

**Modifying automatic responses to
food cues using cognitive control
training and brain stimulation**



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Summary of thesis

This thesis set out to investigate the potential role of brain stimulation and behavioural training paradigms in modifying automatic responses to food cues. A brief summary of the design and key findings of each chapter is detailed below.

In **Chapter 2**, I aimed to replicate previous findings that had demonstrated an effect of tDCS on food craving and food consumption. Participants received either active or sham tDCS. Food craving was measured pre-and post-stimulation, and ad-libitum food consumption was measured following stimulation. Analyses revealed anecdotal to moderate evidence against the effect of tDCS on food craving and food consumption.

In **Chapter 3**, I investigated whether HD-tDCS could reduce food craving and desire to eat. Participants received both active and sham stimulation across two sessions. Food craving and desire to eat were measured pre-and post-stimulation. There was no evidence for an effect of HD-tDCS on food craving or desire to eat with results showing anecdotal to moderate evidence for H0.

In **Chapter 4**, I used a novel training task in an online experiment to investigate the effects on food liking. Explicit and implicit liking of trained foods was compared to untrained foods. Analyses revealed moderate to strong evidence against the effect of the training task on explicit and implicit liking.

In **Chapter 5**, I explored the effects of evaluative conditioning on explicit and implicit food liking across two experiments; the first a lab-based experiment, the second an online experiment. Comparisons were made between foods based on the valence of the stimuli they had been paired with. Experiment 1 & 2 demonstrated anecdotal to very strong evidence against the effect of evaluative conditioning on

liking.

In this thesis, I discuss the importance of task parameters, sample selection, and open science in this research area.

Publications and pre-registrations in the thesis

All of the experimental chapters in this thesis were conducted using Open Science practices. Protocols were made available on the Open Science Framework prior to data collection and any deviations from protocols have been clearly stated throughout the thesis.

Chapter 2

Chapter 2 was pre-registered prior to data collection. The protocol, data, outputs and study materials are available online (<https://osf.io/2597q/>). This chapter was published at the Royal Society of Open Science in 2019:

- Sedgmond, J., Lawrence, N. S., Verbruggen, F., Morrison, S., Chambers, C.D., & Adams, R. C. (2019). Prefrontal brain stimulation during food-related inhibition training: Effects on food craving, food consumption and inhibitory control. *Royal Society Open Science*, 6(1), 181186. <https://doi.org/10.1098/rsos.181186>

Chapter 3

Chapter 3 was submitted as a Stage 1 Registered Report prior to data collection (<https://osf.io/49fmv/>). All data, outputs and study materials are available online (<https://osf.io/wbpgd/>). This chapter was published as a Stage 2 Registered Report at Behavioural Neuroscience in 2020:

- Sedgmond, J., Chambers, C.D., Lawrence, N.S., & Adams, R. C. (2020). No evidence that prefrontal HD-tDCS influences cue-induced food craving. *Behavioral Neuroscience*, 134(5), 369-383. <https://doi.org/10.1037/bne0000345>

Chapter 4

Chapter 4 was pre-planned prior to data collection (<https://osf.io/ejtd6/>). All data, outputs and digital study materials are available online (<https://osf.io/mr69j/>).

Chapter 5

Experiment 1 of Chapter 5 was pre-registered prior to data collection. The study protocol, data, outputs and digital study materials are available online (<https://osf.io/4qpkh/>).

Contents

Summary of thesis	i
Publications and pre-registrations in the thesis	iii
List of abbreviations	xi
Acknowledgements	xiii
Statement of collaborative work	xiv
1 Introduction	1
1.1 Eating behaviour	1
1.1.1 Obesogenic environment	2
1.2 Dual process models	4
1.3 Susceptibility to food cues	5
1.3.1 Cognitive processes	5
1.3.2 Reward sensitivity	9
1.3.3 Neural mechanisms	9
1.4 Interventions	11
1.4.1 Cognitive control training	11
1.4.2 Neuromodulation	18
1.5 Open science	21
1.5.1 Reproducibility in psychology	21
1.5.2 Bayesian statistics	22
1.6 Synopsis	22

2	Prefrontal brain stimulation during food-related inhibition training: Effects on food craving, food consumption and inhibitory control	25
2.1	Introduction	25
2.1.1	Hypotheses	29
2.2	Method	29
2.2.1	Participants	29
2.2.2	Sampling plan	30
2.2.3	Procedure	30
2.2.4	tDCS	31
2.2.5	Training tasks	32
2.2.6	Outcome measures	33
2.3	Exclusion criteria	35
2.4	Deviations from protocol	36
2.5	Results	36
2.5.1	Data exclusions	36
2.5.2	Baseline measures	37
2.5.3	tDCS tolerability and blinding	37
2.5.4	Primary analyses	38
2.5.5	Exploratory analyses	40
2.6	Discussion	43
3	Effects of prefrontal HD-tDCS on cue-induced food craving	49
3.1	Introduction	49
3.1.1	Hypotheses	52
3.2	Method	53
3.2.1	Participants	53
3.2.2	Sampling plan	54
3.2.3	Procedure	54
3.2.4	HD-tDCS	57

3.2.5	Training tasks	58
3.2.6	Outcome measures	60
3.3	Exclusion criteria	61
3.4	Results	62
3.4.1	Data exclusions	62
3.4.2	Baseline measures	62
3.4.3	Primary analyses	62
3.4.4	Exploratory analyses	65
3.5	Discussion	69

4 Combining cognitive control training tasks to modify explicit and implicit food evaluations 75

4.1	Introduction	75
4.1.1	Hypotheses	79
4.2	Method	80
4.2.1	Participants	80
4.2.2	Sampling plan	80
4.2.3	Procedure	81
4.2.4	Stimuli	82
4.2.5	Training task	83
4.2.6	Outcome measures	84
4.3	Exclusion criteria	85
4.4	Results	86
4.4.1	Data exclusions	86
4.4.2	Baseline measures	86
4.4.3	Awareness	87
4.4.4	Primary analyses	87
4.4.5	Exploratory analyses	90
4.5	Discussion	94

5	Investigating the role of evaluative conditioning on implicit and explicit food preferences	98
5.1	Introduction	98
5.2	Experiment 1	101
5.2.1	Hypotheses	101
5.2.2	Methods	102
5.2.3	Exclusion criteria	106
5.2.4	Results	107
5.2.5	Discussion	111
5.3	Experiment 2	112
5.3.1	Hypotheses	113
5.3.2	Methods	114
5.3.3	Results	115
5.3.4	Discussion	120
5.4	General Discussion (Chapter 5 only)	121
6	General Discussion	124
6.1	The role of brain stimulation in behaviour change	124
6.1.1	Summary of findings	124
6.1.2	Limitations and future directions	126
6.2	The role of behavioural training in behaviour change	128
6.2.1	Summary of findings	128
6.2.2	Limitations and future directions	129
6.3	Barriers for behaviour change	135
6.4	Open science	136
6.5	Conclusion	137
A	Supplementary information for Chapter 2	138
	Appendix A	138
A.1	Bayesian stopping rule	138

A.2	Participant debrief	139
A.3	Outliers and exclusions	139
A.4	Additional analyses	140
A.4.1	Predictors of food intake	140
A.4.2	Food consumption	140
A.4.3	Food craving	141
A.4.4	Response inhibition	141
A.4.5	Sweet versus savoury foods	141
A.4.6	Individual foods	142
A.4.7	Debrief	142
A.5	Output of Bayesian comparison of total calories consumed in sham vs. active tDCS conditions using an informative prior	143
A.6	Full ANOVA outputs	144
A.6.1	Effects on food consumption (H1)	144
A.6.2	Exploratory food consumption analyses	144
A.6.3	Effects on food craving (H2)	144
B	Supplementary information for Chapter 3	147
	Appendix B	147
C	Supplementary information for Chapter 4	148
	Appendix C	148
C.1	Pilot studies	148
C.1.1	Food stimuli	148
C.1.2	Evaluative conditioning stimuli	149
C.2	Order of outcome measure and stimulus type	149
C.2.1	Explicit first, high-value stimulus set	149
C.2.2	Implicit first, high-value stimulus set	150
C.2.3	Explicit first, neutral stimulus set	150

C.2.4	Implicit first, neutral stimulus set	150
C.3	Exploratory robustness checks on H2	150
C.3.1	Median RT	151
C.3.2	Percentage errors	151
C.3.3	Inverse efficiency (mean RT)	151
C.3.4	Inverse efficiency (median RT)	151
C.4	Moderators	152
C.4.1	Effect of BMI	152
C.4.2	Effect of hunger	152
C.4.3	Effect of dieting	152
D	Supplementary information for Chapter 5	153
Appendix D		153
D.1	Student project	153
D.1.1	Hunger	153
D.1.2	Socioeconomic status	153
D.1.3	Intention to eat healthily	154
D.1.4	Dietary restraint	154
Bibliography		155

List of abbreviations

AAT	approach-avoid task
APP	affective priming paradigm
BFDA	bayes factor design analysis
BIS	Barratt Impulsiveness Scale
B_{JZS}	bayes factor calculated using JASP
BMI	body mass index
BSI	behavioural stimulus interaction
CAT	cue approach training
DLPFC	dorsolateral prefrontal cortex
EC	evaluative conditioning
FCQ-T-r	Food Craving Questionnaire - Trait Reduced
fMRI	functional magnetic resonance imaging
G-FCQ-S	General Food Craving Questionnaire – State Version
GNG	go/no-go
HD-tDCS	high definition transcranial direct current stimulation
IAT	implicit association test
ICT	inhibitory control training
ITI	inter-trial interval

OFC	orbitofrontal cortex
PANAS	Positive and Negative Affect Schedule
RT	reaction time
SSD	sample size determination
SST	stop-signal task
tDCS	transcranial direct current stimulation
TMS	transcranial magnetic stimulation
VAS	visual analogue scale

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Statement of collaborative work

Experiment 1 of Chapter 5 was part of a final-year undergraduate project and data was collected by four project students. The design of the study, formulation of hypotheses, and data analysis was all conducted by me for the purpose of this thesis.

Chapter 1

Introduction

The psychological mechanisms underlying dietary behaviour are complex, involving both intrinsic and extrinsic drivers. While the primary objective of food consumption is for survival, our dietary choices often go beyond biological requirements and are driven by the interplay between a number of personal, economic and social factors. Understanding the psychology involved in dietary behaviours may aid in understanding why our eating patterns have changed so dramatically in recent years, and why these behaviours are often driven by non-homeostatic determinants. While there are many avenues that require further exploration, among the most impactful is thought to be our food environment and the abundance of food cues we are faced with every day. It is therefore critical to understand whether psychology can provide useful interventions in the absence of any major changes to our environment, to modify the influence these cues have on our food choices. This chapter will provide an overview of theoretical accounts that attempt to explain individual differences in dietary choices, before discussing the behavioural and neural mechanisms that influence the way in which we consume food. Based on these mechanisms, interventions targeted at health behaviours will be discussed and critically evaluated. The chapter concludes with an overview of the experimental studies detailed in this thesis.

1.1 Eating behaviour

Our biology is an important determinant of how we eat. Individual differences in gene variations, circulating levels of hormones, and the body's ability to partition food can all

influence eating behaviour. Similarly, our biology can also influence our susceptibility to weight gain. Research is continually identifying genes that are thought to play a role in body weight (Akbari et al., 2021), with current estimates suggesting a potential role of almost 100 candidates (Locke et al., 2015). Higher circulating levels of ghrelin and leptin resistance have also been implicated in weight gain (Klok et al., 2007). However, while our understanding of these biological factors is improving, their influence has not changed; it is the change in the environment that has led to these susceptibilities being exposed.

1.1.1 Obesogenic environment

Our food environment has changed drastically within our lifetime. The availability of cheap, ultra-processed and energy-dense foods that are marketed based on their low cost and convenience, coupled with a continuous stream of food cues via advertising, has influenced eating behaviour substantially (Rauber et al., 2018). In the UK alone, more than half of energy intake comes from ultra-processed foods at the expense of minimally processed, whole foods, causing a reduction in overall diet quality and subsequently health status (Monteiro et al., 2013; Monteiro et al., 2010; Rauber et al., 2018). The leading causes of death in the UK and other Western societies that also show excessive consumption of ultra-processed foods are often thought to have preventable causes, such as poor diet. For example, recent evidence indicated that in 2017, 11 million deaths globally were attributable to dietary behaviour (Afshin et al., 2019). The increased consumption of these foods which is reducing the overall quality of our diets is thought to be driven by an obesogenic environment, filled with food cues that prompt appetitive behaviour and increase food consumption (Berridge, 1996; Boyland et al., 2016).

Ultra-processed foods were first defined in 2009 by the NOVA food classification system, which categorises foods into four groups based on the level of processing involved in their production (see Monteiro et al., 2019 for an in-depth explanation of each group). Groups 1 to 3 range from unprocessed or minimally processed foods, to foods processed in order to enhance their durability via methods such as smoking and preserving. Diets consisting predominantly of group 1 foods, with small amounts of foods from groups 2 and 3 have been shown to lead to improved health outcomes (Elizabeth et al., 2020; Katz & Meller, 2014), whereas the excessive consumption of foods from group 4 has been linked

to adverse health and metabolic conditions, including but not limited to type 2 diabetes, cancer, cardiovascular disease and mortality (see Elizabeth et al., 2020 for a review). This is thought to be due to the level of processing involved in manufacturing these foods, which involves fractioning and chemical modification. Cosmetic additives such as emulsifiers, colours and flavourings are added to foods in order to make them more palatable, and additional additives make the products longer lasting which results in an end product that contains minimal whole foods, and instead, “industrial formulations of substances derived from foods” (Rauber et al., 2018). As a result, these foods provide energy, but little in the way of nutrition and are typically high in sugar, fat and sodium (Monteiro et al., 2019).

The UK is not only one of the highest consumers of ultra-processed foods (Vandevijvere et al., 2019), but also has some of the highest levels of obesity (OECD, 2019). As a result, discussions of ultra-processed foods are often linked to the effect they have on body weight (Hall et al., 2019; Juul et al., 2018; Monteiro et al., 2018). A large-scale study using UK Biobank data recently examined the link between consumption of ultra-processed foods and the risk of obesity (Rauber et al., 2018). Participants’ self reported food intake was used to determine what percentage was ultra-processed using the NOVA scale. They found that participants in the highest quartile of ultra-processed food consumption had a 79% greater risk of developing obesity than participants in the lowest quartile. Increased consumption of these foods also resulted in an increase in body fat. Food consumption has also been experimentally manipulated to explore the effects of these foods when compared to minimally processed diets (Hall et al., 2019). Participants were exposed to both ultra-processed and unprocessed diets for 14 days, and despite diets being matched for calories, they consumed significantly more from the ultra-processed diet than the unprocessed diet. Furthermore, participants exhibited an increase in both weight and fat following the ultra-processed diet, and a decrease following the unprocessed diet. Interestingly, when taking into account both the weight of and the energy provided by the foods, the volume consumed per minute was significantly greater for the ultra-processed diets. Not only are these foods formulated to be extremely palatable, but due to the processing involved they require little oral processing. This low chewing activity in combination with the low satiating efficiency is thought to drive excessive consumption (Monteiro et al., 2019).

However while the effect that these foods have on body weight is important, arguably more emphasis needs to be placed on the effect that they have on health. The poor nutritional quality of ultra-processed foods is leading to malnutrition caused by a lack of important micronutrients (Monteiro et al., 2019). With any major changes to the food environment likely to take time, an understanding of how food cues are processed, and how individual differences may influence susceptibility could provide an alternative avenue to tackling the problem.

1.2 Dual process models

Dual-process models suggest that behaviour is determined via two systems: an impulsive and a reflective system, and it is thought that health-related problems arise when there is a conflict between the two (Hofmann et al., 2008). The reflective impulsive model distinguishes between these systems to understand how they determine behaviour (Strack & Deutsch, 2004). While the two systems can work cooperatively to direct behaviour, an important distinction for health psychology is what happens when the behavioural schemata generated by each system are incompatible. Models such as this have been applied to health behaviours such as excessive unhealthy food consumption (Hofmann et al., 2009b; Hofmann et al., 2008) which is thought to be caused by a disparity between the two systems (Jones et al., 2018). Which system is successful during the conflict will determine behavioural outcomes.

The impulsive system is the driver of automatic processes and behaviours. These impulsive behaviours are thought to be caused by the development of associations that form and are strengthened from learning via repeated pairings between stimuli and affective reactions (Hofmann et al., 2009b; Hofmann et al., 2008). For example, through consumption of palatable, ultra-processed foods, an association is made that the food is pleasurable and rewarding. This association is then activated - independently of conscious awareness - whenever presented with a cue for these foods, which then triggers the impulsive system. These associations allow for quick evaluations and typically result in an approach or avoidance behaviour that helps to explain why we display approach tendencies towards foods that we enjoy (Friese et al., 2011).

Its contender, the reflective system, allows for conscious and deliberative behaviour that is a result of slow and controlled processing (Strack & Deutsch, 2004). A strong reflective system allows us to override prepotent responses that may not fit in with our long-term goals. In the case of food choice, this may enable us to make more informed dietary choices that take into account attitudes and expectancies. An ineffective reflective system and a strong impulsive system may offer an explanation for why some individuals are more heavily influenced by the obesogenic environment than others. This has led to the development of behavioural interventions that target the overactive impulsive processes such as attentional biases, approach-avoidance tendencies, and automatic associations (Friese et al., 2011). Understanding individual differences in these cognitive processes is vital to understanding how they influence our dietary behaviours (Hofmann et al., 2008).

1.3 Susceptibility to food cues

1.3.1 Cognitive processes

Attentional bias

The control of attention is central to our response to food cues. Poor control can lead to an attentional bias which is the tendency for an individual to overly attend to specific stimuli (Deluchi et al., 2017; Friese et al., 2011). While this may have been an advantageous trait in the past, in an obesogenic environment where food cues are so ubiquitous, a bias that captures and retains attention may offer an explanation for the over-consumption of certain foods (Hardman et al., 2013; Nijs et al., 2010). This proposition has been supported by research showing that an attentional bias towards food can lead to an increase in food craving (Kemps & Tiggemann, 2009) and food consumption (Nijs et al., 2010), as well as bias an individual towards unhealthy food choices in real-world situations (Forman et al., 2018). Further evidence has suggested that this bias may also be a predictor of future weight gain (Meule & Platte, 2016).

A common experimental measure of attentional bias is a visual probe task in which a pair of stimuli are presented alongside each other briefly, after which a visual probe appears in place of one of the stimuli. Participants must respond to the location of the

probe as quickly as possible, with faster reaction times (RT) suggesting that attention was being directed to the stimulus that the probe replaced (Field et al., 2016). This and similar tasks have revealed increased attentional bias in traits such as impulsivity, external eating and restrained eating (Hollitt et al., 2010; Hou et al., 2011). They also seem to be more pronounced in overweight and obese individuals (Castellanos et al., 2009; Werthmann et al., 2011; Yokum et al., 2011). For example, Castellanos et al. (2009) used eye-tracking alongside a visual probe task that paired food stimuli with non-food stimuli to explore attentional differences between normal-weight and obese participants. A bias was observed in the obese participants who attended more frequently, and for longer durations, to the food versus the non-food stimuli. This effect was not observed in the normal-weight participants. Similarly, Werthmann et al. (2011) found that in comparison to normal-weight participants, obese participants directed their attention more frequently towards food stimuli.

However, research has found that while overweight and obese individuals may initially direct their attention towards food stimuli, they do not maintain this attention (Nijs & Franken, 2012) and often display avoidant behaviours (Doolan et al., 2015). Furthermore, a recent systematic review and meta-analysis revealed no significant relationship between body mass index (BMI) and an attentional bias for foods (Hardman et al., 2021). While the role of weight is unclear, the same review did report a significant relationship between food intake and attentional bias, supporting the claim that an increased bias towards food could cause an increase in consumption.

Inhibitory control

In addition to the increased attention towards these food cues, it is thought that poor inhibitory control may also contribute to excessive food consumption due to an inability to inhibit behavioural responses to the cues (Jones et al., 2016). Inhibitory control refers to the capacity to self-regulate actions in accordance with goals (Jansen et al., 2015). Successful inhibitory control allows for the inhibition of responses towards rewarding stimuli, whereas poor inhibitory control has been associated with increased craving for energy-dense foods, less control over eating behaviour, and weight gain (Jansen et al., 2015; Meule et al., 2012a; Nederkoorn et al., 2010).

Two of the most common laboratory measures of inhibitory control are the go/no-go (GNG) task and the stop-signal task (SST). While both are speeded RT tasks that measure inhibitory control based on a participant's ability to withhold a motor response, the GNG task measures action restraint, and the SST measures action cancellation (Eagle et al., 2008). Action restraint refers to the inhibition of a motor response before it has been initiated; in most GNG tasks the no-go signal (that instructs participants to withhold a motor response) occurs before or at the same time as the go signal (though not always, see Aulbach et al., 2021). Inhibitory control using the GNG task is measured using the rate of commission errors (incorrectly responding on no-go trials), with a high rate of commission errors indicative of poor inhibitory control. Action cancellation involves the inhibition of a motor response that has already been initiated. In the SST, the stop-signal is presented after the go signal with a variable delay, making it more difficult to stop the motor response. Inhibitory control is then measured using the stop-signal RT which is the estimated latency of the stop process (Verbruggen & Logan, 2009).

A link between a deficit in inhibitory control and weight status has been identified; overweight and obese individuals tend to exhibit a diminished inhibitory control capacity when compared to normal-weight individuals (Hofmann et al., 2009a; Nederkoorn et al., 2006a; Nederkoorn et al., 2006b). For example, performance as measured using the SST has indicated poorer inhibitory control in obese children who had significantly longer stop-signal RTs compared to normal weight children (Nederkoorn et al., 2006a), and in adults, although overall SST performance was not affected, obese adults exhibited more difficulties with inhibitory control towards the end of the task in comparison to the control group (Nederkoorn et al., 2006b). Poorer performance on the SST specifically has also been linked to future weight gain (Nederkoorn et al., 2010).

In addition to general inhibitory control capacity, a deficit in inhibitory control specific to food cues has also been identified (Houben et al., 2014). Participants completed a SST in which they responded to food stimuli and non-food stimuli, and while results showed no relationship between BMI and inhibition to the non-food stimuli, a higher BMI was significantly associated with poorer inhibitory control towards the food stimuli. What is less clear is whether weight status directly affects inhibitory control capacity, or whether poor inhibitory control results in excessive consumption that can in turn lead to an increase

in body weight.

Approach bias

Sustained attention towards food cues as well as an inability to inhibit a response towards them is likely to result in a physical action tendency that drives an individual to approach these cues. This approach bias is likely to cause an increase in consumption of foods as well as increased weight if an individual is unable to override the action. Indeed, stronger approach tendencies have been exhibited in overweight and obese individuals (Havermans et al., 2011), as well as in individuals with certain trait characteristics such as dietary restraint (Veenstra & de Jong, 2010) and external eating (Brignell et al., 2009).

Approach tendencies can be measured using a number of tasks including the implicit association test (IAT), which requires participants to categorise two groups of stimuli (e.g. food and non-food items) to one of two attribute categories (e.g. positive and negative). Faster RTs in congruent trials (food and positive) in comparison to incongruent trials (food and negative) would suggest an approach bias. However more commonly, approach and avoidance tendencies are measured via RT based on the push or pull of a joystick, as it allows a more specific measure of action tendencies (Friese et al., 2011). In the approach-avoid task (AAT) participants must respond to different stimuli by making an approach (pull) or avoid (push) action. RTs tend to be quicker making congruent responses, usually approaching positive stimuli, and avoiding negative stimuli (Krieglmeyer et al., 2013).

To investigate approach biases towards chocolate, Kemps et al. (2013) used an IAT in which chocolate and other palatable foods were paired with approach or avoid words. Participants were faster at responding to approach words paired with chocolate in comparison to avoid words when paired with chocolate. These findings have been extended upon using specific population groups. When comparing high trait food cravers with low trait food cravers, Brockmeyer et al. (2015a) found that high trait cravers displayed stronger approach tendencies for high-calorie foods. Similar results found overeating to be associated with both a stronger attentional and approach bias towards food cues (Brignell et al., 2009). Furthermore, using an IAT, Kemps and Tiggemann (2015) found that in comparison to participants with a healthy BMI, obese participants displayed an overall approach bias for both high and low calorie foods.

1.3.2 Reward sensitivity

Although the obesogenic environment has contributed to the change in diet quality and eating behaviour, it is clear that there are individual differences in susceptibility to the food cues within this environment based on cognitive mechanisms. Interestingly, this persistent, impulsive drive towards food cues can often occur in the absence of both hunger and liking.

Incentive-sensitisation theory postulates that exposure to rewarding stimuli results in an increase in incentive value, which in-turn drives a wanting for the stimuli (Berridge, 1996). In the case of ultra-processed and energy-dense foods, the increased exposure via food cues can elevate the anticipation of reward, leading to a desire to consume the food. However according to this theory, the desire driven by the stimulus is thought to be unrelated to liking (Berridge, 1996, 2009). In fact the pleasure experienced can decrease, while the desire or wanting simultaneously increases (Berridge, 2009; Berridge et al., 2010). Therefore we may still find ourselves driven to purchase and consume unhealthy foods, despite receiving less pleasure over time.

When testing this theory in a laboratory setting, research found that while wanting for foods was greater in an environment with food-cues compared to a neutral environment, the liking of foods was the same in both conditions (Joyner et al., 2017). Both theory and research support the idea that an environment defined by its availability and prevalence of food and food cues is likely to influence food choice, often in the absence of homeostatic drivers. This increase in reward anticipation caused by exposure to, as well as consumption of rewarding foods is thought to be as a result of individual differences in reward related cortical activity (Lowe et al., 2019; Stice & Burger, 2019).

