Eggs
- Fish
- Crustacean shellfish
- Tree nuts
- Peanuts
- Wheat
- Soybeans
- No

Eating disorders

Have you currently or in the past been diagnosed with any eating disorders? [version 1 - Chapters 4 and 5]
Yes / No

Have you currently or in the past been diagnosed with any eating disorders? [version 2 - Chapters 2 and 3]

- Anorexia
- Bulimia
- Binge eating disorder
- No
- Other (open-ended)

Handedness

Which hand do you use for most of your daily activities, such as writing?
If you are ambidextrous, please indicate which hand you would prefer to use for this study.
Right / Left

Hearing impairments

Do you have any major hearing impairments?
If you have any impairment that would prevent you from hearing tones properly please answer 'Yes' below.
Yes / No

G.2 Demographics and food-related questions

Gender

To which gender identity do you identify?

- Female
- Male
- Transgender female
- Transgender male
- Gender variant / Non-conforming
- Other (open-ended)

Ethnicity

What is your ethnic group? Select one option which bests describes your ethnicity or background.

- Do not wish to answer
- White
- Mixed / Multiple ethnic groups
- Asian / Asian British
- Black / African / Caribbean / Black British
- Other ethnic group (open-ended)

Hours since last meal

How long ago did you last eat? [version 1 - Chapters 4 and 5]

- Less than 1 hour ago
- 1-3 hours ago
- 3-5 hours ago
- More than 5 hours ago

How long ago did you last eat? [version 2 - Chapter 2]

- Less than 3 hours ago
- 3-5 hours ago
- 5-10 hours ago
- More than 10 hours ago

How long ago did you last eat? [version 3 - Chapter 3]

- Less than 1 hour ago
- 1-2 hours ago
- 2-3 hours ago
- 3-4 hours ago
- More than 4 hours ago

Dietary preferences

Are you following a vegan or vegetarian diet? [version 1 - Chapter 3]
Yes / No

Are you following any of the listed diets? [version 2 - Chapters 4 and 5]

- Vegetarian
- Vegan
- Fruitarian
- Pescetarian
- No
- Other (open-ended)

Hunger

How hungry are you right now?
9-point scale (1="Not at all" to 9="Very")

Drug and/or alcohol abuse

Do you have a past or current history of drug and/or alcohol abuse?

- Drug abuse
- Alcohol abuse
- Both
- None

Height and weight

Please input your height and weight in the seperate textboxes as shown in the examples below and indicate whether you are using the metric or imperial system by selecting the appropriate measurement units.

Height measurement system Metric (m & cm) / Imperial (ft & in)

Height
e.g., 1m or 5ft

e.g., 68cm or 10in

Weight measurement system Metric (kg & g) / Imperial (st & lb)

Weight
e.g., 75kgor12st

e.g., 500gor5lb

Psychiatric and/or neurological disorders

Have you currently or in the past been diagnosed with any psychiatric and/or neurological disorders?
If yes, please specify the diagnosed disorder.

- Not sure
- No
- Yes (open-ended)

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