1.3.3 Neural mechanisms

A considerable body of research has identified multiple brain regions implicated in the control of eating, and more specifically, how hypo- and hyper-activity in response to food cues may predict eating behaviour (Giuliani et al., 2018). Exposure to food cues in the environment has been proposed to result in the activation of a network of brain regions shown to be involved in reward processing (Tang et al., 2012). This appetitive network includes the amygdala and hippocampus, the striatum, the orbitofrontal cortex (OFC), and the insula, and it is thought that greater reactivity to food cues is linked to greater

activation in these regions (Charbonnier et al., 2018; Dagher, 2009). This increased re-activity has been shown to predict food choice (Mehta et al., 2012), food consumption (Lawrence et al., 2012), weight gain (Demos et al., 2012; Stice et al., 2010), and risk of obesity (Stice et al., 2011).

For example, in a functional magnetic resonance imaging (fMRI) experiment, participants were presented with a series of food and non-food stimuli. Results indicated that activation in the nucleus accumbens better predicted food consumption than self-reported hunger (Lawrence et al., 2012). Elevated activity in the OFC, nucleus accumbens, amygdala and insula following exposure to high-fat food cues has also been shown to influence calorie consumption with participants consuming a greater proportion of calories from high-fat foods (Mehta et al., 2012). Furthermore research has shown increased activity in reward regions, alongside decreased activity in regions associated with self-control can lead to greater overall consumption of food (Nolan-Poupart et al., 2013).

This activity has also been linked to weight status. Elevated activity in the OFC in response to food cues has been observed in individuals at a high-risk of future weight gain (Stice et al., 2011), and has been shown to predict future weight gain (Yokum et al., 2011). Additional brain regions implicated in reward have also been associated with future weight gain (see Stice et al., 2016 for a review). Moreover, increased activity in brain regions associated with motor response has been observed and is consistent with behavioural research detailing the role of impulsive processes in eating behaviour (Stice et al., 2016).

The role of the pre-frontal cortex has also received a great deal of attention, not only due to its role in reward and motivation, but cognitive control too. Prefrontal brain regions are thought to be implicated in impulsive behaviours in response to stimuli. For example, dysregulation of the dorsolateral prefrontal cortex (DLPFC) can influence stimulus-evoked behaviour (Lowe et al., 2019) and predict later food intake (Cornier et al., 2010). Furthermore, reduced activity in the left DLPFC following food intake has been observed in overweight and obese participants (Gluck et al., 2017), and an inability to recruit the DLPFC as well as brain regions implicated in inhibitory control is evident in those with an increased body weight (Lowe et al., 2019). This reduced activity in the DLPFC has been linked to the perpetuation of problematic eating behaviours via impulsive behavioural

processes (Weygandt et al., 2013; Weygandt et al., 2015).

1.4 Interventions

Based on evidence from brain-imaging and behavioural data, interventions targeted at impulsive processes to food cues via cognitive and neural mechanisms may be useful in influencing automatic associations. The next section discusses the use of behavioural interventions and neuromodulation techniques in changing responses to foods as well as food preferences.

1.4.1 Cognitive control training

Attentional bias modification

The modification of visual probe tasks developed to measure attention has allowed for the retraining of attentional processes. In a standard visual probe task, the location of the probe that replaces a stimulus is random. However, manipulating the stimulus that the probe is paired with can train participants to either attend towards or away from specific stimuli. For example, using a modified dot probe task, Kemps et al. (2014) directed participants' attention away from (active training group) or towards (control group) chocolate stimuli by instructing participants to respond to a visual dot probe. In the active training group, dot probes replaced images of chocolate on only 10% of trials compared to 90% of trials in the control group. Attentional bias for chocolate was measured pre-and post training using a standard visual probe task and revealed a significant decrease in attentional bias for those in the active group, and a significant increase for those in the control group. The active training task also reduced craving and consumption for chocolate. Attentional bias modification can not only train attention away from unhealthy foods, but can also train attention towards healthy foods. Participants who were trained to attend towards healthy foods not only showed a significant increase in attentional bias, but also an increased consumption of healthy foods in comparison to participants who had control training (Kakoschke et al., 2014).

Research findings have also revealed that manipulating attention can influence choice behaviours (Armeli et al., 2008; Shimojo et al., 2003) which has led to the development

of another form of attentional training that utilises a behavioural approach to target attention. Cue approach training (CAT) pairs stimuli with cues (typically auditory) in a similar way to measures of inhibitory control, however rather than withholding a response, participants are instructed to make a response when presented with a cue. The cue is presented after the stimulus with a variable delay that is reduced after successful trials, making it more difficult for participants to make their response in time. Training effects have focused primarily on food choice; following CAT participants are given a food-choice task in which they must choose between two foods for later consumption. The aim is to see whether participants are more likely to choose the cued compared to the uncued food.

Across a series of experiments, Schonberg et al. (2014) used auditory cues to train participants to respond to energy-dense, palatable foods. In a later binary choice task, participants were more likely to select the foods that had been paired with the cues than those that had not (although this effect was only observed in self-reported high-value, and not low-value foods). They also investigated the importance of training duration and found evidence of long-term behavioural maintenance; participants who completed the longest training session still showed a preference for high-value go foods compared to high-value no-go foods up to 2 months later. This effect on food choice has since been replicated on healthy foods (Veling et al., 2017a). Using the same CAT design as Schonberg et al. (2014), images of fruits and vegetables were used in the training task and in a subsequent choice task. Participants were more likely to choose the foods that had been paired with the cue than the uncued foods suggesting the potential for CAT to be used in healthy food training. However, as addressed by Zoltak et al. (2017), in the current obesogenic environment, we are rarely faced with items of equal value. Across two experiments they investigated whether CAT could still lead to the selection of low-value foods, when a high-value food was the alternative. Following training, participants still exhibited a preference for high-value foods, however there was an increase in choices for cued low-value food when high-value foods were uncued. The authors posited that while CAT may not be strong enough to change preferences, it may have the potential to affect choice which could allow for healthier food choices when an unhealthier choice is the alternative.

Although CAT trains a motor response towards stimuli, there are thought to be attentional as well as motor mechanisms involved. For example, in addition to the effects

on food choice, eye-tracking data revealed that during the choice task, participants spent more time fixating on the cued items than the uncued items, even when the cued items were not chosen in the choice task (Schonberg et al., 2014). To gain a greater understanding of the mechanisms involved in CAT, Bakkour et al. (2016) carried out several experiments in which different aspects of the CAT design were manipulated. Removing the auditory cue in Experiment 1, and presenting the auditory cue concurrently with the stimuli in Experiment 2 revealed no effect of CAT on food choice, leading the authors to suggest that merely responding to stimuli is not sufficient. Not only is the cue necessary, but the timing of the cue is important as presenting the cue at a later time-point results in sustained attention to the stimuli. Further research has suggested that CAT may play a role in impulsive decisions (Veling et al., 2017a); allowing participants more time to make their choice eliminated the effect of training, suggesting that while CAT may not be useful in reflective decision making, it could be utilised to target impulsive processes.

Inhibitory control training

Measures of inhibitory control have also been modified for training purposes. While the GNG and SST were originally designed to measure inhibitory capabilities, these tasks can also be used to increase general inhibitory control capacity, and as a method to train participants to associate specific cues with withholding a motor response. Simply pairing stimuli with a signal in a similar way to CAT leads to an association of response inhibition to be made with stimuli, which in turn results in an increase in successful stopping (Sedgmond et al., 2020; Sedgmond et al., 2019). This training can also lead to a reduction in desire to eat and consumption of the foods paired with signals (Houben & Jansen, 2011, 2015) as well as influencing food choice (Veling et al., 2011; Veling et al., 2013a, 2013b).

After completing a GNG task in which palatable foods were presented with either a go or no-go signal, participants with an increased appetite were less likely to choose foods paired with the no-go signal (Veling et al., 2013a). A further study by the same group also revealed that when palatable foods were paired with no-go signals, participants were more likely to select healthy foods than the palatable foods (though this effect was not significant; Veling et al. 2013b).

While most studies have typically only measured these outcomes immediately following training, there is also evidence to suggest long-term effects following multiple training sessions (Lawrence et al., 2015a). Participants who completed active GNG training in which energy dense foods were paired with no-go signals showed a reduction in liking and intake of the foods in comparison to participants who completed a control task after four sessions. Furthermore, follow-up after 6 months revealed a reduction in weight in the active training group.

The SST has also been utilised in the same way but with more mixed findings. Across three experiments Lawrence et al. (2015b) used stop-signal training to investigate the effect on food intake. In the first experiment, withholding a motor response to one food reduced subsequent consumption of that food, however experiments 2 and 3 failed to find an effect of training on food consumption. Similarly, Guerrieri et al. (2012) found no evidence of training on food consumption (though it should be noted that the training task was targeted at general inhibition rather than food-specific inhibition; non-food stimuli were used in the SST). It seems as though GNG training may be more effective in changing attitudes towards foods. In their second experiment, Adams et al. (2017) compared the effects of the SST and GNG training on food consumption. Participants were randomly assigned to one of five training conditions - two of which were the SST and GNG training - in which unhealthy foods were paired with stop and no-go signals respectively. Although both tasks revealed a significant effect of training on reducing food consumption when compared to their respective control conditions, GNG training resulted in the greatest reduction of calories.

Taken together, these findings suggest that improving inhibitory control may enable someone to make dietary changes. It is thought that this is through the process of stimulus devaluation. Across several experiments, Veling et al. (2008) asked participants to rate food stimuli before and after GNG training. They found that following training, participants' evaluations of no-go stimuli were significantly lower than go stimuli - though only for appetitive foods. These findings have since been replicated by other studies (Chen et al., 2016; Veling et al., 2013b). This devaluation effect is of particular importance as we know that reducing evaluations of stimuli can lead to behaviour change as observed by a reduction in consumption, and the change in choice behaviour (Hollands et al., 2011;

Houben et al., 2010a).

Several explanations have been offered for how this devaluation effect occurs; two of which are based on the mechanisms of evaluative conditioning (EC), which can also lead to changes in stimulus value. By pairing a neutral stimulus (the conditioned stimulus) with a second stimulus that is typically positive or negative (the unconditioned stimulus), the affect from the unconditioned stimulus can transfer to the conditioned stimulus (Hollands et al., 2011). Therefore pairing a conditioned stimulus with a positive unconditioned stimulus can lead to an increase in the valuation, and pairing a conditioned stimulus with an negative stimulus can lead to devaluation (Hofmann et al., 2010). Chen et al. (2016) tested two different accounts based on this mechanism; the *no-go cue EC account*, and the *nonresponse EC account*. The *no-go cue EC account* posits that the cue that informs a participants to withhold their motor response acts as a negative unconditioned stimulus. Whereas in the *nonresponse EC account*, the response inhibition rather than the cue itself is perceived negatively. These two accounts were tested across a series of experiments that manipulated the presence and frequency of the no-go cue. Unlike results from CAT that suggest the cue is necessary to observe the effects, it seems this is not the case with response inhibition training. GNG training still led to the devaluation of stimuli even when the cue was removed suggesting that it is the not responding rather than the cue that cause the change in valuation. However it seems as though simply not making a motor response is not sufficient; the devaluation observed occurs only when inhibition is within a condition in which motor responses are being made. This findings seem to dismiss the *no-go cue EC account*, and the *nonresponse EC account*, and instead provide support for a response inhibition account.

The Behavioural Stimulus Interaction (BSI) theory has been proposed to explain how these tasks lead to devaluation via response inhibition (Veling et al., 2008). BSI theory suggests that when we are faced with an appetitive stimulus, an approach reaction is triggered. However when this is followed by a no-go cue, we are faced with a response conflict. In order to mitigate this conflict, the appetitive stimulus is devalued to reduce the approach tendency and meet the situational demands. While the findings from studies such as Chen et al. (2016) support this account, based on the assumptions of BSI theory, devaluation should only occur for appetitive or high-value stimuli. More recently research

has found an effect of GNG training on devaluation regardless of initial stimulus value which does not support BSI theory (Chen et al., 2019), but instead alternative response inhibition accounts such as the stimulus-stop account which does not place importance on stimulus value, and therefore does not require a response conflict (Best et al., 2016; Verbruggen et al., 2014). Alternative theories have also focused on the role of attention (Quandt et al., 2019; Veling et al., 2017b); however more research is still needed to understand what mechanisms are driving the change in stimulus value.

Approach bias modification

Approach bias modification tasks manipulate approach and avoidance responses in an attempt to change biases, using tasks such as the IAT and AAT. While a standard IAT would typically pair both stimulus groups with both attribute categories, the task can be modified for training purposes so that each group of stimuli is only paired with one of the attribute categories. For example, after confirming an approach bias for chocolate in their first experiment, Kemps et al. (2013) examined whether this bias could be modified in their second experiment. Using a modified IAT, baseline approach bias for chocolate was measured before a training stage in which participants were trained to either associate chocolate with approach or avoidance. In the approach condition, 90% of the trials paired chocolate stimuli with approach words, and in the avoidance condition, 90% of the trials paired chocolate stimuli with avoidance words. A post-training measure of associations identical to the baseline measure revealed a significant decrease in approach bias towards chocolate from pre-to post training in the avoidance group.

The AAT can also be modified in a similar way. Rather than pairing stimuli with both approach and avoidance movements, action responses can be grouped to only be associated with a specific group of stimuli. Following a baseline measure of approach bias using a standard AAT, participants completed ten sessions of training over a 5-week period using a modified AAT (Brockmeyer et al., 2015b). Participants were presented with food and control stimuli and were trained to pull a joystick in response to control stimuli (approach) and push the joystick in response to food stimuli (avoid). In addition to the action, a zooming feature was also incorporated which is used to provide visual feedback and disambiguate approach and avoidance movements (Neumann & Strack, 2000). After

the approach action the stimuli would increase in size, and after an avoidance movement the stimuli would decrease in size. The training task resulted in a decrease in both cue-induced and trait food craving. Furthermore, the initial approach bias for foods observed at baseline became an avoidance bias following training.

Similar training tasks have been used to train participants to avoid chocolate stimuli specifically, however the results have been mixed. Promising findings reported that participants consumed less in an ad-libitum taste test following active training in which they had been trained to avoid chocolate stimuli (Schumacher et al., 2016). However other studies have found no effect of training, with two studies reporting an increase in consumption following training (Becker et al., 2015; Dickson et al., 2016). In addition to the findings on food consumption, Becker et al. (2015) reported no effects of approach-avoid training on implicit or explicit food preferences, and Dickson et al. (2016) also found no effect on food craving.

While the findings of approach bias modification seem to be less conclusive than both attentional bias and inhibitory control training (ICT), the training effects are similar with findings suggesting that frequently approaching a stimulus results in a preference that increases the stimulus evaluation, whereas frequently avoiding a stimulus decreases the stimulus evaluation (Van Dessel et al., 2018). The evaluative coding hypothesis posits that approach and avoid responses are interpreted in a similar way as the unconditioned stimuli in EC (Eder & Rothermund, 2008); the approach towards a stimulus is interpreted as positive and the avoidance is interpreted as negative which in turn influences evaluations. Based on this theory, two dominant explanations for approach and avoidance behaviours have been applied to explain the mechanisms of training.

The arm flexion/extension hypothesis is based on the importance of muscular involvement in approach and avoidance behaviours and posits that stimulus evaluations are inferred from actions (Krieglmeyer et al., 2013). For example, when we approach a stimulus we like, our arm extends to reach the item. The distance-change hypothesis places importance of the distance between the individual and the stimulus (Strack & Deutsch, 2004). For example automatic approach and avoidance biases result in a decrease and increase in distance respectively. Van Dessel et al. (2018) carried out a series of experiments to test theories of approach-avoid training that incorporated these two explanations. The

arm flexion/extension hypothesis would assume that the physical component of training is necessary to observe an effect - for example the movement of a joystick - whereas the distance-change hypothesis would require some form of visible distance change in training whether by the incorporation of a zooming element, or the movement of the stimuli. However not only was a change in stimulus evaluation observed when participants observed approach/avoid movements, opposing the arm flexion/extension hypothesis, but changes were also observed when actions did not influence distance between the participants and the stimuli. Furthermore effects of approach-avoid training from the use of the IAT do not incorporate a motor or distance element suggesting that there is another driver influencing the evaluations of these stimuli.

1.4.2 Neuromodulation

The modulation of cortical activity in eating behaviour research has become increasingly common over the last 20 years. Based on what is known about the neural mechanisms involved in food choices, altering neural activity using non invasive brain stimulation seems to be a promising avenue to explore. The two most dominant techniques in this area are transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS) (Paulus, 2011; Wagner et al., 2007). Despite different mechanisms, both techniques are able to modulate brain activity beyond the duration of stimulation which has been of particular interest in the study of eating behaviour.

TMS

TMS is a neurostimulation and neuromodulation technique that exploits the principle of electromagnetic induction to induce currents in the brain using an insulated coil (Wassermann & Zimmermann, 2012). While disruption can be transient, through the use of repetitive stimulation (rTMS), modulation of cortical activity can last beyond the duration of stimulation and can be excitatory or inhibitory (Wagner et al., 2007).

The effects of rTMS on food craving and food consumption have been explored in several studies targeting the left DLPFC. Using participants with high levels of self-reported food craving, Uher et al. (2005) found a significant effect of left prefrontal rTMS on cue-induced food craving. Following exposure to food, craving was reduced in participants

who had received active in comparison to sham stimulation. However, this reduction could have been due to discomfort associated with prefrontal stimulation, as opposed to cortical stimulation itself. To examine whether this was the case, Barth et al. (2011) used the same protocol, however for their sham condition, stimulation was delivered to the motor cortex in order to elicit the same sensation. After 15 minutes of stimulation there was a reduction in food craving from both active and sham stimulation, suggesting that the discomfort associated with prefrontal stimulation may have been a contributing factor in both studies. However further evidence has found that enhancing activity in the left DLPFC can lead to increases in both food craving and food consumption in comparison to sham stimulation (Lowe et al., 2014), suggesting that while discomfort may play a role, modulating activity within these key regions still has the potential to make significant changes.

rTMS protocols have also been used in patients with bulimia nervosa (Van den Eynde et al., 2010) as well as in overweight and obese participants (Kim et al., 2019) with more promising results. After one session of active rTMS, patients with bulimic-type eating disorders exhibited a reduction in cue-induced craving as well as a reduction in bingeing in the 24 hours following compared to those who had received sham stimulation. Further research has explored the potential of rTMS to make long-term changes using multi-session protocols (Kim et al., 2019). Participants received 8 sessions of left prefrontal rTMS over a 4 week period and showed a reduction in weight loss following active stimulation in comparison to sham.

tDCS

While TMS has led to promising results, tDCS has more frequently been applied in this domain and is used to modulate the resting membrane potential using a weak electrical current via scalp electrodes (Paulus, 2011). As the modulation is polarity-dependent, it is thought that anodal stimulation depolarises the resting membrane potential via the inhibition of gamma-aminobutyric acid, whereas cathodal stimulation hyperpolarises the resting membrane potential via the inhibition of glutamate (Stagg et al., 2018). Unlike TMS, tDCS typically causes less discomfort and also offers more effective participant and researcher blinding. Studies utilising tDCS have primarily explored its effects on state

craving and food consumption using 2mA anodal right/ cathodal left stimulation of the DLPFC.

Reductions in both cue-induced and state craving have been observed following a single-session of tDCS (Fregni et al., 2008; Goldman et al., 2011; Kekic et al., 2014; Lapenta et al., 2014; Ljubisavljevic et al., 2016), and research has shown promise for multi-session protocols, with larger effects on craving observed in comparison to single-session protocols (Song et al., 2019) as well as reductions in trait craving (Ljubisavljevic et al., 2016). However more recently these effects on craving have failed to replicate. Using the same protocol Beaumont et al. (2021) and Stevens et al. (2021) found no effect of stimulation on food craving in comparison to sham stimulation.

Effects on food consumption are less clear. While earlier research offered promise for tDCS in reducing food consumption (Fregni et al., 2008), this effect has not been shown in other studies (Goldman et al., 2011; Kekic et al., 2014; Stevens et al., 2021). The importance of trait characteristics in determining the effects of tDCS have been discussed as effects have typically been observed only in participants with high levels of trait food craving. Based on what we know about the neural mechanisms surrounding eating behaviour, it has been suggested that tDCS is unlikely to benefit those with normal eating behaviours (Beaumont et al., 2021; this is discussed further in Chapters 2, 3 and 6).

Hemispheric differences

Although the majority of neuromodulation studies have targeted the DLPFC based on its role in eating behaviours, TMS studies have typically targeted the left hemisphere, while tDCS studies have primarily been interested in the modulation of the right hemisphere.

There is evidence to support the involvement of both hemispheres. For example, the right brain hypothesis is based on evidence that damage, reduced blood flow, and hyperactivity in the right pre-frontal cortex can all independently lead to disordered eating behaviour (see Alonso-Alonso and Pascual-Leone, 2007 for a review). Therefore increasing activity is thought to reduce the desire to eat. More recently, the role of the left DLPFC in self-regulation specific to eating behaviour has emerged. For example, elevated left DLPFC activity has been associated with food choices based on health as opposed to

palatability (Hare et al., 2009).

There is still an uncertainty of hemispheric specialisation in tDCS studies. While it is notable that Fregni et al. (2008) found a reduction in food consumption following both anodal right/ cathodal left and anodal left/ cathodal right stimulation, the effects on food craving were only observed following anodal right/ cathodal left. Despite these findings, further evidence has demonstrated that the most consistent effects on food craving specifically have emerged from left sided stimulation (Hall et al., 2017; Lowe et al., 2017). Future studies may benefit from stimulating both left and right DLPFC to explore the role of hemispheric differences further.

1.5 Open science

1.5.1 Reproducibility in psychology

We are currently facing a well-documented reproducibility crisis in psychological research. In 2011 a large-scale, collaborative project was developed with the goal of estimating the reproducibility of psychological science (Open Science Collaboration, 2012). Despite attempts to use similar replication methodology, using original materials where possible and ensuring studies were well-powered, the majority of replications failed to produce evidence as compelling as the original research, and only 36% of positive results were replicated (Open Science Collaboration, 2015). The failure to replicate results is thought to be caused by a combination of inadequately powered studies, as well as questionable research practices such as p-hacking, HARKing, and selectively reporting results in original studies (Banks et al., 2016; Masicampo & Lalande, 2012). Open science practices offer a potential solution to the challenges faced in psychological science (Munafò et al., 2017).

As detailed previously, open science practices were used throughout this thesis. Chapters 2, 4 and 5 were pre-registered on the Open Science Framework, and Chapter 3 was completed as a Registered Report. Both pre-registrations and Registered Reports require the formulation and declaration of hypotheses and analysis plans to be determined prior to data collection (Chambers, 2013; Munafò et al., 2017). Adhering to these practices not only reduces the risk of questionable research practices, but, for Registered Reports, also reduces the risk of publication bias based on the results (Chambers, 2013) - a pervasive

problem in which only significant and/or novel findings are submitted or published (Nissen et al., 2016). Recent research identified that in Psychology, over 95% of publications had positive results in comparison to less than 50% of Registered Reports (Scheel et al., 2020), providing evidence for the effectiveness of the Registered Reports approach for reducing bias.

Furthermore, Registered Reports also require a justification of sample size which ensures a sufficient sample to detect a true effect, but also reduces the likelihood of obtaining a false positive (Button et al., 2013). Power analyses were conducted for all studies in this thesis. Inadequate statistical power is pervasive in psychological research and specific to this thesis, studies using tDCS in the food domain are typically underpowered and sample size justifications are rarely provided. Therefore the first goal of this thesis was to try to replicate previous findings in an adequately powered sample.

1.5.2 Bayesian statistics

Throughout this thesis I will report both Bayesian and frequentist statistics, but will draw conclusions based on the Bayesian interpretations which allow for the interpretation of null findings and assess the strength of evidence (Dienes, 2011; Rouder et al., 2009). The classification used will be based on that of Lee and Wagenmakers (2013) [Table 1.1].

Unless specified otherwise, all analyses were computed in JASP (JASP Team, 2018) using the default JZS prior ($r = 0.707$) (Rouder et al., 2009). The JZS prior is a non-informative objective prior that minimises assumptions regarding expected effect size.

1.6 Synopsis

The aim of the research reported in this thesis was to investigate the effectiveness of brain stimulation and cognitive control training in modifying automatic responses to food cues. Across five experiments I explored the effects on behaviours such as food consumption, food craving, desire to eat, and implicit and explicit liking. The role of individual differences and task parameters was also investigated.

In the first experiment I aimed to replicate previous findings that had demonstrated an effect of tDCS on food craving and food consumption using a well-powered and pre-

Bayes Factor	Interpretation
>100	Extreme evidence for H1
30-100	Very strong evidence for H1
10-30	Strong evidence for H1
3-10	Moderate evidence for H1
1-3	Anecdotal evidence for H1
1	No evidence
1/3-1	Anecdotal evidence for H0
1/10-1/3	Moderate evidence for H0
1/30-1/10	Strong evidence for H0
1/100-1/30	Very strong evidence for H0
<1/100	Extreme evidence for H0

Table 1.1: Bayesian interpretation table. Throughout the thesis Bayes Factors will be calculated and reported as B_{JZS} . Conclusions will be based upon Bayesian interpretations. H1 refers to the experimental hypothesis, H0 refers to the null hypothesis.

registered study design. In a between-subjects design, participants completed a GNG training task while receiving either active or sham stimulation to investigate whether the stimulation could augment the effects of the training task. A measure of state craving was completed pre-and post-stimulation, and ad-libitum food consumption was measured following stimulation. I found no difference in food consumption between participants who had received active versus sham stimulation, and there was also no significant effect of tDCS on craving scores from pre- to post based on stimulation type. Bayesian analyses revealed anecdotal to moderate evidence for the null hypotheses.

In the second experiment I sought to improve upon the methods used in the previous experiment to investigate whether high-definition tDCS (HD-tDCS) - a more focal form of stimulation - could reduce food craving and desire to eat. Using a within-subjects design, participants received both active and sham stimulation across two separate sessions at least one week apart. As in the first experiment, participants completed GNG training while receiving stimulation. Food craving and desire to eat were measured pre-and post-stimulation using a standardised questionnaire and a taste test respectively. There was no evidence for an effect of HD-tDCS on food craving or desire to eat. Bayesian analyses revealed anecdotal to moderate evidence for the null hypotheses.

Although there was no effect of stimulation in the first or second experiment, participants in both experiments demonstrated evidence of learning from the training task; participants were more successful at withholding responses to unhealthy foods and exhibited

faster reaction times to healthy foods (in comparison to filler stimuli). Subsequently, the remaining experiments focussed specifically on the use of behavioural training in changing attitudes towards foods.

In the third experiment I used a novel training task that incorporated elements of GNG training, CAT, and EC to investigate the effects on both implicit and explicit liking.¹ In an online experiment participants completed a training task in which they were cued to respond to healthy foods that had been paired with pleasant stimuli, and cued to withhold responses to unhealthy foods that had been paired with unpleasant stimuli. Explicit liking of trained and untrained foods was measured pre-and post-training using a visual analogue scale (VAS), and implicit liking was measured following training using an affective priming paradigm (APP). There was no effect of the training task on increasing liking of healthy foods or decreasing liking of unhealthy foods with analyses revealing moderate to strong evidence against the effect of the training task on explicit and implicit liking. I did, however, observe a significant effect of training on learning.

The final two experiments both explored the effects of EC on explicit and implicit liking across two experiments; the first in a lab-based design, and the second an online design. The EC task paired healthy foods with pleasant or neutral stimuli and unhealthy foods with unpleasant or neutral stimuli. Explicit and implicit liking measures were identical to those used in the third experiment. Comparisons were made between foods based on the valence of the stimuli they had been paired with, however once again I found no effect of the behavioural task on liking.

The results obtained from these experiments fails to support a large body of literature showing effects of both tDCS and the behavioural training tasks used to change food-related behaviours. The implications of these findings for theory and methods surrounding the cognitive control of eating behaviour are address in the General Discussion.

¹The original design of the study also incorporated AAT but had to be removed due to that component of the program being technically infeasible in an online setting.

Chapter 2

Prefrontal brain stimulation during food-related inhibition training: Effects on food craving, food consumption and inhibitory control

This chapter is published in *Royal Society Open Science* (Sedgmond et al., 2019; <https://doi.org/10.1098/rsos.181186>)

2.1 Introduction

Unprocessed or minimally processed foods account for less than 30% of the average UK diet, with ultra-processed foods contributing more than 50% of food intake (Monteiro et al., 2018). The availability and low cost of highly palatable and energy-dense food has resulted in increased consumption (Cummins & Macintyre, 2006; Prentice & Jebb, 2003), providing one of the leading explanations for rising rates of obesity (Cummins & Macintyre, 2006; Levitsky, 2005). It has now been noted that this rise in food consumption is often in the absence of hunger and is instead driven by factors unrelated to an individual's physiological requirements, such as pleasure (Burgess et al., 2014). This desire to consume food is referred to as hedonic hunger, and is satisfied by the consumption of these energy and calorie-dense foods (Burgess et al., 2014). Hedonic hunger can manifest as a preoccupation with constant thoughts surrounding food, resulting in persistent cravings (Lowe & Butryn,

2007). It is these cravings - which manifest as a strong desire to consume a specific food - that can result in the overconsumption of food regardless of the caloric requirement (Gendall et al., 1997). However, the extent to which hedonic factors influence eating behaviour varies widely across individuals; for some, healthy eating remains a constant challenge, whereas others appear able to resist temptation and maintain a healthy diet.

Neuroimaging studies have suggested that individual differences in prefrontal brain activity related to goal-oriented behaviour and self-control may help to explain vulnerability to hedonic eating (Batterink et al., 2010; Pignatti et al., 2006; Uher, 2005). A particular region of interest is the DLPFC which has been associated with the impulsiveness often linked to overconsumption (Gluck et al., 2017). In a meta-analysis, Brooks et al. (2013a) found that obese participants showed reduced activation of the left DLPFC in response to food images. Similarly, those who are obese have been shown to have reduced grey matter volume in the left inferior frontal gyrus and bilateral DLPFC (Brooks et al., 2013b). Increased activity in the DLPFC, on the other hand, has been associated with successful self-regulation of food intake and weight loss (DelParigi et al., 2007; Hollmann et al., 2012; Weygandt et al., 2013). It has therefore been proposed that enhancing brain activity within the DLPFC may help to increase self-control and reduce food consumption (Alonso-Alonso & Pascual-Leone, 2007).

tDCS has frequently been used in studies of food-related behaviour with the aim of modifying automatic responses to food stimuli. tDCS involves the delivery of a weak (typically 1-2mA) direct electrical current to the cortex via two scalp electrodes. The effect of tDCS on brain activity is dependent on the stimulation polarity; anodal stimulation is thought to increase cortical excitability by neuronal depolarisation, whereas cathodal stimulation is believed to decrease excitability by hyperpolarising neurons (Antal et al., 2007; Liebetanz, 2002; Nitsche et al., 2003; Nitsche et al., 2005; Priori, 2003).

Activation of the DLPFC using tDCS has indeed shown promise for modulating food-related behaviour. Compared to sham stimulation, active tDCS has been found to reduce food craving in healthy subjects who self-identify as having frequent and strong cravings (Fregni et al., 2008; Goldman et al., 2011; Kekic et al., 2014; Lapenta et al., 2014; Ljubisavljevic et al., 2016). Furthermore, it seems that the effect of tDCS goes beyond craving alone and can result in decreased food consumption (Burgess et al., 2016; Fregni et al.,

2008; Lapenta et al., 2014). For example, Fregni et al. (2008) investigated the potential effects of tDCS on both food craving and food consumption using a within-subjects crossover design. Participants' craving scores were measured before and after exposure to nine processed food items while watching a 5-minute film depicting images of foods known to elicit cravings. These measures were then repeated following sham or active DLPFC stimulation with an ad-libitum eating phase post-exposure. A significant reduction in food craving was found in the anode right/cathode left condition, though not in the anode left/cathode right condition, and sham stimulation resulted in a significant increase in food craving. Overall calorie consumption was also significantly lower in both active conditions compared to sham, with the anode right/cathode left condition resulting in the lowest intake. This finding was replicated by Goldman et al. (2011), who also demonstrated a significantly greater reduction in both food craving and an inability to resist food with active anodal right/ cathodal left stimulation compared to sham stimulation, although they found no difference in food consumption. More recent studies have also replicated effects of tDCS on food craving, although effects on food consumption are more equivocal (Kekic et al., 2014; Lapenta et al., 2014). Potential explanations for variability in outcomes are inadequate statistical power (the largest sample size across these papers was $N=21$; see Lowe et al., 2017) and suboptimal study protocols, including lack of study preregistration to control various forms of analytic and reporting bias.

Unlike some forms of brain stimulation, tDCS is a subthreshold intervention; it is too weak to induce activity, but instead modulates already occurring neuronal activity (Woods et al., 2016). It has been argued, therefore, that the effectiveness of tDCS may be improved with the addition of a cognitive task that promotes activity in the target brain regions (Alonso-Alonso & Pascual-Leone, 2007; Antal et al., 2007; Wiers et al., 2013; Woods et al., 2016). One potential task that could augment the effect of tDCS on food cravings and consumption is food-related inhibition training.

Food-related inhibition training typically requires participants to withhold their responses to images of palatable foods in response inhibition tasks such as the SST or GNG task. Previous studies have suggested that such training may be effective at modifying food-related behaviour and can result in decreased consumption of unhealthy foods, healthier food choices, and even weight loss (Adams et al., 2017; Houben, 2011; Houben

& Jansen, 2011; Lawrence et al., 2015a; Lawrence et al., 2015b; Veling et al., 2014). Two recent meta-analyses have reported small but significant effect sizes for the effect of inhibition training on food consumption and have further indicated that effects are greater for GNG compared to Stop-Signal training (Allom et al., 2015; Jones et al., 2016). Furthermore, inhibitory control (especially in the GNG task) has been linked to activation within the DLPFC (Beeli et al., 2008; Boggio et al., 2007; Garavan et al., 2006; Liddle et al., 2001; MacDonald, 2000; Wager et al., 2005; Zheng et al., 2008). For example, using electroencephalography (EEG), Lapenta et al. (2014) found that bilateral tDCS to the DLPFC (anodal right/ cathodal left) resulted in reduced N2 and increased P3a components of responses to no-go stimuli. The authors also found reduced food craving and consumption following active stimulation and suggested that these effects were mediated by changes in inhibitory control. Although no studies to date have paired food-related inhibition training with DLPFC stimulation, one recent study has combined general inhibition training with stimulation of the inferior frontal gyrus – another area believed to be involved in response inhibition (Ditye et al., 2012). Ditye et al. (2012) found that the combination of training and stimulation was more effective at improving performance than just inhibition training alone. However, because the training-only group did not receive sham stimulation it is possible that these results were due to non-specific effects of brain stimulation, including a placebo effect.

The present study therefore aimed to extend previous findings by investigating whether combining tDCS and food-related inhibition training could have a cumulative effect on decreasing food cravings and consumption. Furthermore, we recruited a larger-than-typical sample size (N=172) and all methods were pre-registered prior to data acquisition to ensure transparency and reduce researcher bias. Using a between-subjects design, participants were randomly assigned to receive either active or sham stimulation; in accordance with previous studies we delivered bilateral, anodal right/ cathodal left DLPFC stimulation (e.g. Fregni et al., 2008). Stimulation was paired with a food-related GNG training task in which unhealthy foods were consistently paired with inhibition and healthy foods were paired with a response. State food cravings were measured before and after tDCS and following stimulation participants were presented with a snack buffet to measure ad-libitum food consumption. The snack buffet contained the same foods presented during training

in addition to two novel foods (one unhealthy and one healthy). To justify the snack phase participants were informed that we were measuring the effect of blood glucose levels on cognitive performance. We therefore needed to measure performance at the beginning of the study, following a three hour fast, and following food intake. Our primary pre-registered hypothesis was that participants receiving active tDCS would consume fewer calories than those receiving sham tDCS (H1), with a secondary pre-registered hypothesis that the active group would also show a decrease in food craving compared with sham (H2). A speeded GNG task was also included at the end of the session as a pre-registered manipulation check for the effect of tDCS on inhibitory control; we predicted that participants in the active group would make fewer commission errors compared with the sham group (the percentage of erroneous responses made on no-go trials; H3).

2.1.1 Hypotheses

Primary hypotheses

H1. Effect of tDCS on food consumption: Participants receiving active stimulation will consume fewer overall calories than those receiving sham stimulation. Consumption: Active < Sham

H2. Effect of tDCS on food craving: Participants receiving active stimulation will show a decrease in food craving compared to those receiving sham stimulation. Craving: Active < Sham

H3. Effect of tDCS on response inhibition: Participants receiving active stimulation will make fewer commission errors during the speeded GNG task compared to those receiving sham stimulation. % Errors: Active < Sham

2.2 Method

2.2.1 Participants

One hundred and eighty-one participants (141 females, age: $M = 20.81$, $SE = 0.26$) were recruited from the staff and student population at Cardiff University and 172 participants

were included in the final analyses following exclusions according to pre-registered criteria (134 females, age: $M = 20.8$, $SE = 0.26$). Participants were all aged 18-45, right-handed, and had no contraindications for tDCS. Participants were excluded if they were currently dieting (with the aim to lose weight), if they had any history of eating disorders or if they had previously taken part in any studies involving inhibition training and food consumption. All participants were reimbursed at a rate of £10 per hour. The study was approved by the School of Psychology Research Ethics Committee, Cardiff University.

2.2.2 Sampling plan

Sample size was determined according to an *a priori* power calculation. Although we used a Bayesian inferential stopping rule for the main effect of total calorie intake between groups, we achieved our maximum possible sample size before the Bayes factor reached the recommended threshold for early research - $BF > 6$ or $BF < 1/6$ to provide moderate evidence for the experimental or null hypothesis, respectively (Schönbrodt et al., 2017). Our maximum sample size of 172 participants determined using G*Power (Faul et al., 2007) provided us with 90% power to detect an effect size of $d = 0.5$ using a two-tailed independent t-test with an alpha level of 0.05 (see Appendix A for further details).

2.2.3 Procedure

At least one week prior to the study, all participants were screened for eligibility criteria and were asked to complete the Restraint Scale (Herman & Polivy, 1980). On the day of testing, participants were asked to eat something small three hours before the study and to then refrain from eating during this period, thus standardising appetite and food motivation. All testing sessions therefore took place between 12pm and 8pm. This instruction was also consistent with the cover story that justified the snacking phase (that we were measuring the effects of glucose levels on task performance). Upon arrival, participants completed a consent form and two brain stimulation safety screening questionnaires, followed by the task-relevant questionnaires before receiving tDCS. The first five minutes of tDCS were delivered in isolation, and the remaining 15 minutes were delivered alongside GNG training. Following training, participants completed the task-relevant questionnaires for a second time. Participants were then taken to another room for the snack buffet and

were left for 20 minutes with the filler-questionnaires. Finally, participants completed the speeded GNG task in the original testing room. After completion, all participants were debriefed and their awareness of the study’s aims and tDCS condition was questioned (see Appendix A for all debrief questions and analyses). Participants’ height and weight was then recorded to calculate their body mass index (BMI; kg/m²) [Figure 2.1].

Scales (pre)	tDCS & training		Scales (post)	Food consumption	Measure of inhibitory control
Hunger, PANAS, discomfort & nausea, G-FCQ-S	Active or sham		Hunger, PANAS, discomfort & nausea, G-FCQ-S	Snack buffet & filler questionnaires	Speeded GNG task
	tDCS only	GNG training			

Figure 2.1: Schematic diagram of the procedure. Participants initially completed measures of hunger, mood and craving before being randomly allocated to receive either active or sham stimulation. After 5 minutes of stimulation a food-related GNG training task was introduced. Following this task participants were presented with the hunger, mood and craving scales and then a snack buffet with various unhealthy and healthy foods for consumption. Filler questionnaires were provided during the buffet to keep participants occupied for 20 min. Participants then completed a speeded version of the GNG task to measure inhibitory control.

2.2.4 tDCS

Participants received either active or sham tDCS. Two 7x5cm (35cm²), saline-soaked, sponge electrodes were positioned bilaterally with the anode placed over the right DLPFC and the cathode over the left DLPFC (F4 and F3 respectively using the 10-20 EEG system). For the active condition a 2mA current was applied using a battery-driven constant-current stimulator (Neuroconn DC-STIMULATOR PLUS, neuroConn GmnH, Illmenau, Germany) for 20 minutes (with a 10 second ramp up and down). For the sham condition, the stimulator delivered a 2mA current for 30 seconds before being ramped down to 0mA over a 1 minute period. The experimenter was provided with a study code for each participant that would generate either active or sham stimulation, ensuring that the experimenter was blinded to the condition.

2.2.5 Training tasks

GNG task

The training task lasted approximately 15 minutes and consisted of eight blocks of 36 trials with a 15 second break between each block. The blocks randomly presented nine images of unhealthy foods (three images each of chocolate, crisps and biscuits), nine images of healthy foods (three images each of fruit, rice cakes and salad vegetables) and 18 filler images (clothes; three each of jeans, shirts, jumpers, socks, skirts and ties). One stimulus of each food type was a photographed image of the corresponding food item that was presented in the snack buffet. All images were close-up views of the food item against a white background; images were carefully selected on the basis that there were no additional ingredients or packaging, and they were matched for size and complexity. Each trial began with the presentation of a central rectangle (inter-trial interval; ITI, 1250ms). A stimulus was then presented within this rectangle randomly, and with equal probability, to either the left or right hand side. Participants were required to respond to the location of the stimulus as quickly and accurately as possible using their left and right index fingers (using the ‘C’ and ‘M’ keys, respectively). A no-go signal (the fixation rectangle turned bold for the duration of the trial) was presented on 50% of trials indicating that the participant must withhold their response for that trial. All of the unhealthy food images were presented with a signal (100% mapping), none of the healthy foods were presented with a signal (0% mapping) and half of the filler images were presented with a signal (50% mapping; see Figure 2 for visual schematic). All instructions were presented electronically before the training task and read verbatim by the experimenter. All tasks were programmed in Matlab (Mathworks, Natick, MA) using Psychophysics Toolbox (www.psychtoolbox.org) and all stimuli were presented on a 19-inch flat-panel LCD monitor. The training task was identical to that used by Adams et al. (2017) [Figure 2.2].

Speeded GNG task

As a manipulation check for the effect of tDCS on inhibitory control we included a second GNG task. To avoid floor effects and improve the detection of potential improvements in inhibitory control, we modified the training task in three ways: firstly, we used a speeded

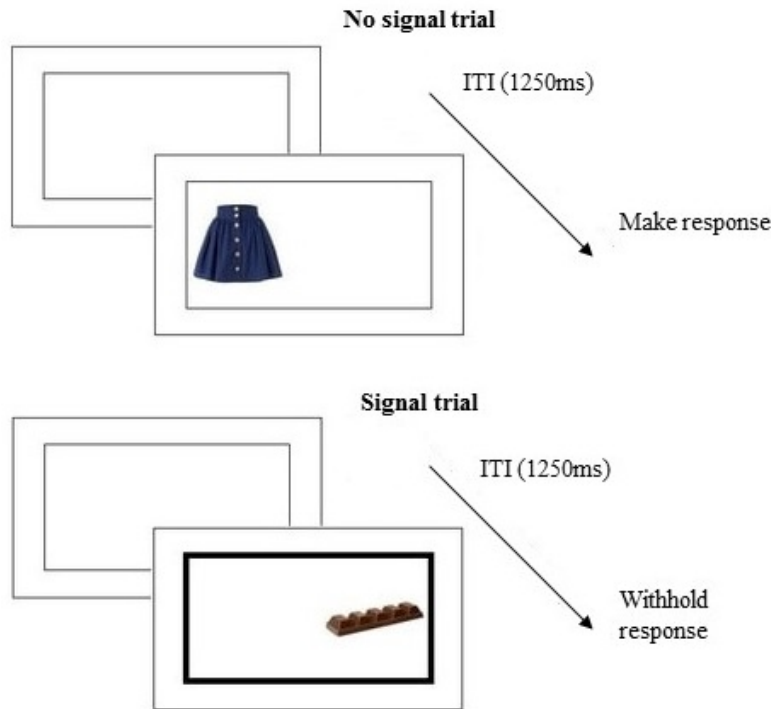


Figure 2.2: Visual schematic of the GNG training task.

version in which the ITI and stimulus presentation time was reduced to 500ms; secondly, we reduced the percentage of no-go trials from 50% to 33.3%; thirdly, all foods were inconsistently paired with a no-go signal (33.3% mapping).¹ The task consisted of 15 blocks of 45 trials and lasted approximately 15 minutes. The stimuli were the same as those presented in the training task with the addition of nine novel unhealthy foods (5 sweet, 4 savoury). Instructions were presented electronically and participants were warned verbally about the faster presentation time for this task.

2.2.6 Outcome measures

Snack buffet

Ad libitum food consumption was measured using a snack buffet. The use of a snack buffet has frequently been utilized in studies of food take and is considered to be a valid measure of consumption (Robinson et al., 2017). Four unhealthy (crisps, biscuits, choco-

¹The commission error rate on the training task is typically very low (5%) making it difficult to detect any potential improvements in inhibitory control. It was believed that these changes would encourage rapid responding, which, as a result of the speed-accuracy trade-off would also increase the rate of commission errors (Collins & Mullan, 2011). A pilot study (N=13) we conducted with non-food images (e.g. household items including electrical goods and furniture) showed this to be the case with a mean commission error rate of 24.44%, SE = 3.53%.

late and cheese bites) and four healthy foods (carrots, grapes, rice cakes and breadsticks) were presented in a pseudorandom order (to minimise the effect of proximity on intake; nutritional information is listed in the appendix) [Appendix A: Table A.4]. Upon entering the buffet, participants were instructed to eat as much food as they liked, but to ensure that they were not feeling hungry when the experimenter returned after 20 minutes (in order to replenish their glucose levels, consistent with the cover story). They were then left alone with a battery of filler questionnaires. Unknown to the participants, all food was weighed before and after the buffet to determine calorie consumption. The snack buffet and cover story were also identical to those used by Adams et al. (2017).

State food craving

State food craving was measured with the General Food Craving Questionnaire – State Version (G-FCQ-S) (Nijs et al., 2007). The questionnaire consists of 15 items that measure the strength of food cravings; participants are asked to indicate how much they agree with each statement ‘at this very moment’ using a five-point scale (from 1 ‘strongly disagree’ to 5 ‘strongly agree’). There are five craving subscales including: intense desire to eat, anticipation of relief from negative states, physiological craving, preoccupation with food or lack of control over eating and anticipation of positive reinforcement. Scores can be calculated for specific subscales or a total score can be calculated (ranging from 15-75).

Task-relevant questionnaires

Participants completed three 100mm VASs to measure hunger, fullness and desire to eat. We also measured mood (using the Positive and Negative Affect Schedule; PANAS, Watson et al., 1988) and included two questions regarding discomfort/pain and nausea to rule out differences in food consumption due to these potential effects of tDCS.

Filler questionnaires

As in our previous studies (Adams et al., 2017; Lawrence et al., 2015b), filler questionnaires were provided during the snack buffet to keep participants occupied for the duration of the snacking phase. The questionnaires included the Brief Self Control Scale (Tangney et al., 2004), the Big Five Inventory (John et al., 2008), the Emotion Regulation Questionnaire

(Gross & John, 2003), the UPPS impulsive behaviour scale (Whiteside & Lynam, 2001), the Attentional Control Questionnaire (Derryberry & Reed, 2002), and the Mood and Anxiety Symptom Questionnaire (Watson et al., 1995).

2.3 Exclusion criteria

Participants were excluded from the analyses if any of the following criteria were met:

- Failure to comply with the study's eligibility requirements including:
 - Not eating for 3 hours before the study
 - Not having a current/ history of eating disorders
 - Not being on a calorie-controlled diet
- Inability to perform the training task correctly based on the following:
 - >15% error rate for no-signal trials, including incorrect responses (judging the stimulus to be on the incorrect side of the screen) and missed responses, within either session (sham or active tDCS)
 - RTs for no-signal trials exceed 3 SDs from the group mean within either session (sham or active tDCS)
 - Commission error rate for either session (active or sham tDCS) is > 3 SDs from the group mean within the relevant tDCS condition
- Failure to consume any food during the food consumption phase for the sham session
- Any reason to discontinue with tDCS based on adverse reaction during the session
- The participant exercises their right to withdraw from the study or their right to withdraw data
- The participant correctly guesses the aim of the study during debrief, when probed for knowledge of the study's aims, or realises that we are measuring food intake
- Any unforeseen errors resulting in the loss of data or inability to complete a session

2.4 Deviations from protocol

We originally hypothesised that all predicted effects would be greater in those who scored highly on measures of restrained eating. However, of the 172 participants included in the analyses, only 15 participants met the cut-off score for dietary restraint (a score of 15+ on the Restraint Scale; Herman & Polivy, 1980) meaning that subgroup analyses could not be conducted, however based on the recommendation of a reviewer, we analysed data with linear mixed effect models (see section 2.5.5).

In addition to the between-subjects factor of tDCS (active vs. sham), the design in the pre-registered protocol included separate groups of participants receiving no-go training and go-only training (i.e. 2 x 2 design of active vs sham x go vs no-go). The no-go groups (active and sham tDCS) were tested first in the sequence of data collection, and in light of the null effect of tDCS reported here, the go-only groups were abandoned (no data collected). This chapter thus reports the hypotheses and analysis plans for the no-go group only.

The study protocol (13 Feb 2015) is available at <https://osf.io/z2xf8/>. Data collection commenced on 16/02/15 and was completed on 30/01/18. The protocol was updated on 1 Aug 2016, after collection of 52 participants (but prior to the final analysis), to include fasting and food allergies as exclusion criteria (<https://osf.io/a5gqu/>). No participants that were included in the sample prior to the protocol amendment were excluded from further analysis.

2.5 Results

2.5.1 Data exclusions

Four participants were excluded in the sham group, and three in the active group based on failure to comply with task instructions. A further two participants (1 active, 1 sham) were excluded because they indicated knowledge of the study aim and one participant (active) was excluded after disclosing history of an eating disorder during debrief. Following exclusions there was a final sample of 172 participants: 84 in the sham condition (66 females) and 88 in the active condition (68 females). A further four participants were

excluded from analysis of the speeded GNG task due to failure to comply with task instructions: 2 from the sham condition and 2 from the active condition. All exclusions were in accordance with pre-registered criteria.

Food consumption data was explored for statistical outliers to ensure that any strong food preferences did not skew the results. The data was split according to food type and tDCS condition and values that exceeded 3 SDs from the mean were replaced with the highest non-outlier value for that food +1. This method reduces the impact of a univariate outlier while maintaining the score as the most deviant (Tabachnick & Fidell, 2007). Food consumption was analysed as a function of food type and food novelty by calculating the mean calorie value for each food category (the total calories for each food category was divided by the number of foods in that category). The consumption of healthy foods was also analysed in grams to avoid potential floor effects.

2.5.2 Baseline measures

Demographic, state and trait variables were analysed to ensure there were no statistically significant differences between tDCS groups at baseline. There were no significant differences in gender ratio ($B_{JZS} = 0.16$, $\chi^2(1) = 0.04$, $p = 0.84$, $\phi = 0.02$), age, BMI, dietary restraint, hunger, fullness, desire to eat, positive affect, negative affect, total craving score, craving subscales or hours since food (all all $B_{JZS} < 0.44$, $ts < 1.5$, all $ps > 0.05$). Within-subjects differences in hunger, fullness, desire to eat, positive affect and negative affect between pre and post tDCS phases were then compared between tDCS groups; no significant differences were found (all all $B_{JZS} < 0.53$, $ts < 1.6$, all $ps > 0.05$; see Appendix A for all outputs) [Appendix A: Table A.5].

2.5.3 tDCS tolerability and blinding

Both active and sham stimulation were well tolerated; participants were emailed a post-monitoring form 24 hours after study completion and of the 114 that completed the form, only 7 participants reported a minor adverse reaction (4.9%). However, participants receiving active stimulation did report higher levels of pain after stimulation ($M = 1.4$, $SE = 0.07$) compared with those receiving sham stimulation ($M = 1.16$, $SE = 0.05$; $B_{JZS} = 5.08$, $t(170) = 2.74$, $p = 0.01$, $d = 0.42$). There was no significant group difference

in reported nausea after stimulation ($B_{JZS} = 0.19$, $t(170) = 0.49$, $p = 0.63$, $d = 0.08$;), nor in awareness of tDCS condition ($B_{JZS} = 0.34$, $\chi^2(2) = 4.68$, $p = 0.1$, $\phi = 0.17$), suggesting that participants remained blind to the stimulation condition.

2.5.4 Primary analyses

All primary analyses have been summarised in Table 2.1.

Hypothesis		B_{10}	F	p	ηp^2	Evidence interpretation
H1	Consumption: Active < Sham	0.18	1.54	0.22	0.01	Moderate evidence for H0
H2	Craving: Active < Sham	0.37	0.66	0.42	0.004	Anecdotal evidence for H0
H3	%Errors: Active < Sham	0.33	0.86	0.36	0.01	Moderate evidence for H0

Table 2.1: Outcomes of the primary hypothesis tests. In all cases, the evidence favoured the null hypothesis (H0) over the corresponding alternative hypothesis.

Effect of tDCS on food consumption (H1)

A 2x2x2 mixed ANOVA (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factors: *food type* [healthy or unhealthy] and *food novelty* [old or new]) revealed no significant main effect of tDCS (**H1**: $B_{JZS} = 0.18$, $F(1,170) = 1.54$, $p = 0.22$, $\eta p^2 = 0.01$; addressing the primary pre-registered hypothesis). Contrary to the hypothesis, total calorie consumption was higher in the active tDCS group ($M = 631.18$, $SE = 31.42$) compared with the sham group ($M = 577.62$, $SE = 31.78$) [Figure 2.3]. A Bayesian comparison of sham and active tDCS with an informative prior revealed a Bayes factor of 0.19, indicating moderate evidence in favour of the null hypothesis (H0) over the experimental hypothesis (H1).

The mixed ANOVA also revealed no significant interaction between tDCS and food type ($B_{JZS} = 0.12$, $F(1,170) = 0.87$, $p = 0.35$, $\eta p^2 = 0.001$), or between tDCS and food novelty ($B_{JZS} = 0.11$, $F(1,170) = 0.08$, $p = 0.77$, $\eta p^2 < 0.001$). The three-way interaction between tDCS condition, food type, and food novelty was also non-significant ($B_{JZS} = 0.18$, $F(1,170) = 0.004$, $p = 0.95$, $\eta p^2 < 0.001$).

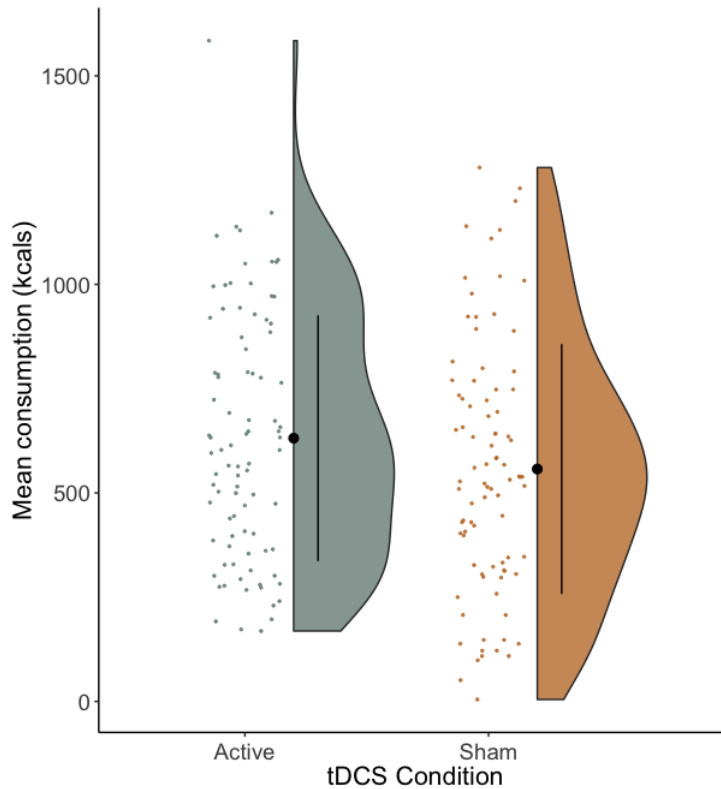


Figure 2.3: Total calorie intake as a function of tDCS condition.

Effect of tDCS on food craving (H2)

A 2x2 mixed ANOVA for total state craving scores (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factor: *time* [pre or post stimulation]) revealed no significant effect of tDCS (**H2**: $B_{JZS} = 0.37$, $F(1,170) = 0.66$, $p = 0.42$, $\eta p^2 = 0.004$) as well as no significant interaction between tDCS and time ($B_{JZS} = 0.28$, $F(1,170) = 0.88$, $p = 0.35$, $\eta p^2 = 0.004$) [Figure 2.4].

Effect of tDCS on response inhibition (H3)

A 2x4 mixed ANOVA on percent of successful no-go responses in the speeded task (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factor: *stimulus type* [unhealthy old, unhealthy new, healthy, filler]) revealed no significant main effect of tDCS condition (active: $M = 86.18$, $SE = 0.8$; sham: $M = 87.4$, $SE = 0.7$; **H3**: $B_{JZS} = 0.33$, $F(1,170) = 0.86$, $p = 0.36$, $\eta p^2 = 0.01$) and no statistically significant interaction between tDCS condition and stimulus type ($B_{JZS} = 0.1$, $F(1,170) = 1.54$, $p = 0.21$, $\eta p^2 = 0.01$). There was, however a significant main effect of stimulus type ($B_{JZS} = 155,512$, $F(1,170) = 12.75$, $p < 0.001$, $\eta p^2 = 0.07$), with more successful response inhibition for unhealthy

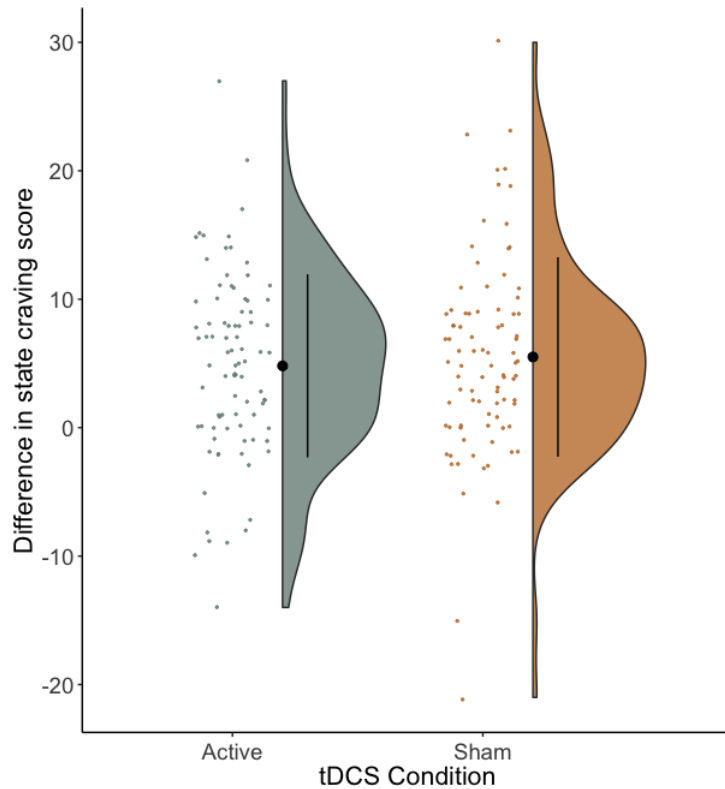


Figure 2.4: Change in state craving score as a function of tDCS condition (pre-stimulation scores were subtracted from post-stimulation scores so that a positive score indicates increased craving and a negative score would indicate decreased craving).

old foods ($M = 88.13$, $SE = 0.61$) than healthy foods ($M = 85.3$, $SE = 0.69$; $p < 0.001$), as well as more successful response inhibition for unhealthy new foods ($M = 87.99$, $SE = 0.62$) compared with healthy foods ($p < 0.001$) and filler items ($M = 86.66$, $SE = 0.59$; $p = 0.04$).

2.5.5 Exploratory analyses

Food consumption

Foods were split between unhealthy and healthy and analysed separately. Participants receiving active stimulation consumed 6% more calories from unhealthy foods (active: $M = 497.1$, $SE = 30.4$; sham: $M = 467.65$, $SE = 28.83$; $B_{JZS} = 0.21$, $t(170) = 0.7$, $p = 0.48$, $d = 0.11$ suggesting anecdotal-to-moderate evidence in favour of H_0 over H_1) and 22% more calories from healthy foods than those receiving sham stimulation (active: $M = 134.07$, $SE = 8.15$; sham: $M = 109.98$, $SE = 6.7$; $B_{JZS} = 1.77$, $t(170) = 2.27$, $p = 0.02$, $d = 0.35$ suggesting anecdotal evidence that active tDCS resulted in greater consumption

of healthy calories compared with sham tDCS).

To account for possible floor effects caused by the low caloric value of the healthy foods, we also analysed healthy food consumption in grams using a 2x2 mixed ANOVA (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factor: *food novelty* [old or new]). There was a significant main effect of tDCS condition with participants in the active group consuming more healthy food compared with the sham group ($B_{JZS} = 0.52$, $F(1,170) = 7.08$; $p = 0.01$, $\eta p^2 = 0.04$). A significant interaction between tDCS condition and novelty was also observed ($B_{JZS} = 7.86$, $F(1,170) = 7.37$; $p = 0.01$, $\eta p^2 = 0.01$). Analysis of simple main effects revealed that participants consumed significantly more calories from healthy old foods in the active stimulation group ($M = 160.1$, $SE = 11.5$) compared with sham ($M = 122.6$, $SE = 7.98$; $B_{JZS} = 4.41$, $p = 0.01$, but not for healthy new foods (active: $M = 5.4$, $SE = 0.67$; sham: $M = 5.9$, $SE = 0.69$; $B_{JZS} = 0.19$, $p = 0.57$).

Furthermore, we additionally split foods by sweet and savoury to see whether food type played a role in the effectiveness of tDCS. A 2x2 ANOVA (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factor: *food type* [sweet or savoury]) revealed a main effect of food type ($B_{JZS} = 20.73$, $F(1,170) = 11.01$, $p = 0.001$, $\eta p^2 = 0.06$) indicating that participants ate significantly more calories from sweet foods than savoury foods. However, there was no significant main effect of tDCS ($B_{JZS} = 0.29$, $F(1,170) = 1.44$, $p = 0.23$, $\eta p^2 = 0.01$) and no significant interaction between the two factors ($B_{JZS} = 0.21$, $F(1,170) = 0.51$, $p = 0.48$, $\eta p^2 = 0.003$).

Training data

Analyses of the data from the training task revealed that there were no significant differences between tDCS conditions for successful inhibition ($B_{JZS} = 0.17$, $t(170) = 0.21$, $p = 0.83$, $d = 0.03$), go RT ($t(170) = 1.81$, $p = 0.07$, $d = 0.28$, $B_{JZS} = 0.74$), or percentage of errors ($B_{JZS} = 0.22$, $t(170) = 0.81$, $p = 0.42$, $d = 0.12$).

To demonstrate evidence of learning in the training task we performed a 2x2 mixed ANOVA on go RT (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factor: *stimulus type* [healthy, filler]) to investigate whether participants were faster to respond to healthy foods compared to filler images. A significant main effect of

stimulus type ($B_{JZS} = 1.259e+28$, $F(1,170) = 210.75$, $p < 0.001$, $\eta p^2 = 0.55$) confirmed that participants were faster at responding to healthy foods ($M = 481.01$, $SE = 5.18$) compared to filler images ($M = 504.06$, $SE = 5.77$), however we found no significant main effect of tDCS ($B_{JZS} = 1.08$, $F(1,170) = 3.26$, $p = 0.07$, $\eta p^2 = 0.02$) or interaction between tDCS and stimulus type ($B_{JZS} = 0.01$, $F(1,170) = 0.87$, $p = 0.35$, $\eta p^2 = 0.002$).

We also undertook a corresponding 2x2 mixed ANOVA on successful response inhibition (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factor: *stimulus type* [unhealthy, filler]) to test whether, as expected by the training, participants would be better at inhibiting to unhealthy foods compared with filler images. This analysis revealed a significant main effect of stimulus type ($B_{JZS} = 2.434e+8$, $F(1,170) = 50.01$, $p < 0.001$, $\eta p^2 = 0.23$) with participants exhibiting a higher percentage of successful stopping to unhealthy foods ($M = 96.55$, $SE = 0.23$) compared with filler images ($M = 94.54$, $SE = 0.29$), but again, no significant main effect of tDCS ($B_{JZS}=0.16$, $F(1,170) = 0.04$, $p = 0.83$, $\eta p^2 < 0.001$), or interaction between tDCS and stimulus type ($B_{JZS} = 0.16$, $F(1,170) = 0.04$, $p = 0.85$, $\eta p^2 < 0.001$).

Speeded data

Based on the weak evidence that active tDCS resulted in greater consumption of healthy calories compared with sham tDCS, we performed a further exploratory analysis to investigate whether this increase in consumption might be explained by active tDCS enhancing go-training effects to healthy foods. Descriptively, participants in the active tDCS group exhibited faster go RTs to healthy foods ($M = 354.06$, $SE = 2.37$) compared with the sham group ($M = 359.71$, $SE = 2.81$). However a 2x4 mixed ANOVA on go RT in the speeded task (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factor: *stimulus type* [unhealthy old, unhealthy new, healthy, filler]) revealed no significant main effect of tDCS ($B_{JZS} = 1.35$, $F(1,165) = 3.62$, $p = 0.06$, $\eta p^2 = 0.02$) and no significant interaction ($B_{JZS} = 0.1$, $F(3,495) = 1.51$, $p = 0.21$, $\eta p^2 < = 0.01$).

Dietary restraint

As previous research has shown that inhibition training may be most effective for individuals who score higher on measures of dietary restraint, we hypothesised in our pre-

registration that the effects of active tDCS and GNG training would be greatest or only present for those who met the cut-off score for restrained eating. However as only 15 of 172 participants met the criteria for dietary restraint we could not perform the analyses as defined in the pre-registered protocol. Instead we undertook a linear mixed effects analysis in R (R core team, 2016) using the lme4 package (Bates et al., 2015). P-values were calculated from degrees of freedom estimated using Satterthwaite’s method (Kuznetsova et al., 2016). This analysis revealed no significant main effect of tDCS ($F(1,168) = 1.27$, $p = 0.26$), restraint ($F(1,168) = 0.55$, $p = 0.46$) or time ($F(1,168) = 3.08$, $p = 0.08$), and no significant interactions between tDCS and restraint ($F(1,168) = 0.68$, $p = 0.41$), tDCS and time ($F(1,168) = 0.04$, $p = 0.84$), time and restraint ($F(1,168) = 0.01$, $p = 0.92$) or the three-way interaction between time, tDCS and restraint.

2.6 Discussion

The aim of this study was to investigate whether the application of tDCS to the DLPFC, alongside inhibition training, could reduce food consumption and food craving. Previous research has shown tDCS to be an effective way of reducing food cravings, although findings for food consumption are more uncertain (Georgii et al., 2017; Goldman et al., 2011; Kekic et al., 2014; Ray et al., 2017). Here we recruited a larger-than-typical sample size to ensure sufficient statistical power to detect moderate changes in eating behaviour, and we added a cognitive target (GNG training) in an attempt to boost the effectiveness of active stimulation (Alonso-Alonso & Pascual-Leone, 2007; Antal et al., 2007; Wiers et al., 2013; Woods et al., 2016). Our protocol was sham-controlled and double-blind to rule out potential experimenter effects and demand characteristics; our results suggest that blinding was successful. In addition, our protocol and analyses were pre-registered to ensure transparent research practices and minimise bias. Contrary to our hypotheses, we found no evidence for an effect of active tDCS on reduced food cravings or total food consumption.

Although these results are in contrast to previous research they are consistent with a recent study that failed to show an effect of tDCS on cravings and consumption in a sample of healthy individuals (Bravo et al., 2016; Georgii et al., 2017). Furthermore, a

recent meta-analysis concluded that single-session tDCS of the DLPFC was not effective at modulating food cravings and that effects on food consumption were unreliable (Lowe et al., 2017). The current literature on the effectiveness of tDCS as an intervention for eating-related behaviour therefore appears to be conflicting. One possible explanation for the difference across findings is the samples used. Previous studies showing positive results have typically recruited participants who self-identified as having strong and frequent food cravings (Goldman et al., 2011; Kekic et al., 2014; Ljubisavljevic et al., 2016) as well as cravings specific to the foods used in the experiments (Fregni et al., 2008; Lapenta et al., 2014). Although we selected commonly craved foods for the current study we did not make any attempt to pre-screen participants for trait food craving. Similarly, Georgii et al. (2017) recruited an unselected sample and found no difference between active and sham stimulation for either state food cravings or desire to eat the foods. Studies that have found positive effects of tDCS without selecting individuals based on trait craving have either included obese samples or have used repeated sessions of tDCS (Gluck et al., 2015; Jauch-Chara et al., 2014; Ray et al., 2017); with a sample of healthy men Jauch-Chara et al. (2014) only reported a significant reduction in food intake after eight daily stimulation sessions, with no effects after a single session. Furthermore, the results reported by Ray et al. (2017) were also dependent on gender, restrained eating and different facets of impulsivity; a reduction in craving was specific to women with low attentional impulsivity and a reduction in food consumption was only found for men who were either low in restrained eating or high in non-planning impulsivity. With a very small sample size (eight females, 10 males) and lack of explicit bias control (pre-registration) it is difficult to draw firm conclusions from this study alone, yet together the current literature indicates a need to consider the role of cognitive traits and individual differences in this line of research.

Studies have also reported specific effects of tDCS according to different macronutrients, which may explain why we did not see positive results for a general food craving measure such as the G-FCQ-S (Nijs et al., 2007). However, these results again appear variable across the literature. For example, Goldman et al. (2011) reported a reduction in craving for carbohydrates following active stimulation whereas two subsequent studies found no effects for carbohydrate craving (Burgess et al., 2016; Ljubisavljevic et al.,

2016). Likewise, Jauch-Chara et al. (2014) reported that the effect of repeated tDCS on total calorie consumption was mainly due to a reduction in carbohydrate intake, although, Gluck et al. (2015) reported no effect on carbohydrate intake following three sessions of anodal compared to cathodal stimulation. Contrasting results have also been reported for fat (Gluck et al., 2015; Goldman et al., 2011; Ljubisavljevic et al., 2016) and protein (Burgess et al., 2016; Gluck et al., 2015); however, the one food that does appear to be consistently associated with reduced craving and consumption is sweet foods (Burgess et al., 2016; Gluck et al., 2015; Goldman et al., 2011; Kekic et al., 2014; Ljubisavljevic et al., 2016).

Sweet foods, more specifically foods high in sugar, are often thought of as having addictive potential with reward often considered a key driver for consumption in the absence of hunger. Neurotransmitters have been shown to modulate food intake, particularly for specific macronutrients, for example consumption of sugar releases dopamine in the same way as consumption of addictive substances, and the behavioural effects of sugar consumption and substance use are similar (Avena et al., 2008; Benton, 2010). In addition to dopamine, research also indicates the importance of endogenous opioids in the preference of high-sugar foods (Olszewski & Levine, 2007). Cravings for sweet foods are also more common compared to those for savoury foods which may explain why effects of tDCS are more consistent for such foods (Hill, 2007). Exploratory analyses in the current study indicated that participants consumed significantly more calories from sweet foods, however, we found no interaction between food type and tDCS condition. As well as exploring differences across macronutrients, another approach is to consider personal preferences. By asking participants to rank their favourite of the foods presented, both Burgess et al. (2016) and Ray et al. (2017) were able to demonstrate that effects of active stimulation on food consumption were specific to preferred foods.

Taken together, this literature indicates that the utilisation of tDCS as a potential intervention for eating-related behaviour is preliminary. There remain questions with regards to who can benefit the most from such an intervention and under what circumstances. Lessons and future directions can be taken from similar interventions such as food-related cognitive control training, which has been shown to be most effective for those who are high in impulsivity and restrained eating (Jones et al., 2016; Lawrence et al., 2015a).

There is already some evidence in the tDCS literature to suggest that cognitive traits may play a significant role in determining the direction of effects (Kekic et al., 2014; Ray et al., 2017); however, replication with larger sample sizes is necessary to verify such claims. The investigation of individual differences may also help us to understand more about the underlying mechanisms, for example tDCS may be more effective for those who are impulsive due to hypoactivity in prefrontal areas related to inhibitory control. In the current study, we explored whether stimulation of the DLPFC during inhibition training would result in improved inhibitory performance (Ditye et al., 2012). Our results revealed no significant differences between active and sham stimulation during training but provided weak evidence that active stimulation may speed reaction times without increasing commission errors in a later task. Lapenta et al. (2014) also investigated whether the effect of DLPFC stimulation on reduced craving was due to modulation of inhibitory control. They found that tDCS resulted in a significant increase in the frontal P3a component suggesting enhanced inhibition of an overt response; however, they found no significant differences in behavioural performance between active and sham conditions, which could have been due to ceiling effects.

Another possibility is that stimulation of the DLPFC serves to reduce the hedonic value of food. Hare et al. (2009) showed that increased activity in the DLPFC was associated with successful self-control when making food choices and was also found to down-regulate the goal value of unhealthy palatable foods. It is possible therefore that tDCS effects could be stronger for those who demonstrate high reward sensitivity and who find food particularly rewarding. As discussed above, early evidence for this proposal comes from positive effects with samples of individuals who score highly on trait food craving (Fregni et al., 2008; Goldman et al., 2011; Lapenta et al., 2014). Moreover, inhibition training studies have proposed that devaluation of food stimuli may be a potential mediator for the effect of training on behaviour (Veling et al., 2013a). However it should be noted that recent research has shown that devaluation as a result of inhibitory control training to correlate with brain regions other than the DLPFC (Stice et al., 2017).

An exploratory analysis indicated that active prefrontal tDCS may cause increased consumption of healthy foods in comparison to sham tDCS, raising the question of whether this tDCS protocol could have the potential to enhance consumption when used alongside

go-training such as CAT. Whereas inhibitory control training is used with the aim of reducing food consumption, CAT aims to increase consumption for pre-determined foods. For example Kakoschke et al. (2014) used a visual dot probe task to investigate whether training attention towards foods could modify food consumption. They found that when participants were trained to attend toward healthy foods and away from unhealthy foods, they consumed significantly more healthy food in a subsequent taste test in comparison to a group that had trained to orient attention toward unhealthy foods and away from healthy foods. Combining tDCS with CAT may be a promising route to explore the increase the consumption of healthy, minimally processed foods, which could potentially reduce consumption of more heavily processed foods.

An additional avenue for future investigation is to consider improvements in brain stimulation techniques as well as comparison between different methodologies. TMS is another method that has been used to modulate food cravings and consumption (Lowe et al., 2014; Van den Eynde et al., 2010). In the same meta-analysis that indicated no effect of tDCS on food craving, Lowe et al. (2017) found a significant effect of TMS in the reduction of food cravings. In addition producing stronger stimulation of cortex (Wagner et al., 2007), TMS also has greater spatial focality than tDCS depending on the type of coil used (Wagner et al., 2009). Conventional tDCS involves the delivery of a current via 2 electrodes, typically quite large in size. Electrical field modelling of the current flow indicates that large areas of the cortex can be disrupted during stimulation leading to concerns regarding focality (Datta et al., 2008). These concerns have fuelled developments in tDCS techniques and the production of a more focal application. HD-tDCS involves the use of much smaller electrodes (typically 1cm) placed in a 4x1 montage, with one single electrode placed over the region of interest, and the remaining four arranged in a ring around the outside of the central electrode, resulting in a smaller area of stimulation (Datta et al., 2009). Few studies have yet compared the effects of the two techniques, but preliminary research has found the duration of effects to be improved with HD-tDCS (Kuo et al., 2013). If the negative findings we observed are due to lack of focality then HD-tDCS may provide a fruitful next step, as may the application of multiple sessions.

In summary, the current study failed to replicate the effects of tDCS on reduced food craving or food consumption within a larger-than-usual sample. While there may be

potential for tDCS as an intervention for unhealthy eating behaviour, our findings and those of Lowe et al. (2017) highlight the need for such studies to include larger sample sizes and explicit bias control (including study pre-registration), thus allowing for more robust and transparent insights (Russo et al., 2017). After a surge in papers reporting the effectiveness of tDCS in the last decade, the effects have also been questioned more recently with reference to individual differences (Horvath et al., 2014) and the efficacy of single-sessions (Horvath et al., 2015). Future research should be guided by these findings to focus on the importance of optimal study design as well as the potential role of individual differences.

Chapter 3

Effects of prefrontal HD-tDCS on cue-induced food craving

This chapter is published as a Registered Report in *Behavioral Neuroscience* (Sedgmond et al., 2020; <https://doi.org/10.1037/bne0000345>)

3.1 Introduction

Food cravings are an overwhelming desire to consume a specific food, experienced by 60–100% of the Western adult population (Pelchat, 1997; Taylor, 2019). Given the established link between cravings, increased food consumption and weight gain (Boswell & Kober, 2016; Gendall et al., 1997; Lafay et al., 2001), understanding the neurocognitive mechanisms underlying food craving presents an important goal for basic and translational cognitive neuroscience. The present study tests whether electric stimulation of prefrontal cortex can be effective in modulating food cravings.

Neuroimaging research has indicated that differences in both cortical structure and function may play a role in the regulation of food-related behaviours (Lowe et al., 2019). Functional differences in prefrontal brain regions such as the DLPFC have been linked to differences in dietary self-regulation (Gluck et al., 2017). For example, hypo-activity of the DLPFC in response to food images has been identified in obese participants (Brooks et al., 2013b), whereas hyper-activity of the DLPFC has been associated with successful self-control when making food choices (Hare et al., 2009). Structural differences have also been revealed; increased grey matter volume in the DLPFC has been linked to dietary

self-regulatory success (Schmidt et al., 2018), whereas reduced grey matter volume is associated with increased weight (Brooks et al., 2013a).

Non-invasive brain stimulation research has supported these findings, indicating that increasing activity within the DLPFC can lead to a decrease in both food craving and food consumption (Lowe et al., 2017). tDCS is a form of non-invasive brain stimulation that involves passing a weak electrical current through the cortex via scalp electrodes (Nitsche et al., 2003). tDCS has been utilised across multiple studies, modulating the DLPFC in order to investigate its efficacy for modifying food-related behaviours.

In the first study to investigate the effect of tDCS on food craving and consumption, (Fregni et al., 2008) found 20 minutes of stimulation using an anode right/ cathode left montage significantly reduced food craving and food consumption. Using the same montage and outcome measure, Goldman et al. (2011) and Lapenta et al. (2014) also found a significant reduction in food craving, although, Goldman et al. (2011) did not replicate the effects on food consumption. However, later studies employing very similar tDCS parameters have produced inconsistent findings (Lowe et al., 2017) reporting that effects may be specific to food type, gender and different facets of impulsivity (Kekic et al., 2014). Furthermore, non-significant effects have also been reported (Ray et al., 2019; Sedgmond et al., 2019).

In a recent study, Sedgmond et al. (2019) combined the same 20-minute tDCS protocol with a food specific GNG training task to investigate whether these two interventions could have a cumulative effect on reducing both food craving and consumption. Previous research has indicated that such training tasks can result in decreased consumption of unhealthy foods and weight loss (Adams et al., 2017; Houben & Jansen, 2011; Lawrence et al., 2015a; Lawrence et al., 2015b) and it has been suggested that effects of tDCS may be augmented when coupled with such training (Alonso-Alonso & Pascual-Leone, 2007). However, Sedgmond et al. found no reliable effect of tDCS on either food consumption or food craving measured using a standardised state craving questionnaire.

One possible explanation for these null results is the lack of focality when using conventional tDCS. In a recent meta-analysis looking at the effects of non-invasive brain stimulation on food craving and food consumption, Lowe et al. (2017) found no significant effect of tDCS on food craving, but did find a significant effect of TMS. TMS differs

to tDCS in that it has the ability to deliver far greater spatial focality (Wagner et al., 2009). To our knowledge, all tDCS studies within this field have used conventional tDCS with electrodes typically measuring 5x7cm. Electrical field modelling has indicated that large areas of the cortex are disrupted during conventional stimulation (Datta et al., 2008), leading to the development of more focal applications of tDCS, specifically high-definition tDCS (HD-tDCS) which involves the use of much smaller electrodes (typically 1cm). One electrode is placed over the region of interest, with the remaining four arranged in a ring around the outside of the central electrode. Comparisons of the two methods reveal that the smaller HD electrodes result in a more focal area of stimulation (Datta et al., 2009) [Figure 3.1].

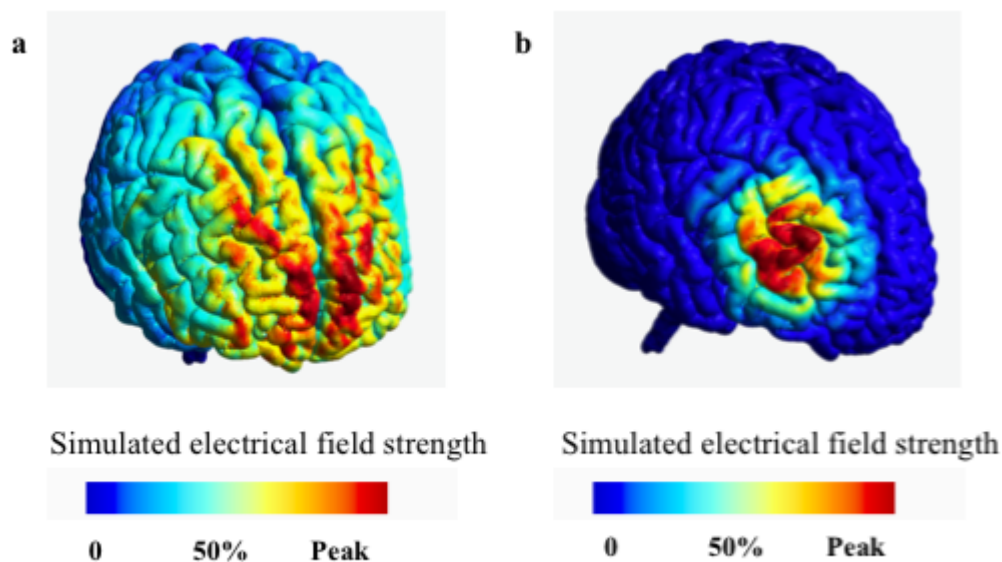


Figure 3.1: Visualization of the simulated electrical field strength using SimNIBS (Thielscher et al., 2015). a) A 1.5mA current was simulated using a conventional tDCS montage with 7 x 5 cm (35 cm²) electrodes. b) A 1.5mA current was simulated using a 4x1 HD-tDCS montage with 1 cm electrodes. These simulations confirm that HD-tDCS should result in a much more focal current.

The present study sought to further the findings of previous literature with improved tDCS methodologies to investigate effects on food craving. Using a within-subjects design, participants received active and sham HD-tDCS across two separate testing sessions. Based on previous findings all participants received anodal right-hemisphere stimulation due to the inconsistent results produced using anodal left-hemisphere stimulation (Carvalho et al., 2019; Fregni et al., 2008). The stimulation was paired with food-related GNG training and food craving was measured before and after stimulation. Most studies

that have reported a significant effect of tDCS on food craving have recruited participants identified as high food cravers (e.g. Fregni et al., 2008; Goldman et al., 2011; Lapenta et al., 2014; Ljubisavljevic et al., 2016), whereas those reporting non-significant effects did not include any measures of self-reported trait food craving (Ray et al., 2019; Sedgmond et al., 2019). Trait food craving is known to be positively associated with a loss of control around craved foods, often leading to excessive consumption (Taylor, 2019); furthermore, scores on measures of trait food craving have been positively related to BMI (Meule et al., 2012b) and symptoms of food addiction (Meule et al., 2012a). As such, trait craving was assessed before stimulation using a standardised questionnaire, and changes in *state* food craving were measured before and after stimulation using a desire to eat scale and a standardised questionnaire. Differences in inhibitory control between stimulation conditions were investigated with a speeded GNG task (see Sedgmond et al., 2019).

Broadly consistent with previous research (Goldman et al., 2011; Lapenta et al., 2014; Montenegro et al., 2012) we expected active prefrontal HD-tDCS to reduce desire to eat for foods associated with response inhibition (H1a) but not for foods associated with response execution (H1b). We also expected a decrease in overall state food craving for active, compared to sham stimulation (H2). Independently of HD-tDCS, we expected to observe effects of training: in particular, any reduction in craving (H3a) or liking (H3b) before vs. after training should be greater for foods associated with response inhibition than for foods associated with response execution. Further evidence of training effects were expected in the speeded task, where RTs to no-go foods should be greater than RTs to novel foods (H3c; see Best et al., 2016). Finally, if prefrontal stimulation boosts inhibitory control then we expected to see fewer commission errors in the speeded task following active HD-tDCS (H4).

3.1.1 Hypotheses

Primary hypotheses

H1a. Effect of HD-tDCS on desire to eat for inhibited foods: Participants will show a greater reduction in desire to eat no-go foods (unhealthy foods that are associated with the inhibition of a response during GNG training) from pre-post HD-tDCS following active stimulation compared to sham stimulation. Desire to Eat: $(NoGo_{POST} - NoGo_{PRE})_{Active}$

$< (\text{NoGo}_{POST} - \text{NoGo}_{PRE})_{Sham}$

H1b. Effect of HD-tDCS on desire to eat for non-inhibited foods: Participants will show no change in desire to eat go foods (healthy foods associated with a response during GNG training) from pre-post HD-tDCS following active stimulation compared to sham stimulation. Desire to Eat: $(\text{Go}_{POST} - \text{Go}_{PRE})_{Active} = (\text{Go}_{POST} - \text{Go}_{PRE})_{Sham}$

H2. Main effect of HD-tDCS on craving: Participants will show a greater decrease in state food craving from pre-post HD-tDCS following active stimulation compared to sham stimulation. State Food Craving: $(\text{POST} - \text{PRE})_{Active} < (\text{POST} - \text{PRE})_{Sham}$

H3a. Effect of training on desire to eat, independent of HD-tDCS: For sham stimulation, any reduction in desire to eat scores for no-go foods from pre-post stimulation should be greater than the corresponding difference in desire to eat scores for go foods. Desire to Eat: $(\text{NoGo}_{POST} - \text{NoGo}_{PRE})_{Sham} < (\text{Go}_{POST} - \text{Go}_{PRE})_{Sham}$

H3b. Effect of training on liking, independent of HD-tDCS: For sham stimulation, any reduction in liking for no-go foods from pre-post stimulation should be greater than the corresponding difference in liking for go foods. Liking: $(\text{NoGo}_{POST} - \text{NoGo}_{PRE})_{Sham} < (\text{Go}_{POST} - \text{Go}_{PRE})_{Sham}$

H3c. Training effects independent of HD-tDCS: RTs on correct trials for no-go foods should be greater than RTs for novel foods during the speeded GNG task. RT: $\text{NoGoRT} > \text{NovelRT}$

H4. Effect of HD-tDCS on commission errors after training: Participants receiving active HD-tDCS will make fewer commission errors during a subsequent speeded GNG task compared to those receiving sham HD-tDCS. % Errors: $\text{Active} < \text{Sham}$

3.2 Method

3.2.1 Participants

A total of 67 participants aged 18-45 were recruited from a university staff and student population as well as participant databases. We recruited male and female participants. To comply with our ethics for brain stimulation techniques participants were required to have no contraindications to tDCS safety. Participants were excluded if they were currently dieting (with the aim to lose weight), if they had any history of clinically diagnosed eating

disorders, if they were fasting or had any allergies to the foods used in the experiment, or if they had a clinical diagnosis of bipolar disorder. All participants were reimbursed for their time at a rate of £10 per hour. The study was approved by the Research Ethics Committee at the School of Psychology, Cardiff University. All participants provided informed consent and were debriefed at the end of the study.

3.2.2 Sampling plan

A Sequential Bayes Factor design with maximal n was utilised. We planned for data collection to continue until the desired level of evidence was obtained for all primary hypotheses or until the resource limit was reached (Schönbrodt & Wagenmakers, 2018); however, due to the COVID-19 pandemic and consequent university closure, we were required to terminate data collection before either condition was met. Analyses began when a minimum of 40 datasets had been collected (n_{min}) and analyses were then conducted for every ≈ 10 participants from that point. We planned for data collection to continue until BF_{10} was ≥ 6 or $\leq 1/6$ for all primary hypotheses, or a maximum of 100 participants (n_{max}) was reached, whichever happened first. $BF_{10} \geq 6$ would indicate moderate evidence for H1, while $BF_{10} \leq 1/6$ would indicate moderate evidence for H0 (Lee & Wagenmakers, 2013).

A Bayes Factor design analysis was conducted to plan for the probability of obtaining the target level of evidence while also controlling for the probability of generating misleading evidence (Schönbrodt & Wagenmakers, 2018). For H1 an informative prior was used based on all available data from studies investigating the effects of conventional tDCS on food craving (specifically desire/urge to eat; Goldman et al., 2011; Lapenta et al., 2014; Montenegro et al., 2012). The raw mean effect and standard error of each study was entered into a meta-analysis to produce a posterior mean of 0.6367, which was then used as the prior (Dienes, 2014) [Figure 3.2]. For H2, H3 and H4, previous data was not available, therefore a default scale parameter of $\sqrt[3]{2}$ for the half-Cauchy distribution was used (Rouder et al., 2009) [Figure 3.3].

3.2.3 Procedure

Prior to the study, participants were electronically screened for eligibility criteria and were asked to complete the Food Craving Questionnaire - Trait Reduced (FCQ-T-r; Meule et

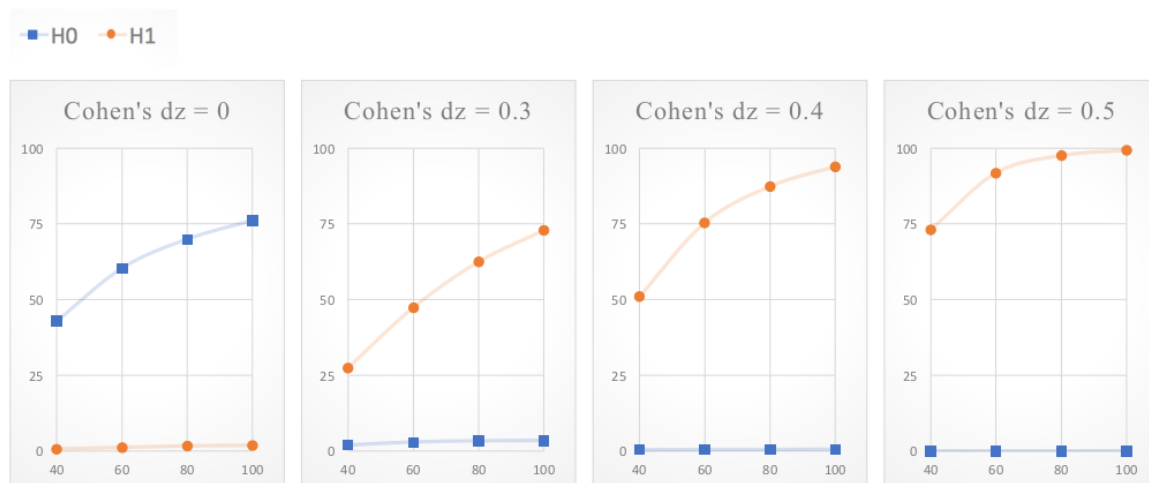


Figure 3.2: The results of a Bayes factor design analysis (BFDA) for H0 and H1 in a simulated sequential design for the proposed Bayesian paired-sample t-tests for H1a and H1b (informed prior). 10,000 studies were simulated for sample sizes of 40 (n_{min}), 60, 80 and 100 (n_{max}), at hypothetical effect sizes of 0, 0.3, 0.4 and 0.5 to highlight the percentage of studies terminating at the correct H0 or H1 when the boundary is $BF_{10} \leq 1/6$ and ≥ 6 . For H0, 76.2% of studies terminated at the correct boundary at n_{max} and 1.9% at H1. For an effect size of 0.3 for H1 at n_{max} , 72.9% of studies terminated at the correct threshold and 3.5% terminated at the H0 boundary. For an effect size of 0.4, 94% of studies terminated the H1 boundary and 0.6% at the H0 boundary. And for an effect size of 0.5, 99.4% of studies terminated at H1 and 0% at H0.

al., 2014) and the Barratt Impulsiveness Scale (BIS; Patton, 1995). These instruments were included for the purposes of exploratory analyses. Participants were informed that they were taking part in a study investigating the effects of personality type on food preferences and were instructed to eat three hours before the study and then refrain from eating. During the first session, participants were required to initially pass safety screening for HD-tDCS and provide their consent. Participants were then additionally required to pass pre-session screening before both sessions (e.g. to exclude recent use of caffeine and/or alcohol). At the beginning of each session participants completed scales measuring their hunger (three VASs rating on a 100mm scale a. how hungry they feel, b. how full they feel and c. their current desire to eat) and mood (PANAS; Watson et al., 1988); including measures of discomfort/pain and nausea to rule out differences in food craving due to these potential influences of HD-tDCS). Participants then completed the G-FCQ-S (Nijs et al., 2007) before completing a further twelve VASs to measure food-specific desire to eat and liking. After this, participants received HD-tDCS in isolation for 5 minutes before beginning the GNG training task for a further 15 minutes. Following HD-tDCS

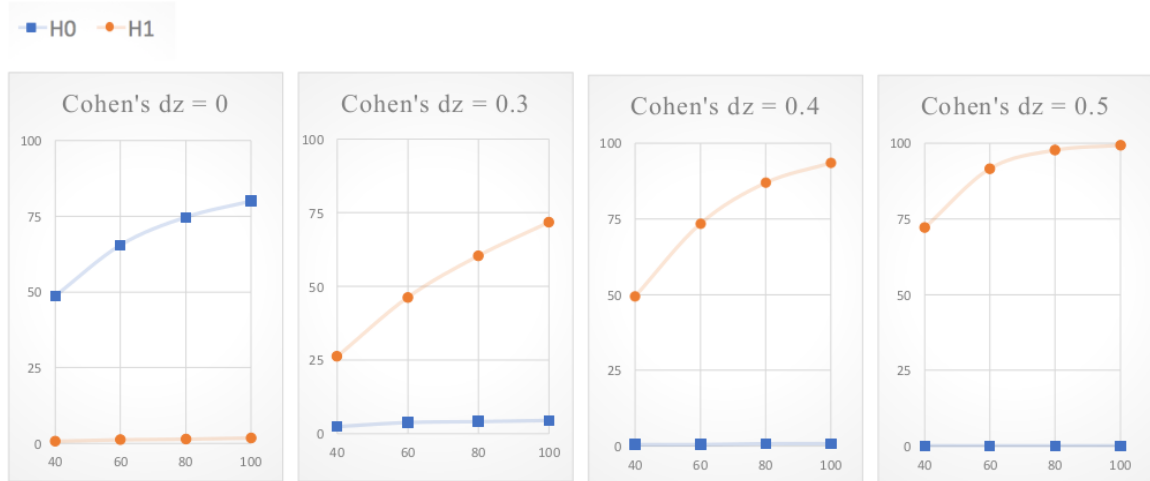


Figure 3.3: The results of a BFDA for H0 and H1 in a simulated sequential design for the proposed Bayesian paired-sample t-tests for H2, H3 and H4 (default prior). 10,000 studies were simulated for sample sizes of 40 (n_{min}), 60, 80 and 100 (n_{max}), at effect sizes of 0, 0.3, 0.4 and 0.5 to highlight the percentage of studies terminating at the correct H0 or H1 when the boundary is $BF_{10} \leq 1/6$ and ≥ 6 . For H0 80% of studies terminated at the correct boundary at n_{max} and 1.8% at H1. For an effect size of 0.3 for H1 at n_{max} 71.8% of studies terminated at the correct threshold and 4.5% terminated at the H0 boundary. For an effect size of 0.4, 93.5% of studies terminated the H1 boundary and 0.8% at the H0 boundary. And for an effect size of 0.5, 99.3% of studies terminated at H1 and 0.1% at H0.

and training, participants completed all scales again before completing the speeded GNG task [Figure 3.4].

The above procedure was repeated for the second session with the exception that participants did not need to complete HD-tDCS safety screening. The second session was at least seven days after the initial session and efforts were made to ensure that testing took place at the same time for both sessions. At the end of the second session participants were probed for their awareness of the HD-tDCS condition (participants were asked whether they believed they received active or sham HD-tDCS in each session) and the experimenter also recorded participants' height and weight to calculate BMI and probed for awareness of the study's aims. During the debrief participants were asked directly if they were aware of the aim of the study. If they answered 'no' they were reminded of the cover story (that we were interested in the effects of personality types on food preferences). In addition, they were probed for awareness of the stimulus mappings; specifically, they were asked whether they noticed anything in particular in the computer task. If they answered 'no' they were asked whether they thought the signals were distributed evenly, randomly or

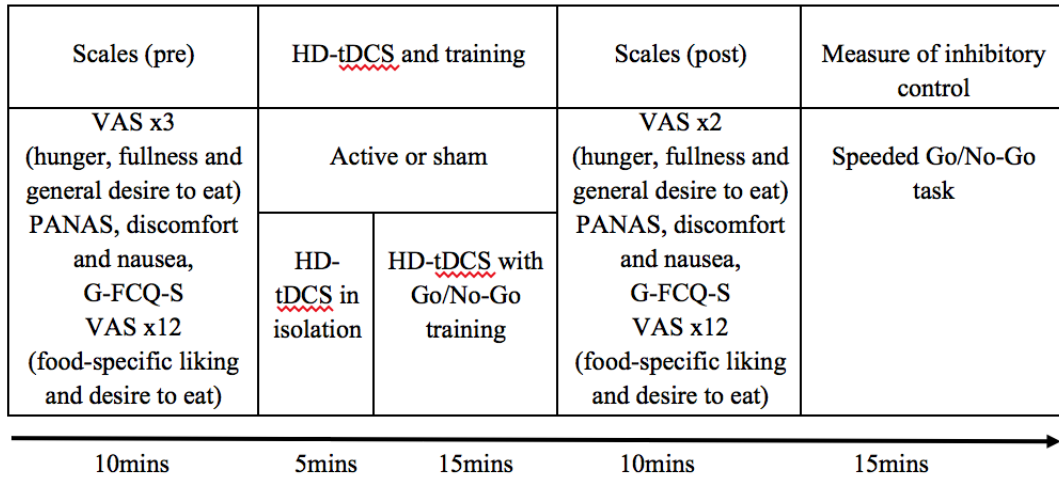


Figure 3.4: Schematic diagram of the procedure. Participants undertook two sessions in a within-subjects design. Participants initially completed measures of hunger, mood and craving before receiving either active or sham stimulation, receiving the opposite stimulation condition in their second session. To allow for participants to adjust to the stimulation, participants initially received 5 minutes of stimulation in isolation before beginning the GNG task. The task and the stimulation then continued for a further 15 minutes. Following the task and stimulation, participants repeated the measures of hunger, mood and craving before completing a speeded version of the GNG task.

whether they thought they were grouped. Finally, participants were asked to confirm that they were not currently dieting, and that they had no history of eating disorders.

Twenty-four hours after the completion of each session, participants were emailed a post-monitoring form consisting of 15 questions aimed to monitor whether participants experienced any adverse effects following stimulation. Effects include dizziness, headaches, and skin irritation.

3.2.4 HD-tDCS

Participants received both active and sham stimulation across two separate sessions (order counterbalanced). Four circular electrodes, 1cm in diameter were positioned in the 4x1 HD-tDCS montage with the centre electrode (anode) placed over the right DLPFC (F4), positioned according to the international 10-20 EEG system. The four return electrodes (cathodes) were placed at AF4, F2, F6 and FC4. For active stimulation a 1.5mA¹

¹We originally proposed to use a 2mA current with a 10-second ramp-up time, but pilot testing revealed this to be intolerable with participants reporting pain underneath the site of the anode. We considered increasing the ramp-up time to 30 seconds (while maintaining current at 2mA), but as the pain was still being reported midway through the stimulation, we decided instead to apply a lower and more commonly used current of 1.5mA. Participants still reported some discomfort

current was applied using a battery-driven constant-current stimulator (NeuroConn DC-STIMULATOR PLUS with the DC-S Equaliser Kit, neuroConn GmbH, Illmenau, Germany) for 20 minutes (with a 30 second ramp up and down). For sham stimulation the stimulator delivered a 1.5mA current for 30 seconds following a 30 second ramp up, before being slowly ramped down to 0mA over a 1-minute period. The experimenter was provided with a study code for each participant that generated either active or sham stimulation, ensuring that the experimenter was blinded to the condition.

3.2.5 Training tasks

GNG task

All tasks were programmed in Matlab (Mathworks, Natick, MA) using Psychophysics Toolbox (www.psychtoolbox.org) and all stimuli were presented on a 24-inch widescreen LED monitor. The training task was largely identical to that used in Sedgmond et al. (2019) but with some of the stimuli changed to improve the design. Specifically, filler images were changed from clothes to household items to avoid associations between clothes and dieting. Some food images were also replaced to make food categories clearer e.g. various fruit images were replaced with three images of grapes to enhance category-level learning. The training task lasted approximately 15 minutes and consisted of eight blocks of 36 trials with a 15 second break between each block. The blocks randomly presented nine images of unhealthy foods (three images each of chocolate, crisps and biscuits), nine images of healthy foods (three images each of grapes, rice cakes and carrots) and 18 filler images (three each of books, pens, buckets, baskets, chairs and candles). All images were close-up views of the food item against a white background; images were carefully selected on the basis that there were no additional ingredients or packaging, and they were matched for size and complexity.

Each trial began with the presentation of a central rectangle (ITI; 1250ms). A stimulus was then presented within this rectangle randomly, and with equal probability, to either

during pilot sessions when stimulating at 1.5mA using a 10 second ramp-up, but stimulation was tolerable with 1.5 mA and a 30-second ramp-up. We therefore modified the protocol in line with these parameters prior to data collection. Previous research has found no significant difference between intensities of 1.5mA and 2mA (Shekhawat & Vanneste, 2018) and there is a substantial body of evidence suggesting that stimulation of the DLPFC at 1.5mA can influence behaviour (Guo et al., 2018; He et al., 2016; Ke et al., 2019; Naka et al., 2018).

the left- or right-hand side (1250ms). Participants were required to respond to the location of the stimulus as quickly and accurately as possible using their left and right index fingers (using the ‘C’ and ‘M’ keys, respectively). A signal (the fixation rectangle turns bold for the duration of the trial) was presented on 50% of trials indicating that the participant must withhold their response for that trial. All of the unhealthy food images were presented with a signal (100% mapping), while none of the healthy foods were presented with a signal (0% mapping) and half of the filler images were presented with a signal (50% mapping). Instructions were presented electronically before the task and read verbatim by the experimenter.

Speeded GNG task

To investigate whether HD-tDCS has any effect on inhibitory control we included a second GNG task. The commission error rate (the percentage of erroneous responses made on no-go trials) on the training task is typically very low ($\approx 5\%$) making it difficult to detect any potential improvements in inhibitory control. This second, speeded GNG task, was very similar to the training task but with a faster presentation time (500ms ITI and stimulus presentation time compared to 1250ms) and a lower percentage of no-go trials (33.3% compared to 50%). It has been shown that these changes encourage rapid responding and, as a result of the speed-accuracy trade-off, also increase the rate of commission errors (Collins & Mullan, 2011; Sedgmond et al., 2019). The speeded GNG task consisted of 15 blocks of 45 trials (a total of 675 trials, lasting 15 minutes with a 15 second break between each block). Each block randomly presented nine healthy foods, nine unhealthy foods and 18 filler images (identical to those in the training task) as well as nine novel unhealthy foods (three images each of chips, pastries and doughnuts). Three images for each food category and 6 filler images were presented alongside a no-go signal (33.3% mapping). This task also allowed us to compare inhibitory control towards images previously associated with inhibition and novel images. The instructions for this task were presented electronically at the beginning. Participants were informed that this was the same task that they previously performed and were warned about the faster presentation time.

3.2.6 Outcome measures

Food liking and desire to eat

Participants completed twelve 100mm VASs to measure liking and desire to eat for task-specific foods (from ‘not at all’ to ‘very much’). As in Rogers and Hardman (2015), participants were asked to taste one piece of each of the six foods used in the GNG task and rate their desire to eat the remaining portion (see Appendix B for foods and quantities). Foods were presented in a pseudorandom order.

G-FCQ-S

The G-FCQ-S includes 15 statements to measure food craving in the current moment, for example “I’m craving tasty food” (Nijs et al., 2007). There are five subscales: desire to eat, anticipation of positive reinforcement from eating, anticipation of relief from negative feelings from eating, lack of control over eating and craving as a physiological state. Participants were asked to indicate how much they agreed with each statement ‘at this very moment’ using a five-point scale (from 1 ‘strongly disagree’ to 5 ‘strongly agree’). Scores can be calculated for specific subscales or a total score can be calculated (ranging from 15 to 75). As the G-FCQ-S measures food craving as a transient state, retest reliability is low (Taylor, 2019) and construct validity is high with scores correlating with when food was last consumed (Meule et al., 2012a).

FCQ-T-r

The FCQ-T-r measures trait food craving generally (Meule et al., 2014) across 15 statements, for example “I find myself preoccupied with food”. There are five subscales: intentions and plans to consume food, lack of control over eating, thoughts or preoccupation with food, emotions before or during food craving and environmental cues that may trigger craving. Participants respond on a six-point scale (from 1 ‘never or not applicable’ to 6 ‘always’) indicating how frequently each of the statements would be true for them in general. Scores can be calculated for specific subscales or a total score can be calculated (ranging from 15 to 90). The FCQ-T-r has been shown to have high retest reliability and high construct validity, confirming that it does assess craving as a trait (Meule, Teran, et al.,

2014). Scores on the FCQ-T-r have also been correlated with external eating, emotional eating and body weight (Hormes & Meule, 2016; Innamorati et al., 2015).

3.3 Exclusion criteria

Participants were excluded from the analyses if any of the following criteria were met:

- Failure to comply with the study's eligibility requirements including:
 - Not having a current/ history of eating disorders
 - Not being on a calorie-controlled diet

- Inability to perform the training task correctly based on the following:
 - >15% error rate for no-signal trials, including incorrect responses (judging the stimulus to be on the incorrect side of the screen) and missed responses, within either session (sham or active HD-tDCS)
 - RTs for no-signal trials exceed 3 SDs from the group mean within either session (sham or active HD-tDCS)
 - Commission error rate for either session (active or sham HD-tDCS) is > 3 SDs from the group mean within the relevant HD-tDCS condition

- Any reason to discontinue with HD-tDCS based on adverse reaction during the session

- The participant exercised their right to withdraw from the study or their right to withdraw data

- The participant correctly guessed the aim of the study during debrief, when probed for knowledge of the study's aims.

- Any unforeseen errors resulting in the loss of any data or inability to complete the entire session

3.4 Results

All primary analyses were conducted with the primary investigator still blinded to the HD-tDCS conditions.

3.4.1 Data exclusions

Based on the preregistered exclusion criteria 12 participants were excluded from data analyses. Of those excluded, 4 participants failed to perform the training task correctly, including 2 for a commission error rate exceeding 3 SDs from the group mean for signal trials, 1 for their RTs for no-signal trials exceeding 3 SDs from the group mean, and 1 for a 54% error rate for no-signal trials in their second session. The remaining 8 participants were excluded due to the inability to complete their second session due to the COVID-19 lockdown. As noted, due to the COVID-19 pandemic, data collection was terminated prior to the original stopping rule.

3.4.2 Baseline measures

Following exclusions, the final sample consisted of 55 participants (76.36% female, mean age = 22.25, $SE = 0.76$, mean BMI = 23.34, $SE = 0.43$). State variables were analysed to test for any statistically significant differences between active and sham conditions at baseline. We found no statistically significant differences in hunger, fullness, desire to eat, state craving, positive affect, negative affect, nausea or discomfort/pain at baseline (all $B_{JZS} < 0.68$, all $t_s < 1.82$, all $p_s > 0.07$) [Table 3.1].

3.4.3 Primary analyses

All primary analyses have been summarised in Table 3.2.

Effect of HD-tDCS on desire to eat for inhibited and non-inhibited foods (H1a and H1b)

A paired samples t-test was conducted to assess whether participants showed a greater reduction in desire to eat no-go foods after receiving active stimulation in comparison to sham stimulation. Despite active stimulation resulting in a numerical decrease in desire to

Gender (% female)	76.36%					
Age	22.25 (0.76)					
BMI	23.34 (0.43)					
	Active	Sham	B_{JZS}	t	p	dz
Hunger	5.27 (0.27)	5.76 (0.24)	0.68	1.81	0.08	0.24
Fullness	2.87 (0.29)	2.74 (0.25)	0.17	0.6	0.55	0.08
Desire to eat	5.65 (0.33)	6.09 (0.28)	0.33	1.31	0.2	0.18
State craving	47.66 (1.13)	48.16 (1.15)	0.16	0.46	0.65	0.06
Positive affect	28.13 (0.8)	27.36 (0.96)	0.24	1.01	0.32	0.14
Negative affect	12 (0.36)	11.86 (0.32)	0.16	0.36	0.72	0.05
Nausea	1.09 (0.06)	1.04 (0.03)	0.22	0.9	0.37	0.12
Discomfort/pain	1.24 (0.06)	1.13 (0.05)	0.63	1.77	0.08	0.24

Table 3.1: Group characteristics and within-subject significant tests (SE within parentheses).

eat ($M = -0.12$, $SE = 0.6$) compared to sham stimulation ($M = 0.81$, $SE = 0.48$), there was no statistically significant difference, with a BF indicating anecdotal evidence for H0 (**H1a**: $B_{JZS} = 0.53$, $t(54) = 1.22$, $p = 0.11$, $dz = 0.17$). We also found no evidence for a change in desire to eat go foods following active ($M = 0.51$, $SE = 0.46$) compared to sham stimulation ($M = 0.71$, $SE = 0.44$), with analyses suggesting moderate evidence for H0 (**H1b**: $B_{JZS} = 0.16$, $t(54) = 0.4$, $p = 0.69$, $dz = 0.06$) [Figure 3.5].

Main effect of HD-tDCS on craving (H2)

A paired samples t-test comparing the difference in state craving score from pre to post stimulation indicated no significant difference between active ($M = 0.46$, $SE = 0.92$) and sham stimulation ($M = -0.07$, $SE = 0.97$; **H2**: $B_{JZS} = 0.11$, $t(54) = 0.43$, $p = 0.66$, $dz = 0.06$), indicating moderate evidence for H0 [Figure 3.6].

Training effects independent of HD-tDCS (H3a, H3b, H3c)

Differences in changes in desire to eat and liking in the sham sessions were analysed to assess the effects of the training task, independently of HD-tDCS. No significant differences were found in desire to eat no-go food from pre-post sham stimulation ($M = 0.81$, $SE = 0.48$) in comparison to go foods ($M = 0.71$, $SE = 0.44$; **H3a**: $B_{JZS} = 0.13$, $t(54) = 0.18$, $p = 0.57$, $dz = 0.02$). Similarly, no significant difference was found in liking of no-go foods from pre to post sham stimulation ($M = 0.35$, $SE = 0.35$) in comparison to go foods ($M = 0.64$, $SE = 0.39$; **H3b**: $B_{JZS} = 0.34$, $t(54) = 0.87$, $p = 0.2$, $dz = 0.12$). These outcomes

Hypothesis		B_{10}	t	p	dz	Evidence interpretation
H1a	Desire to eat: NoGo($POST-PRE$) <i>Active</i> < NoGo($POST-PRE$) <i>Sham</i>	0.53	1.24	0.11	0.17	Anecdotal evidence for H0
H1b	Desire to eat: Go($POST-PRE$) <i>Active</i> = Go($POST-PRE$) <i>Sham</i>	0.16	0.4	0.69	0.06	Moderate evidence for H0
H2	Craving: ($POST-PRE$) <i>Active</i> < ($POST-PRE$) <i>Sham</i>	0.11	0.43	0.66	0.06	Moderate evidence for H0
H3a	Desire to eat: NoGo($POST-PRE$) <i>Sham</i> < Go($POST-PRE$) <i>Sham</i>	0.13	0.18	0.57	0.02	Moderate evidence for H0
H3b	Liking: NoGo($POST-PRE$) <i>Sham</i> < Go($POST-PRE$) <i>Sham</i>	0.34	0.87	0.2	0.12	Moderate evidence for H0
H3c	RT: NoGo > Novel	0.04	2.99	0.99	0.4	Strong evidence for H0
H4	%Errors: Active < Sham	0.07	1.15	0.87	0.16	Strong evidence for H0

Table 3.2: Outcomes of the primary hypothesis tests. In all cases, the evidence favoured the null hypothesis (H0) over the corresponding alternative hypothesis.

provide anecdotal-to-moderate evidence that the training task had no reliable effect on changes in desire to eat or liking.

For H3c, a paired samples t-test found no significant difference in RT on correct trials for no-go foods ($M = 348.9$, $SE = 3.78$) in comparison to novel foods ($M = 352$, $SE = 3.67$) when performance from both active and sham trials was collapsed (**H3c**; $B_{JZS} = 0.04$, $t(54) = 2.99$, $p = 0.99$, $dz = 0.4$). This outcome provides strong evidence that participants did not learn the association between the no-go foods and stopping a response; thus the preregistered manipulation check did not succeed.

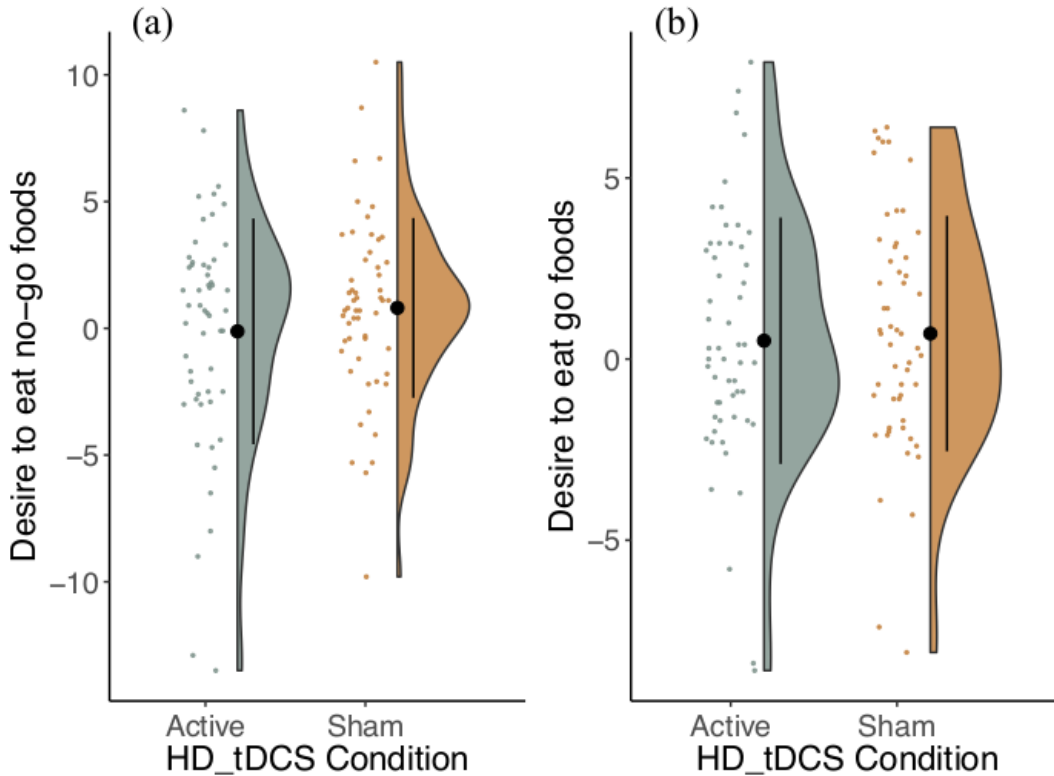


Figure 3.5: Change in desire to eat no-go foods (a) and go foods (b) from pre-to post stimulation as a function of HD-tDCS condition. A positive score indicates increased desire to eat and a negative score indicates decreased desire to eat. No significant difference was found between HD-tDCS conditions.

Effect of HD-tDCS on commission errors after training (H4)

The final confirmatory analysis investigated the number of commission errors made during the speeded GNG task following active vs. sham stimulation. No statistically significant difference was observed (Sham: $M = 8.11$, $SE = 0.47$ vs Active: $M = 8.53$, $SE = 0.55$; **H4**: $B_{JZS} = 0.07$, $t(54) = 1.15$, $p = 0.87$, $dz = 0.16$), providing strong evidence that active HD-tDCS did not reliably decrease commission errors.

3.4.4 Exploratory analyses

HD-tDCS tolerability and blinding

Tolerability of HD-tDCS was measured following stimulation. There was no significant difference in reported nausea following active ($M = 1.24$, $SE = 0.07$) compared to sham stimulation ($M = 1.18$, $SE = 0.06$; $B_{JZS} = 0.19$, $t(54) = 0.72$, $p = 0.47$, $dz = 0.11$), but there was weak evidence for a difference in discomfort/pain, with participants reporting

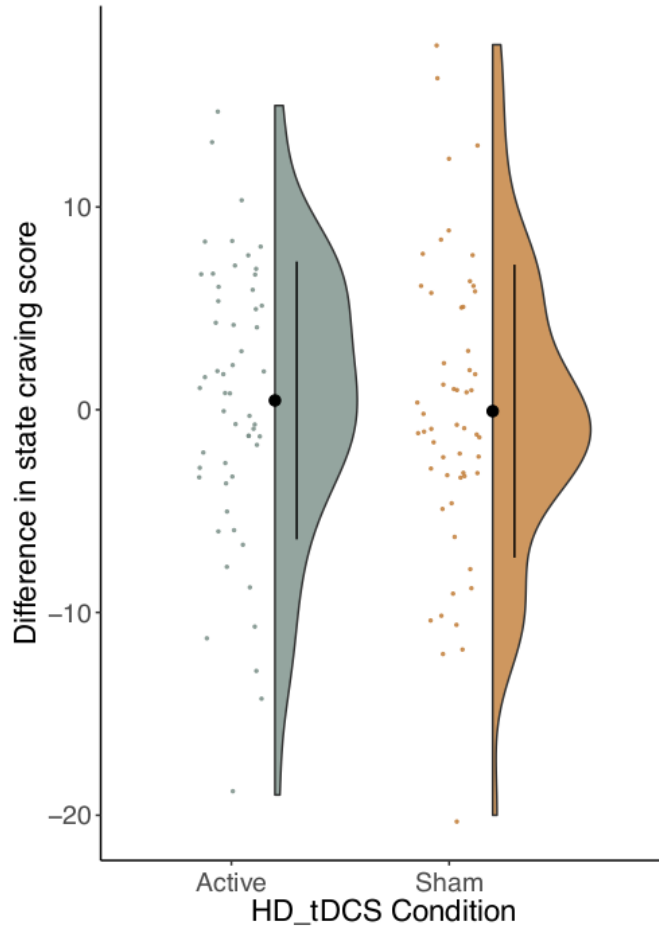


Figure 3.6: Change in state craving score from pre- to post stimulation as a function of HD-tDCS condition. A positive score indicates increased craving and a negative score indicates decreased craving. No significant difference was found between stimulation groups.

a higher discomfort/pain level after active stimulation ($M = 1.29$, $SE = 0.08$) than after sham ($M = 1.13$, $SE = 0.05$; $B_{JZS} = 0.96$, $t(54) = 2.02$, $p = 0.05$, $dz = 0.27$).

To investigate participants' awareness of HD-tDCS condition after each session, they were asked whether they thought they had been receiving active or sham stimulation. Following active stimulation 65.45% of participants correctly guessed in comparison to 47.27% correctly guessing after sham. Inferential analyses revealed no evidence that participants were systematically aware of which type of stimulation they had been receiving ($B_{JZS} = 0.570$, $\chi^2(1) = 1.843$, $p = 0.18$, $\phi = 0.13$).

We then investigated whether participants were more likely to correctly identify which type of stimulation they had received in the second session but not in the first. This appeared to be the case, with participants significantly more likely to identify the stimulation condition in the second ($B_{JZS} = 3$, $\chi^2(1) = 4.56$, $p = 0.03$, $\phi = 0.29$) session compared

to the first ($B_{JZS} = 0.33$, $\chi^2(1) = 0.09$, $p = 0.76$, $\phi = 0.04$)

Desire to eat

In addition to measuring participants' desire to eat each food item, participants also completed a general measure of desire to eat using a VAS before and after stimulation. The VAS has been a primary outcome measure in several studies reporting an effect of conventional tDCS on reducing food craving (Fregni et al., 2008; Goldman et al., 2011; Lapenta et al., 2014; Montenegro et al., 2012), so we conducted a paired samples t-test to explore whether there was any difference in desire to eat based on stimulation type. We found no significant difference in overall desire to eat after active stimulation ($M = 0.04$, $SE = 0.31$) compared to sham stimulation ($M = -0.12$, $SE = 0.31$; $B_{JZS} = 0.16$, $t(54) = 0.41$, $p = 0.68$, $dz = 0.06$).

Sweet vs savoury foods

Based on findings from previous research that has indicated that food type may play a role on the effect of tDCS (e.g. Goldman et al., 2011; Kekic et al., 2014), we split the foods by sweet and savoury (3 sweet, 3 savoury). We found no effect of HD-tDCS on desire to eat sweet ($B_{JZS} = 0.17$, $t(54) = 0.54$, $p = 0.59$, $dz = 0.07$) or savoury foods ($B_{JZS} = 0.34$, $t(54) = 1.34$, $p = 0.19$, $dz = 0.18$).

Exploratory training effects

It is notable that our manipulation check for the training task (H3c) failed. To test for additional evidence of learned associations between no-go stimuli and stopping, we therefore examined the rate (%) of successful response inhibition in the speeded task, collapsed across sham and active sessions. We found that participants were significantly more successful at response inhibition for overall unhealthy food stimuli ($M = 88.12\%$, $SE = 0.53$) in comparison to novel stimuli ($M = 85.76\%$, $SE = 0.51$; $B_{JZS} = 105,642.56$, $t(54) = 6.06$, $p < 0.001$, $dz = 0.82$) and healthy food stimuli ($M = 86.08\%$, $SE = 0.62$; $B_{JZS} = 457.27$, $t(54) = 4.43$, $p < 0.001$, $dz = 0.6$). These results provide post hoc evidence that participants learned an association between the no-go stimuli and stopping. Taken together with the lack of support for H3c, it is possible that response inhibition provides a

more sensitive measure of the effect of trained associations than RT for previously inhibited foods.

To further demonstrate evidence of learning we looked at performance in the training task itself as is typically done in inhibition training studies (Camp & Lawrence, 2019; Lawrence et al., 2015a; Stice et al., 2017). We first collapsed the data across sham and active sessions and found that, consistent with learning, RTs for healthy foods ($M = 468.4$, $SE = 7.92$) were significantly faster than RTs for filler stimuli ($M = 489.2$, $SE = 8.93$) on go trials ($B_{JZS} = 6.715e+10$, $t(54) = 9.86$, $p < 0.001$, $dz = 1.33$). We also found moderate evidence for an effect of learning when analysing performance on no-go trials. Participants exhibited a higher percentage of successful stopping to unhealthy foods ($M = 97.36$, $SE = 0.23$) in comparison to filler stimuli ($M = 96.57$, $SE = 0.36$) on no-go trials ($B_{JZS} = 3.58$, $t(54) = 2.67$, $p = 0.01$, $dz = 0.36$).

To investigate whether this evidence of learning in the training task was determined by stimulation type, we analysed performance during active and sham sessions separately. During both active and sham stimulation, RTs for healthy foods were significantly faster than for filler stimuli (active: $B_{JZS} = 1.082e+7$, $t(54) = 7.37$, $p < 0.001$, $dz = 0.99$; sham: $B_{JZS} = 1.281e+9$, $t(54) = 8.72$, $p < 0.001$, $dz = 1.18$). However when looking at successful response inhibition it seems the significant effect was being driven by performance during sham stimulation ($B_{JZS} = 18.04$, $t(54) = 3.32$, $p = 0.002$, $dz = 0.45$); during active stimulation there was no significant difference in successful response inhibition for unhealthy foods compared to filler stimuli ($B_{JZS} = 0.15$, $t(54) = 0.21$, $p = 0.84$, $dz = 0.03$).

Moderators

Much of the research showing effects of tDCS on food craving has focused on high food cravers (Fregni et al., 2008; Goldman et al., 2011; Lapenta et al., 2014; Ljubicavljovic et al., 2016). We therefore analysed trait craving score as a moderator for the effect of HD-tDCS on state craving score. We used a linear mixed effects analysis in R (R core team, 2016) using the lme4 package (Bates et al., 2015; within-subjects factor: HD-tDCS condition [active or sham]; within-subjects factor: time [pre- or post- stimulation]; continuous factor: trait craving). p-values were calculated from degrees of freedom estimated

using Satterthwaite’s method (Kuznetsova et al., 2016). This analysis revealed no significant main effects of HD-tDCS, trait craving or time (all F s < 3.56 , all p s > 0.06) and no significant interactions between HD-tDCS and trait craving, HD-tDCS and time, time and trait craving, or the three-way interaction between time, HD-tDCS and trait craving (all F s < 3.53 , all p s > 0.06).

Similarly, previous research has indicated that different facets of impulsivity may influence the efficacy of tDCS. Ray et al. (2017) found no main effect of conventional tDCS on food craving in female participants until the BIS attentional subscale was taken into account. A second linear mixed effects analysis was therefore conducted to explore the effects of HD-tDCS on food craving in female participants with the attentional subscale as a moderator. However, this revealed no statistically significant main effects or interactions when only female participants’ data was included (all F s < 1.14 , all p s > 0.28) or when male and female participants were included (all F s < 3.77 , all p s > 0.05).

Finally, given evidence for an effect of conventional tDCS on craving in both overweight and obese participants (Gluck et al., 2015; Montenegro et al., 2012), we studied BMI as a moderator. Average BMI was 23.3 (SE = 0.43); 67.3% of participants were in the healthy weight range, 27.3% were overweight, 3.6% were obese and 1.8% were underweight. A linear mixed effects analysis found no significant main effects or interactions (all F s < 1.52 , all p s > 0.1).

3.5 Discussion

Previous studies have provided mixed evidence that brain stimulation – specifically tDCS – may be an effective technique to reduce food craving (Fregni et al., 2008; Goldman et al., 2011; Lowe et al., 2017; Sedgmond et al., 2019). Here we sought to improve upon our previous methods (Sedgmond et al., 2019) by increasing the focality of prefrontal stimulation with HD-tDCS and investigating individual differences thought to play a role in the efficacy of tDCS. Using a double-blind within-subjects design, HD-tDCS was administered alongside inhibition training to assess the combined effect on cue-induced food craving. Overall, results revealed no evidence that prefrontal HD-tDCS influences state food craving or desire to eat, nor did we find any moderating effects of trait craving, BMI,

or impulsivity.

Despite our lack of evidence supporting earlier studies displaying an effect of tDCS on craving (e.g. Fregni et al., 2008; Goldman et al., 2011; Lapenta et al., 2014), our findings are consistent with more recent evidence. Combining tDCS with a cognitive bias modification task, Carvalho et al. (2019) found stimulation was not able to reduce craving for chocolate. Similarly, in a previous study we combined conventional tDCS with a food-specific GNG training task and found no significant effect of tDCS on reducing craving (Sedgmond et al., 2019). Furthermore, a meta-analysis investigating the findings from published and unpublished data using brain stimulation to modulate food craving and consumption concluded that the effect on food cravings was not significant for tDCS (Lowe et al., 2017). The same meta-analysis did, however, find a significant stimulation effect when TMS was used. A later review also concluded that TMS seems to show more promise than tDCS (Hall et al., 2017). For example, a single session of repetitive TMS (rTMS) to the DLPFC was found to reduce cue-induced food craving in a clinical group (Van den Eynde et al., 2010), and in another study rTMS was found to maintain craving level after exposure to food whereas sham stimulation resulted in an increase (Uher et al., 2005). One explanation as to why TMS may produce more robust findings is due to its ability to stimulate an area of the brain with greater spatial focality. However, we addressed this issue in the present study by using HD-tDCS which is far more focal than conventional tDCS [Figure 3.1]. The mechanisms behind tDCS and TMS also differ; while tDCS is thought to manipulate the membrane potential of neurons, TMS can modulate cortical plasticity and trigger action potentials (Paulus, 2011), which could explain why TMS seems to produce stronger results. However, not all research has been able to replicate these findings. Using a clinical sample in a multi-session study, no significant effects of TMS were found when compared to sham stimulation (Gay et al., 2016). Although the effects of TMS seem promising (Lowe et al., 2017), the need for more studies with larger sample sizes, and sufficient power are necessary to better understand these potential effects; the number of studies that have used TMS to investigate its effect within this field is still very small.

While multi-session protocols have produced conflicting results in the TMS literature (e.g. Gay et al., 2016), research has indicated that they may be beneficial in tDCS re-

search. In one study investigating the effect of tDCS on food consumption, there was no effect immediately after stimulation, but there was a significant reduction following eight daily sessions when compared to sham stimulation (Jauch-Chara et al., 2014). This evidence is further supported by a recent meta-analysis that compared the effects of single session tDCS and TMS to multiple sessions, looking at craving and consumption for different substances. Effects did not differ between stimulation type or the substance being investigated, and it was revealed that multi-session protocols were more effective for reducing both craving and consumption, in comparison to single sessions (Song et al., 2019). To our knowledge, only one study thus far has investigated the effects of multiple tDCS sessions on food consumption (Jauch-Chara et al., 2014), and none have looked at food craving. A worthwhile area of investigation could be multiple-session protocols of HD-tDCS.

Much of the research that has demonstrated a reduction in food craving following tDCS has done so in food cravers; either those who self-reported experiencing strong and frequent cravings (Fregni et al., 2008; Goldman et al., 2011; Lapenta et al., 2014), or those identified using a validated measure (Ljubisavljevic et al., 2016). Although we did not specifically recruit food cravers, all participants completed the FCQ-T-r, a questionnaire designed to measure trait craving. In exploratory analyses we included global scores from the FCQ-T-r as a continuous variable to explore whether trait craving acted as a moderator for the effect of HD-tDCS on food craving. Despite sufficient variability in scores across participants (range = 43, min = 16, max = 64), we found no significant effects. Furthermore, a cut off score of 50 has previously been proposed to classify individuals as high food cravers (Meule, 2018).). In our sample, almost a quarter of participants met this criterion (23.6%; 13 of 55). Although we found no evidence to suggest a moderating role of trait craving, in future, researchers may consider recruitment of high trait cravers only.

Previous studies have found that the effects of tDCS on food craving may be dependent on different types of food. While Goldman et al. (2011) and Ljubisavljevic et al. (2016) both found a significant effect of tDCS on craving, they also found that active stimulation decreased craving for sweet foods more substantially than other foods (although Goldman et al., 2011 did also find a significant reduction for savoury foods too). Furthermore, Kekic et al. (2014) found no main effect of tDCS on food craving, however, when foods were

split between sweet and savoury, a significant reduction in craving for sweet foods was revealed. Sweet foods are known to produce both stronger and more frequent cravings than savoury foods (Hill, 2007), likely due to the addictive potential of sugar (Avena et al., 2008). Based on this evidence we analysed desire to eat sweet and savoury foods from pre- to post stimulation separately but found no significant difference between active and sham stimulation. This analysis could be insensitive due to participants' personal preferences for the foods used in the study; not accounting for personal preferences could have reduced the potential for observed effects of prefrontal stimulation. For example, Ray et al. (2017) gave participants a food craving task in which they ranked foods based on liking and wanting and the lowest ranked foods were removed to avoid floor effects. Similarly, Burgess et al. (2016) also removed foods that participants did not score highly for liking, stating that craving is unlikely to vary for foods that are not liked. Both studies demonstrated the effects of active stimulation on preferred foods though this was for a decrease in food consumption rather than craving.

Food cravings have been linked to calorie intake (Lafay et al., 2001), BMI (Franken & Muris, 2005), the ability to lose weight (Batra et al., 2013) and binge eating (Ng & Davis, 2013). It seems imperative, therefore, that we have a better understanding of the mechanisms involved in food craving and interventions to help reduce them. While there is some evidence that brain stimulation may help to alleviate food cravings, the conflicting evidence suggests that the potential for tDCS, *specifically*, is still preliminary and that other interventions – such as behavioural training – may be worth investigating. In both this study and in Sedgmond et al. (2019) we combined brain stimulation with cognitive control training – specifically GNG training – on the assumption that the training could augment the effects of stimulation. Go training – on the assumption that the training could augment the effects of stimulation. Similarly, Carvalho et al. (2019) combined tDCS with an approach/avoid task to investigate whether the combination could reduce craving for chocolate, although they also found no significant effect of stimulation. Despite the lack of evidence for an effect of tDCS, in both studies we found evidence that participants learned the association between stopping responses and specific foods. Although this learning did not translate into a reduction in craving, there remains an abundance of evidence suggesting that cognitive training interventions, such as GNG training, have the

potential to not only reduce craving but to also lead to other health-related behaviour changes (see Jones et al., 2018 for a review).

While there are many types of behavioural training tasks being used to retrain attention, and modify automatic associations, the most robust evidence seems to come from studies using response inhibition tasks like the GNG training that we implemented. For example, several studies have found that pairing foods with response inhibition has led to a reduction in both craving and consumption of those foods (Camp & Lawrence, 2019; Chen et al., 2019; Houben & Jansen, 2015). Furthermore, this type of training has also been linked to long term effects of continued reduced consumption as well as weight loss (Lawrence et al., 2015a). It is thought that the continual inhibition of a motor response towards specific stimuli leads to a reduction in how much value the individual attributes to the items (Camp & Lawrence, 2019; Chen et al., 2016). As the overvaluation of appetitive foods can lead to excessive consumption (Stice et al., 2008), devaluing these items via response inhibition tasks offers a promising and well supported avenue for further research, especially with regards to the potential long term effects.

In conclusion, the current study failed to replicate previous observations that prefrontal tDCS reduces food cravings, despite using similar tDCS parameters, outcome measures, and improving tDCS methods by being the first such study to assess the effect of HD-tDCS. While tDCS may have the potential to be a useful tool in modifying food related behaviours, the evidence is still conflicting. We had thought that the increased focality of HD-tDCS would increase the likelihood of observing an effect, however, there is a need for more studies comparing these effects to those of conventional stimulation to better understand how important focality is. Alongside this, findings from multi-session protocols indicate that this could be the next step in understanding the benefits of stimulation. There is also still a great deal to be understood regarding how individual differences may affect findings, with factors such as food preferences, trait craving and body weight to be taken into consideration. However, based on findings from using cognitive interventions alone, a worthwhile avenue might be to explore how to make these as impactful as we can. While tDCS is a relatively inexpensive form of stimulation when compared to TMS, cognitive interventions are not only cheaper still, but also more pragmatic. They can be run online and conducted outside of a lab environment, making both long term testing

and measurement of effects much easier.

Chapter 4

Combining cognitive control training tasks to modify explicit and implicit food evaluations

4.1 Introduction

Food choices are often automatic and impulsive (Hofmann et al., 2009b) and people are consistently surrounded by an abundance of food cues that can make it difficult to override automatic urges (Friese et al., 2011). Since evaluations of these cues influence behaviour (Krajbich et al., 2010), for many people this obesogenic environment not only triggers excessive urges towards food cues, but also increased consumption (Boyland et al., 2016). Changes to the environment are likely to be slow, prompting the need for an alternative to facilitate more deliberative food choice.

A growing body of research has tested the efficacy of computerised training interventions in changing automatic associations with food cues to reduce liking and craving, and to promote healthier choices. Various tasks have focussed on training attention towards and away from specific foods (Kakoschke et al., 2014; Kemps et al., 2014), pairing foods with signals to either make or withhold a motor response (Adams et al., 2017; Chen et al., 2019; Lawrence et al., 2015b), and pairing foods with pleasant or aversive stimuli (Hensels & Baines, 2016; Hollands et al., 2011; Lascelles et al., 2003), but all with the same goal of triggering behaviour change. One of the most popular interventions in eating behaviour research is response inhibition training, which aims to override or interrupt a pre-potent

motor response (Jones et al., 2018). For example, in a typical GNG training task, a participant may be instructed to make a key press when a stimulus appears on the screen; however, they are instructed to withhold that key press on the presentation of a signal, which is typically a visual or auditory cue that is selectively (or predominantly) paired with unhealthy foods. Over time, participants learn to associate the cues with response inhibition which in turn leads to an increase in the rate of successful stopping (Lawrence et al., 2015b; Sedgmond et al., 2019). But in addition to this basic learning, this type of training may also reduce food craving (Houben & Jansen, 2015), food consumption (Lawrence et al., 2015b), and even body weight (Lawrence et al., 2015a).

Although the primary focus of response inhibition training has been the stimuli paired with the no-go cue, research has also identified training effects from go trials in which a response is made. For example, following GNG training, participants not only exhibit a higher percentage of successful stopping to unhealthy foods when compared to filler images in no-go trials, but RTs to healthy foods are also faster when compared to filler images in go trials (Sedgmond et al., 2019). Findings like these have led to the design of GNG paradigms that simultaneously alter behaviour towards both unhealthy and healthy foods. For example, Porter et al. (2018) used GNG training to encourage healthier snack choices in children by pairing unhealthy foods with no-go signals and healthy foods with go signals. This not only resulted in faster responses towards healthy foods, but also led to an increase in healthy food selection during a food choice task. Similarly, Chen et al. (2019) paired healthy and unhealthy foods with go and no-go cues to investigate whether training could be used to encourage healthy food choices. Not only did training promote healthy food choices, but preferences for these foods also increased when the choice was between a healthy food paired with a go signal and an unhealthy food paired with a no-go signal.

These findings have prompted the development of other behavioural paradigms focussing specifically on cueing responses towards rather than away from stimuli. In a similar way to response inhibition training, CAT pairs specific groups of stimuli with signals or cues. However, it exploits the opposite association; rather than pairing a stimulus with a cue for action cancellation, a stimulus is paired with a cue to respond. While in a GNG task participants are instructed to respond unless cued to withhold that response,

in CAT the instructions are reversed, and participants are instructed to only make a response when cued to do so. CAT experiments follow a similar design to GNG training, with a food image presented on a subset of trials alongside a cue signalling that a motor response is necessary (Schonberg et al., 2014; Veling et al., 2017a; Zoltak et al., 2017). For example, using only palatable, energy dense food items, Schonberg et al. (2014) found a consistent effect of CAT for foods that participants had rated as high value in a subsequent food choice task. When participants had to choose between two food items of equal value, they were more likely to select the food that had been paired with the cue. These findings were also replicated by later studies (e.g. Veling et al., 2017) before the investigation turned to whether these effects were still present between foods not of equal value. Using high energy snack foods, Zoltak et al. (2017) found an increase in choice for cued low value foods when paired with non-cued high value foods. While these findings are important, the understanding of how this training might be able to modify the choice of healthy foods is also crucial, and research has now suggested that CAT can also lead to increased selection of fruits and vegetables that have been paired with cues when paired alongside a non-cued food of equal value (Veling et al., 2017).

Although effects of GNG and CAT training have often been measured directly via behaviour (for example food consumption or food choice; Chen et al., 2019; Zoltak et al., 2017), there is also evidence that explicit evaluations of these foods are affected. For example, in addition to finding an effect of no-go cues on food choice, Veling et al. (2013a) also found that this effect was mediated by a reduction in the valuation of the foods. This devaluation effect has also been found in further studies (Chen et al., 2016; Veling et al., 2008), and it has been suggested that the no-go signals used in training may be perceived in a similar way to the aversive stimuli used in EC (Chen et al., 2016).

EC is also thought to change evaluations of foods in a similar way by pairing the foods with stimuli that are considered aversive or pleasant with the goal of transferring the valence of one stimulus to the other (De Houwer et al., 2001). This approach has been used to study the effects of pairing energy-dense foods with aversive images in an attempt to not only devalue the unhealthy foods, but to encourage the selection of healthier food choices. For example, participants who saw neutral foods paired with pictures of obese bodies showed a decrease in explicit liking of the foods from pre-to post training, whereas

no change was found for the foods that had been paired with pictures showing healthy weight bodies (Dwyer et al., 2007). Similar results were also found after unhealthy foods were paired with images of potential health consequences such as obesity and arterial disease (Hollands et al., 2011). A significant effect was reported on implicit attitudes and food choices; attitudes towards the unhealthy foods were more negative and participants were more likely to select a healthier food option than one of the unhealthy foods.

EC has also been used to increase the evaluations of healthy foods. For example, when participants saw images of fruit paired with either positive, negative or neutral words, those who had seen the positive pairings were significantly more likely to choose fruit in a food choice task than those in the other conditions (Walsh & Kiviniemi, 2014). A later study investigated the effect of EC on explicit and implicit behaviours, as measured by eating behaviour and food evaluations, respectively, and reported that participants who had been seen healthy foods paired with happy faces, and unhealthy foods with angry faces, had a stronger preference for healthy foods using an implicit attitudes test, although no effects were found on food choice (Hensels & Baines, 2016).

While these training tasks may have the potential to modify behaviours and attitudes towards foods, so far, they have primarily been applied as isolated interventions. Recent research has suggested that supplementing one form of cognitive control training with another may increase effect sizes and lead to more consistent results (Allom et al., 2015). Similarly, in their review, Kakoschke et al. (2017a) also suggested that future research could benefit from a combined method, more specifically training participants to avoid unhealthy substances and approach healthy substances. Of those studies that have tried this, the results have been inconclusive. While one study found the combination of inhibitory control training and implementation intention training to result in increased weight loss in comparison to just one of the interventions (Veling et al., 2014), a second study found the same combination of training tasks no more effective than just the one (van Koningsbruggen et al., 2014). Furthermore, the combination of inhibitory control training and avoidance training was found to be effective at reducing implicit liking and food choice, but had no effect on food consumption (Kakoschke et al., 2017b).

In this current study, we investigated whether a novel training task that incorporates both response inhibition and EC could influence both implicit and explicit food liking.

The majority of research using cognitive training to influence food-related behaviours has predominantly focussed on unhealthy foods (Veling et al., 2017a); we aimed to explore the effects on both unhealthy and healthy foods. Here, participants completed a GNG task in an online setting. During the go trials participants were cued via a green fixation cross to make a response towards a healthy food stimulus which was then replaced by a positively-valenced stimulus to incorporate EC. In the no-go trials, a red fixation cross cued participants to withhold their responses to unhealthy food stimuli. This was then replaced by a negatively valenced stimulus. Using a within-subjects design, changes in explicit liking for trained foods from pre-to post training were compared to untrained foods, and differences in implicit liking were also compared for trained and untrained foods. An APP in which positive or negative words (targets) were preceded by the trained and untrained foods was used to measure indirect attitudes towards the foods. Implicit liking was determined based on the RT to classify the targets as either positive or negative. To our knowledge, no studies have yet combined GNG and EC, although the use of happy and sad emoticons were used as go and no-go cues to integrate an EC element in a study by Porter et al. (2018). As previous research has indicated that high value foods are preferable for the effects of GNG training (Veling et al., 2008) and EC tends to be particularly effective for neutral stimuli (Hofmann et al., 2010), two sets of stimuli were created to explore the potential importance of stimulus selection in exploratory analyses. All hypotheses, methods and confirmatory analyses were pre-planned prior to collection and analysis (<https://osf.io/ejtd6/>) and all deviations from the preregistered plan are explicitly noted in the sections that follow.

4.1.1 Hypotheses

Primary hypotheses

H1. Effects of training on explicit liking

H1a. Participants will show a greater increase in liking of trained healthy foods from pre-post (thd) compared to untrained healthy foods (uhd). Explicit liking: $thd > uhd$

H1b. Participants will show a greater decrease in liking of trained unhealthy foods from pre-post (tud) compared to untrained unhealthy foods (uud). Explicit liking: $tud < uud$

H2. Effects of training on implicit liking.

H2a. RTs will be faster in positive target trials for trained healthy foods (thp) compared to untrained healthy foods (uhp). RT: thp < uhp

H2b. RTs will be slower in negative target trials for trained healthy foods (thn) compared to untrained healthy foods (uhn). RT: thn > uhn

H2c. RTs will be faster in negative target trials for trained unhealthy foods (tun) compared to untrained unhealthy foods (uun). RT: tun < uun

H2d. RTs will be slower in positive target trials for trained unhealthy foods (tup) compared to untrained unhealthy foods (uup). RT: tup > uup

H3. Training effects

H3a. RTs for healthy foods will be faster than RTs for filler stimuli on go trials. RT: Healthy < Filler

H3b. Participants will have a greater percentage of successful stopping to unhealthy foods in comparison to filler stimuli on no-go trials. % Errors: Unhealthy > Filler

4.2 Method

4.2.1 Participants

A total of 824 participants were recruited via Prolific (www.prolific.co) and reimbursed with monetary compensation at a rate of £6.21 per hour. The study was completed online using Psychopy Builder (Peirce et al., 2019) and Qualtrics (Qualtrics, Provo, UT). Participants were aged 18 years or over, fluent English speakers, and had normal or corrected-to-normal colour vision. Participants were excluded if they reported a history of eating disorders. The study was approved by the Research Ethics Committee at the School of Psychology, Cardiff University. All participants provided informed consent and were debriefed at the end of the study.

4.2.2 Sampling plan

A sample size determination (SSD) was used to estimate the required sample size for a fixed-N design. A series of SSDs were undertaken based on different effect sizes with the

default scale parameter of $\sqrt[3]{2}$ for the half-Cauchy distribution used for all determinations (Rouder et al., 2009). An upper boundary of 6, and a power of .80 were held constant in all determinations. Though SSDs were determined for primary hypotheses, as exploratory analyses involved splitting the data, we ensured that there would be sufficient power for these analyses too. A final sample size of 800 (following exclusions) allowed sufficient power for exploratory analyses [Figure 4.1].

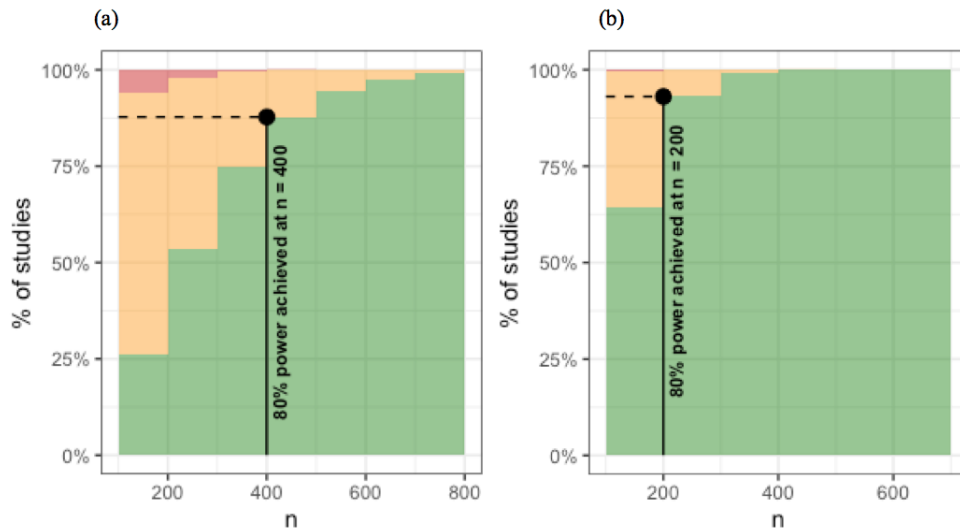


Figure 4.1: The results of a sample size determination for a fixed-N design based on 10,000 stimulations for Bayesian paired-sample t-tests for H1, H2 and H3 (default prior). The simulations determined what proportion of resulting Bayes factors would be equal to or larger than an upper boundary of 6. For a population effect size of 0.2 (a), 87.8% power was achieved with a sample size of 400. With a population effect size of 0.3 (b), 93% power was achieved with a sample size of 200.

4.2.3 Procedure

Participants were initially directed to a Qualtrics survey and presented with an on-screen consent form and a demographics questionnaire which included a measure of hunger, before being re-directed to PsychoPy for the main experiment. Due to the measure of hunger and exploratory analyses based on the potential effect of hunger, experimental slots were posted at different times (9am, 12pm, 3pm and 6pm GMT). Participants then completed a measure of baseline explicit liking. The task was self-paced but participants were encouraged to respond without too much deliberation. Participants then began the training task which consisted of 6 blocks of 36 trials. A 15 second break was programmed between each block of the experiment with instructions for participants to continue when

they were ready. A reminder of the task instructions was also provided during this period. Following completion of the training task, participants completed measures of implicit and post-training explicit liking (counterbalanced across participants). Participants were finally redirected to a second Qualtrics survey where they recorded their height and weight, were questioned on their awareness of the study, and also recorded whether they were currently dieting [Figure 4.2].

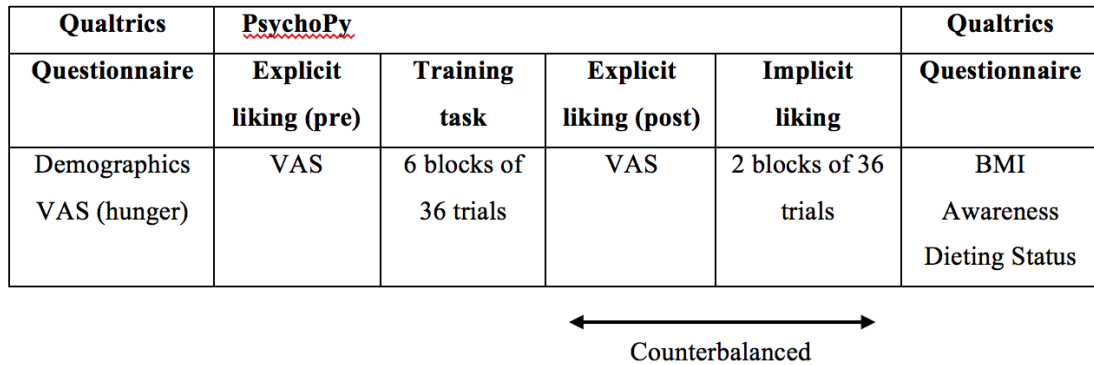


Figure 4.2: An overview of the experimental procedure. Participants initially completed a demographics questionnaire and a measure of hunger. To allow for a comparison between pre-and post-explicit liking, participants rated their liking of 12 foods before and after the training task. During the training task, these foods had an additional 2 exemplars. Following the task participants also completed a measure of implicit liking. Explicit liking and implicit liking following training were counterbalanced across participants. Finally, participants completed a second questionnaire.

4.2.4 Stimuli

Food stimuli

A total of 54 food stimuli were used for the experiment; 18 individual food items (6 healthy, 12 unhealthy), each of which had 3 exemplars. All images were presented against a white background and were selected to represent a standard serving size where possible. Healthy foods were defined as having no more than 100kcal per 100g and were selected to ensure that half were fruits and half were vegetables/ salad items. The unhealthy foods contained at least 300kcal per 100g and both sweet and savoury items were included.

Participants were randomly allocated one set of food stimuli. In group 1, all unhealthy foods were selected be high-value, palatable items and in group 2, unhealthy foods were selected to be neutral based on explicit liking ratings collected from pilot data (see Appendix

C for pilot data). All participants saw the same set of healthy foods in the experiment which were selected based on neutral ratings from the same set of pilot data.¹

Filler stimuli

Eighteen neutral stimuli were also selected to be included in the task as filler images and included pictures such as stationery and household items.

EC stimuli

A total of 18 EC stimuli were used for the experiment; 3 pleasant and 3 unpleasant stimuli, each of which had 3 exemplars. Pilot data was used to ensure that the images used in the EC component were suitable. Participants rated how pleasant they found a series of images on a 200-point VAS from very unpleasant to very pleasant. The images that repeatedly scored at the extreme ends of the scale were selected for use in this experiment (see Appendix C for all stimuli).

4.2.5 Training task

The training task was based on a GNG task. Participants received instructions at the beginning of the task which informed them that their responses would be dependent upon the colour of a fixation cross; if the fixation cross was green, they would make a response, but if the fixation cross was red they would not respond. During go trials, participants were presented with a green fixation cross for 1000ms, after which time a healthy food stimulus or filler stimulus would appear on the left or right hand side of the screen. Participants were instructed to respond to the location of the stimuli as quickly and as accurately as possible ('C' for left or 'M' for right on a standard keyboard). The stimuli appeared for 1000ms before being replaced by one of the pleasant EC stimuli which remained on the screen for 250ms. Stimulus presentation was identical in no-go trials; participants were initially presented with a red fixation cross for 1000ms followed by an unhealthy food stimulus or a filler stimulus. Participants were instructed to withhold their responses on these trials and not respond to the location of the stimulus. Finally, the stimulus was

¹Our original protocol stated that food stimuli would be personalised based on individual preferences. However, due to programming constraints, we were unable to individualise stimuli.

replaced by an unpleasant EC stimulus² [Figure 4.3]. In both groups, there were 6 primary foods; 3 healthy, 3 unhealthy, each with 3 exemplars. There were 6 blocks of 36 trials; all 18 food exemplars were presented once in each block, and the neutral filler stimuli were used in the remaining 18 trials. Stimulus presentation was randomised for each block to ensure the same foods were not paired with the EC stimuli.

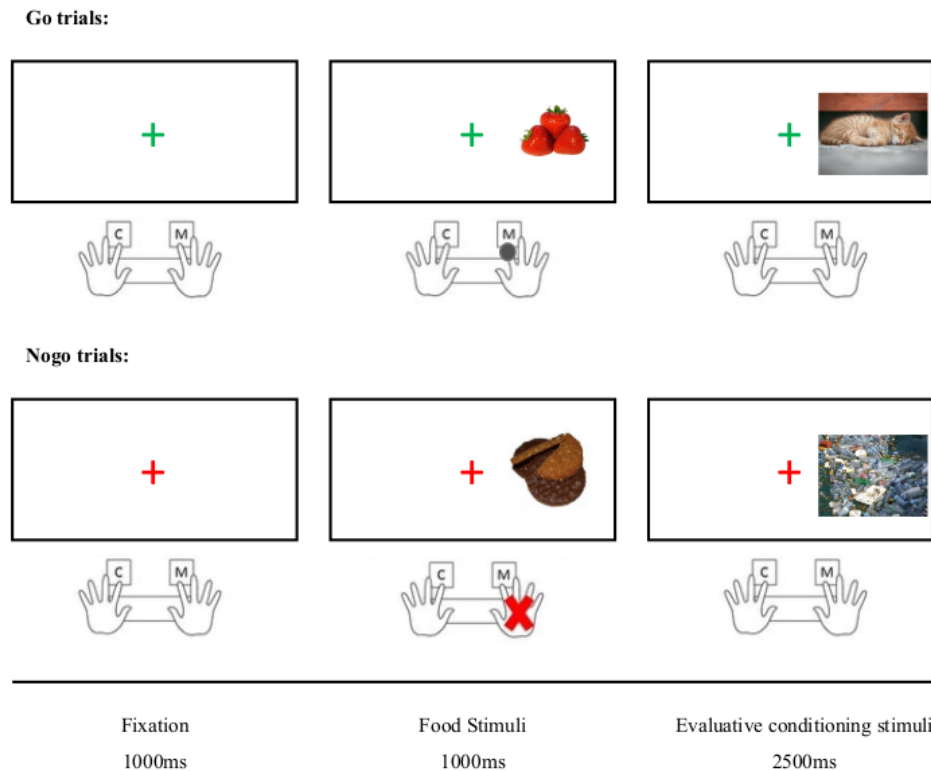


Figure 4.3: Schematic of the training task. During all trials a fixation cross appeared for 1000ms to indicate the trial type. During the go trials, a green fixation cross preceded a healthy food or filler stimulus which appeared on the left- or right-hand side of the screen. The participant responded to the location of the stimuli. In the no-go trials, a red fixation cross indicated to participants that they were to withhold a motor response when a stimulus appeared (either an unhealthy food or a filler stimulus). Each stimulus was then replaced by an EC stimulus. There was an ITI of 1000ms.

4.2.6 Outcome measures

Explicit liking

Participants completed a measure of explicit liking before and after the training task. Participants were presented with the 6 foods used in the training task and for each food

²Our protocol stated that we would also combine elements of approach/avoid training, however, due to programming constraints we were unable to use this feature.

were asked to indicate how much they liked the taste of the item; “Imagine this food is in your mouth. How much do you like the taste of this food?”, ranging from ‘not at all’ (0) to ‘very much’ (100). Participants were instructed to respond quickly and instinctively. Each image appeared independently in the centre of the screen with a 100-point VAS underneath.

Implicit liking

Implicit liking was measured using the APP (Fazio et al., 1986) across 2 blocks of 36 trials. The primes were the 6 foods and their corresponding exemplars (18 total repeated twice in each block) and the targets were 36 words (18 positive and 18 negative). Each trial began with a black fixation cross in the centre of the screen. The fixation cross was then replaced by the prime which appeared on the screen for 250ms before being replaced by a target (a positive or negative word) which appeared for 1500ms. Participants were instructed to quickly and accurately identify whether the target was positive or negative by pressing ‘c’ or ‘m’ (key presses were counterbalanced across participants). Participants were not able to proceed to the next trial until they had made a response to ensure participants were engaging with the task. Each food stimulus was paired with both a positive and negative word (randomised) [Figure 4.4].



Figure 4.4: Schematic of the APP. Participants had to categorise target words as positive or negative as quickly as possible following the presentation of a prime.

4.3 Exclusion criteria

Participants were excluded from the analyses and replaced if any of the following criteria were met:

- Failure to comply with the study’s eligibility requirements including:
 - Not having a current/ history of eating disorders
- The participant exercised their right to withdraw from the study or their right to withdraw data
- Any unforeseen errors resulting in the loss of any data or inability to complete the entire session

APP data were checked for RTs, responses, and missing data. Incorrect trials and trials with RTs of <350ms or >1000ms were removed before the final analyses. Data were removed from analyses if more than 20% of trials were missing or had been removed based on RT and response made. Explicit liking responses were also checked to ensure that no more than 20% of responses had been missed.

4.4 Results

4.4.1 Data exclusions

Based on the pre-planned exclusion criteria, 24 participants were excluded from the data analyses. 17 participants were excluded based on missed responses for explicit liking as it became apparent that a small subset of participants was unable to see the VAS based on a combination of the device and web browser being used for the experiment. The remaining 7 participants were removed based on the exclusion criteria set out for the affective priming data. All data and statistical analyses are available online (<https://osf.io/qa6hp/>).

4.4.2 Baseline measures

Following exclusions, the final sample consisted of 800 participants. Descriptive statistics of demographic information were recorded for the majority of participants; all participants recorded their gender but 1 participant did not provide their age, and 3 participants did not provide their ethnicity. The sample was predominantly male (61.83%) and white (83.69%). Mean age was 29.75 ($SE = 0.39$) and the average BMI across participants was 24.58 ($SE = 0.23$).

4.4.3 Awareness

At the end of the study participants were asked whether they had noticed anything specific and were given the opportunity to provide further information. From the 772 participants that provided responses, 43.52% of participants said yes. Of these, 91.96% of participants elaborated further and 46.73% (20.34% of total responses) recorded responses that suggested an awareness of the study aim or design. Awareness was classified as a response based on noticing a pattern between the food stimuli/fixation cross colour and the EC stimuli (specifically that healthy foods were paired with pleasant images and unhealthy foods paired with unpleasant images), or that they thought we were trying to change their liking of foods.

4.4.4 Primary analyses

All primary analyses have been summarised in Table 4.1.

Effects of training on explicit liking (H1)

A paired samples t-test was conducted to investigate the effect of training on explicit liking of healthy foods. There was an overall increase in liking for all healthy foods regardless of training status from pre-to post (trained: $M = 1.24$, $SE = 0.32$; untrained: $M = 0.93$, $SE = 0.3$), but there was no significant difference between the increase in liking of healthy trained foods compared to healthy untrained foods (**H1a**: $B_{JZS} = 0.09$, $t(799) = 0.85$, $p = 0.2$, $dz = 0.03$). For explicit liking of unhealthy foods, there was an overall decrease in liking for all foods (trained: $M = -1.56$, $SE = 0.32$; untrained: $M = -1.55$, $SE = 0.32$), but the difference between trained and untrained foods was not significant (**H1b**: $B_{JZS} = 0.04$, $t(799) = -0.02$, $p = 0.49$, $dz = -7.652e-4$). Both of these analyses provide strong evidence for H0. [Figure 4.5].

Effects of training on implicit liking (H2)

To investigate the effect of training on implicit liking of healthy foods, RTs were compared for trained and untrained foods in positive and negative target trials separately. In positive target trials there was no significant difference in RTs for untrained ($M = 655$, $SE = 3.07$) and trained healthy foods ($M = 658$, $SE = 3.15$; **H2a**: $B_{JZS} = 0.02$, $t(799) = 1.29$, $p =$

Hypothesis		B_{10}	t	p	dz	Evidence interpretation
H1	Explicit liking					
H1a	thd > uhd	0.09	0.85	0.2	0.03	Strong evidence for H0
H1b	tud < uud	0.04	-0.02	0.49	-7.65	Strong evidence for H0
H2	Implicit liking					
H2a	thp < uhp	0.02	1.29	0.9	0.05	Strong evidence for H0
H2b	thn > uhn	0.29	1.63	0.05	0.06	Moderate evidence for H0
H2c	tun < uun	0.02	0.95	0.83	0.03	Strong evidence for H0
H2d	tup > uup	0.01	-2.23	0.99	-0.08	Strong evidence for H0
H3	Training effects					
H3a	RT: Healthy < Filler	30.86	-3.47	< .001	-0.12	Very strong evidence for H3a
H3b	%Errors: Unhealthy > Filler	2.242e+7	6.33	< .001	0.22	Extreme evidence for H3b

Table 4.1: Outcomes of the primary hypothesis tests. *Note.* thd = trained healthy difference, uhd = untrained healthy difference, tud = trained unhealthy difference, uud = untrained unhealthy difference, thp = trained healthy positive, uhp = untrained healthy positive, thn = trained healthy negative, uhn = untrained healthy negative, tun = trained unhealthy negative, uun = untrained unhealthy negative, tup = trained unhealthy positive, uup = untrained unhealthy negative

0.9, $dz = 0.05$). Similarly, for negative target trials there was also no significant difference between RTs for untrained ($M = 658$, $SE = 3.21$) versus trained healthy foods ($M = 662$, $SE = 3.19$; **H2b**: $B_{JZS} = 0.29$, $t(799) = 1.63$, $p = 0.05$, $dz = 0.06$). Taken together these findings provide strong and moderate evidence, respectively, that training had no effect on implicit liking of healthy foods. RTs times to trained and untrained unhealthy foods for positive and negative target trials were also compared. In negative trials, there was no significant difference in RTs for untrained foods ($M = 660$, $SE = 3.13$) compared to trained foods ($M = 662$, $SE = 3.16$; **H2c**: $B_{JZS} = 0.02$, $t(799) = 0.95$, $p = 0.83$, $dz = 0.03$). Similarly, for positive trials there was also no significant difference in RTs for

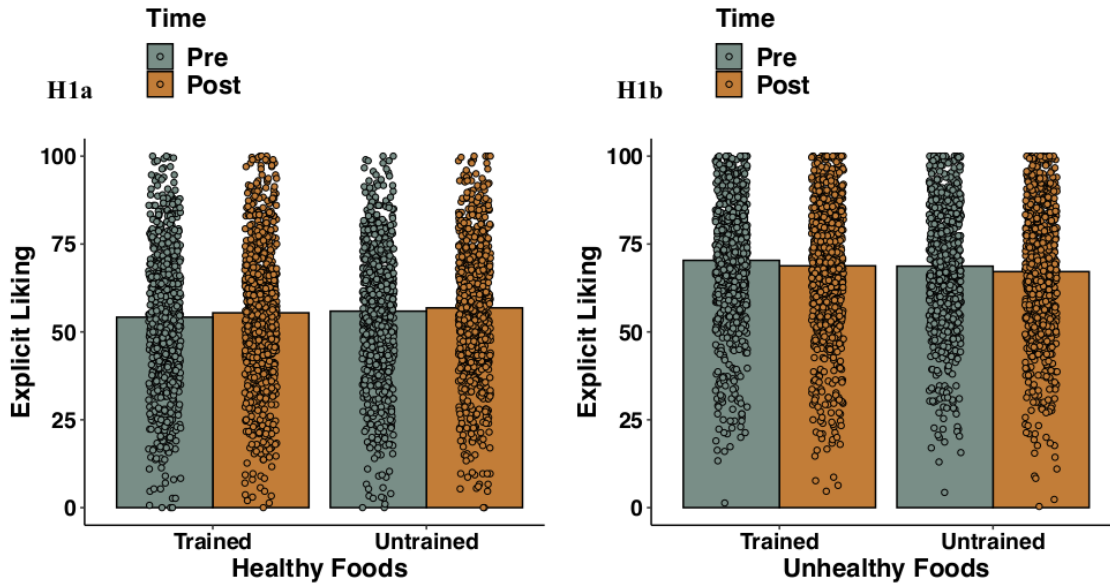


Figure 4.5: Mean explicit liking of healthy and unhealthy foods based on training status and time. Individual data points highlight the variability of food liking across participants. Contrary to predictions there was no effect of training status on explicit liking of healthy (H1a) or unhealthy (H1b) foods from pre-to post training.

untrained foods ($M = 655$, $SE = 3.13$) compared to trained foods (**H2d**: $M = 650$, $SE = 3.04$; $B_{JZS} = 0.01$, $t(799) = -2.23$, $p = 0.99$, $dz = -0.08$). Both of these results provide strong evidence that training had no effect on implicit liking of unhealthy foods. [Figure 4.6].

Training effects (H3)

The final confirmatory analyses tested for evidence of learning in the training task. RTs in go trials were faster for healthy food trials ($M = 466$, $SE = 2.77$) than trials with filler stimuli ($M = 470$, $SE = 2.83$), providing very strong evidence for training effects in go trials (**H3a**: $B_{JZS} = 30.86$, $t(799) = -3.47$, $p < .001$, $dz = -0.12$). We also investigated whether participants would be more successful at inhibiting to unhealthy foods in no-go trials than filler stimuli. Participants exhibited a higher percentage of successful stopping to unhealthy foods ($M = 99.09$, $SE = 0.06$) compared to filler stimuli ($M = 98.65$, $SE = 0.07$) providing extreme evidence for training effects in the no-go trials (**H3b**: $B_{JZS} = 2.242e+7$, $t(799) = 6.33$, $p < .001$, $dz = 0.22$).

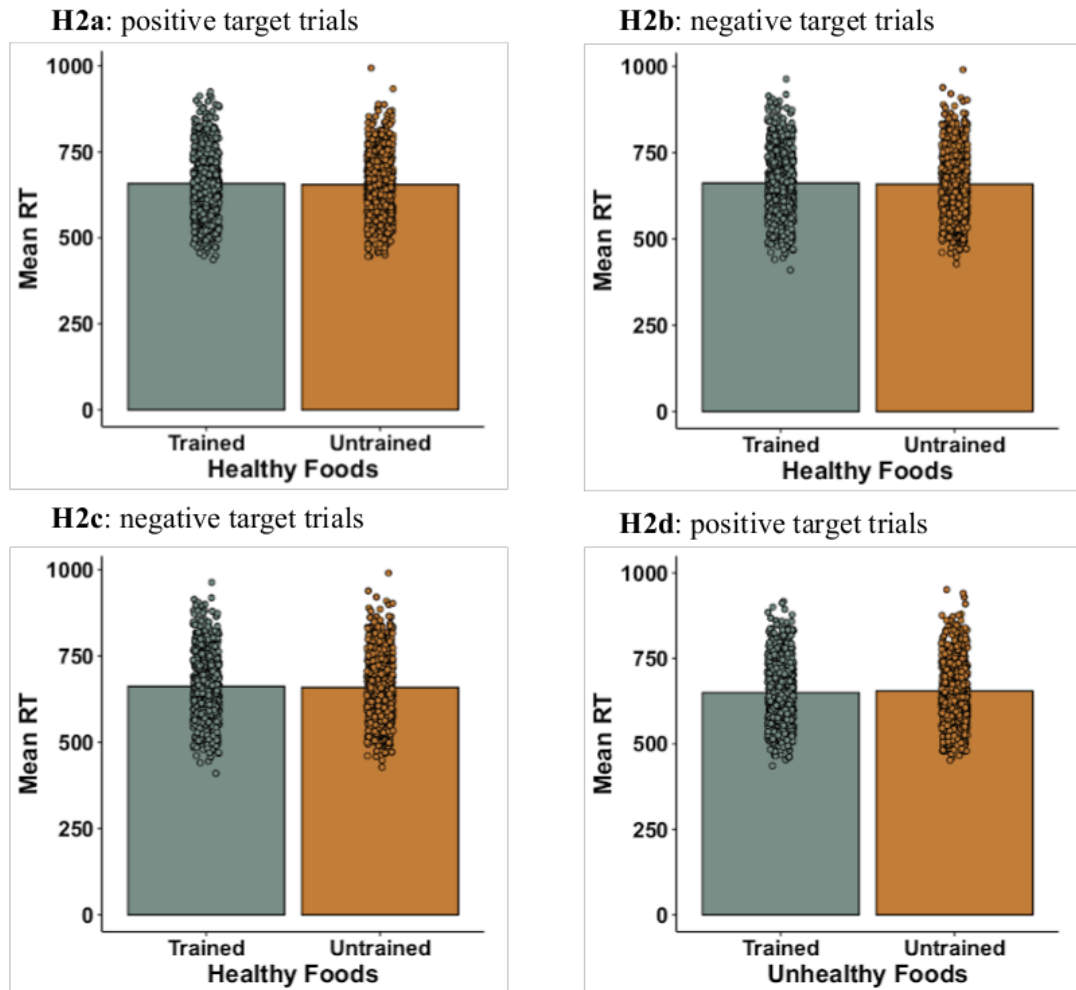


Figure 4.6: Mean RTs for trained compared to untrained foods. Analyses revealed moderate to strong evidence against the effect of the APP on implicit liking (H2).

4.4.5 Exploratory analyses

Order of outcome measures

To investigate whether there were any crossover effects based on the order in which participants completed the outcome measures, data was split into two groups; explicit first, and implicit first.

For participants who completed the explicit task first, there was no significant effect of training on explicit liking of healthy ($B_{JZS} = 0.06$, $t(399) = 0.06$, $p = 0.48$, $dz = 0.003$) or unhealthy foods ($B_{JZS} = 0.03$, $t(399) = 1.28$, $p = 0.9$, $dz = 0.06$). Similarly there was no significant effect of training on implicit liking of healthy foods in positive trials ($B_{JZS} = 0.06$, $t(399) = -0.16$, $p = 0.56$, $dz = -0.01$), healthy foods in negative trials ($B_{JZS} = 0.04$, $t(399) = -0.65$, $p = 0.74$, $dz = -0.03$), unhealthy foods in negative trials, ($B_{JZS} =$

0.05, $t(399) = 0.07$, $p = 0.53$, $dz = 0.004$) or unhealthy foods in positive trials ($B_{JZS} = 0.03$, $t(399) = -1.13$, $p = 0.87$, $dz = -0.06$). Taken together, all of these analyses provide strong evidence for H0.

The same analyses were then carried out for participants who completed the implicit liking measure immediately following the training task. There was no significant effect of training on explicit liking of healthy ($B_{JZS} = 0.2$, $t(399) = 1.18$, $p = 0.12$, $dz = 0.06$) or unhealthy foods ($B_{JZS} = 0.23$, $t(399) = -1.3$, $p = 0.1$, $dz = -0.07$) providing moderate evidence for H0. For the effects of training on implicit liking, the results were similar with no significant effect on implicit liking of healthy foods in positive trials ($B_{JZS} = 0.02$, $t(399) = 1.94$, $p = 0.97$, $dz = 0.1$), unhealthy foods in negative trials ($B_{JZS} = 0.03$, $t(399) = 1.31$, $p = 0.9$, $dz = 0.07$), or unhealthy foods in positive trials ($B_{JZS} = 0.02$, $t(399) = -2.03$, $p = 0.98$, $dz = -0.1$) indicating strong evidence for H0. However, for the effect of training on healthy foods in negative trials, RTs for untrained foods were significantly faster ($M = 640$, $SE = 4.77$) than RTs for trained foods ($M = 649$, $SE = 4.93$) providing moderate evidence for H2b ($B_{JZS} = 8.29$, $t(399) = 3.05$, $p = 0.001$, $dz = 0.15$).

Stimuli-specific effects

To investigate whether there was any difference in the effect of training based on the foods used, the data was once again split into two groups; those who had been presented with high-value unhealthy foods during the experiment, and those who had been presented with neutral unhealthy foods.

Analyses of the high-value unhealthy food group revealed there was no significant difference in explicit liking between trained and untrained foods from pre to post ($B_{JZS} = 0.04$, $t(399) = 0.44$, $p = 0.67$, $dz = 0.02$). There was also no effect of training on implicit liking in negative trials ($B_{JZS} = 0.05$, $t(399) = 0.21$, $p = 0.58$, $dz = 0.01$) or positive trials ($B_{JZS} = 0.06$, $t(399) = 0.12$, $p = 0.45$, $dz = 0.01$). Analyses of the neutral unhealthy food group also found no effect of training on explicit liking ($B_{JZS} = 0.08$, $t(399) = -0.46$, $p = 0.33$, $dz = 0.02$), or on implicit liking in negative ($B_{JZS} = 0.03$, $t(399) = 1.15$, $p = 0.87$, $dz = 0.06$) or positive trials ($B_{JZS} = 0.01$, $t(399) = -3.33$, $p = 0.99$, $dz = -0.17$). Together, these results suggest that the value of foods had no influence on the effects of

training.

Further analyses were also conducted to determine the effect of both order of outcome measure as well as the foods used. All findings were non-significant (all $B_{JZS} < 0.48$, all $t_s < 4.75$, all $p_s > 0.06$; see Appendix C) except for in participants who completed the implicit measure first with neutral foods. Mean RT was significantly slower in negative trials for trained healthy foods ($M = 670$, $SE = 6.45$) than untrained healthy foods ($M = 658$, $SE = 6.63$; **H2b**: $B_{JZS} = 14.47$, $t(199) = 3.06$, $p = 0.001$, $dz = 0.22$).

Baseline liking

As foods were selected based on pilot data rather than participant's preferences, baseline liking was analysed to see how ratings compared. Analyses confirmed that high value unhealthy foods were rated as significantly more pleasant than neutral foods ($B_{JZS} = 1.435e+15$, $t(399) = 9.15$, $p < 0.001$, $dz = 0.46$). Mean liking for high value foods was 74.4 ($SE = 0.75$) compared to 64.67 ($SE = 0.76$) for the neutral foods. We also compared baseline liking for trained unhealthy foods to untrained unhealthy foods and found no significant difference for the high value group ($B_{JZS} = 0.06$, $t(399) = 0.32$, $p = 0.75$, $dz = 0.02$), however, there was a significant difference for the neutral foods ($B_{JZS} = 11.56$, $t(399) = 3.3$, $p < 0.001$, $dz = 0.17$), indicating that trained foods were rated higher in the baseline explicit measure ($M = 66.22$, $SE = 0.91$) in comparison to untrained foods ($M = 63.12$, $SE = 0.87$).

The same healthy foods were used for all participants, however we compared baseline liking for trained and untrained foods and found that untrained foods received significantly higher ratings ($M = 55.91$, $SE = 0.67$) than trained foods ($M = 54.19$, $SE = 0.69$; $B_{JZS} = 1.35$, $t(799) = -2.66$, $p = 0.01$, $dz = -0.09$) though the evidence is anecdotal.

Positivity bias

Exploratory analyses were also conducted to investigate the potential effects of training on the positivity bias in the APP. To investigate the effect of training on the positivity bias in healthy foods, bias scores were calculated by subtracting positive target trial RTs from negative trial RTs. Bias scores were compared for trained healthy and untrained healthy primes for mean RTs ($B_{JZS} = 0.05$, $t(799) = 0.2$, $p = 0.42$, $dz = 0.01$), median RTs (B_{JZS}

= 0.04, $t(799) = -0.1$, $p = 0.54$, $dz = -0.003$), and percentage error rates ($B_{JZS} = 0.03$, $t(799) = -0.7$, $p = 0.76$, $dz = -0.03$). All analyses revealed strong evidence for H0. Inverse efficiency was also calculated as RT / the proportion of correct responses, but revealed no effect on the positivity bias when calculated with mean RT ($B_{JZS} = 0.04$, $t(799) = 0.13$, $p = 0.9$, $dz = 0.01$) or median RT ($B_{JZS} = 0.04$, $t(799) = -0.14$, $p = 0.56$, $dz = -0.01$). The same analyses were repeated for unhealthy trials. There was no significant difference in positivity bias for mean RT ($B_{JZS} = 0.01$, $t(799) = 2.26$, $p = 0.99$, $dz = 0.08$), median RT ($B_{JZS} = 0.02$, $t(799) = 1.52$, $p = 0.94$, $dz = 0.05$), percentage errors ($B_{JZS} = 0.01$, $t(799) = 1.93$, $p = 0.97$, $dz = 0.07$), mean inverse efficiency ($B_{JZS} = 0.01$, $t(799) = 2.53$, $p = 0.99$, $dz = 0.09$) or median inverse efficiency ($B_{JZS} = 0.02$, $t(799) = 1.74$, $p = 0.96$, $dz = 0.06$) with all analyses providing very strong evidence for H0 (see Table 4.2 for a summary of all findings relating to implicit liking).

Trial type	MeanRT	MedianRT	%Errors	IE_Mean	IE_Median
thn	662 (3.19)	650 (3.38)	0.59 (0.04)	666 (3.23)	654 (3.41)
thp	658 (3.15)	645 (3.34)	0.76 (0.04)	663 (3.15)	650 (3.35)
thb (thn-thp)	3.94 (2.17)	4.8 (2.46)	-0.18 (0.05)	2.92 (2.25)	3.8 (2.54)
uhn	658 (3.21)	646 (3.38)	0.55 (0.04)	662 (3.22)	650 (3.4)
uhp	655 (3.07)	641 (3.25)	0.68 (0.04)	659 (3.09)	646 (3.27)
uhb (uhn-uhp)	3.39 (2.12)	5.12 (2.42)	-0.13 (0.05)	2.55 (2.17)	4.27 (2.47)
tun	662 (3.16)	650 (3.38)	0.66 (0.04)	666 (3.41)	654 (3.41)
tup	650 (3.04)	638 (3.25)	0.49 (0.03)	653 (3.27)	642 (3.27)
tub (tun-tup)	11.96 (2.15)	11.73 (2.54)	0.16 (0.04)	13.11 (2.62)	12.86 (2.62)
uun	660 (3.13)	648 (3.34)	0.66 (0.05)	664 (3.12)	653 (3.33)
uup	655 (3.13)	642 (3.38)	0.61 (0.04)	659 (3.15)	646 (3.4)
uub (uun-uup)	5.54 (2.28)	6.74 (2.56)	0.04 (0.05)	5.8 (2.32)	7.01 (2.61)

Table 4.2: Descriptive statistics for implicit liking RTs and positivity bias. *Note.* SE in parentheses, thn = trained healthy negative, thp = trained healthy positive, thb = trained healthy bias, uhn = untrained healthy negative, uhp = untrained healthy positive, uhb = untrained healthy bias, tun = trained unhealthy negative, tup = trained unhealthy positive, tub = trained unhealthy bias, uun = untrained unhealthy negative, uup = untrained unhealthy positive, uub = untrained unhealthy bias

Moderators

To investigate whether BMI, hunger or dieting status had an effect on the training task, H1 and H2 were analysed again with each as a moderator using a linear mixed effects analysis. There was no effect of the moderators for any of the hypotheses. All analyses are reported in Appendix C.

4.5 Discussion

Previous research has suggested that cognitive control training tasks such as GNG training, CAT, and EC may be effective at changing automatic responses to foods (Chen et al., 2019; Porter et al., 2018; Walsh & Kiviniemi, 2014), thought to be driven by a change in evaluation (Veling et al., 2013a). Furthermore, evidence has suggested that these tasks may have a stronger effect on behaviour if used in combination (Allom et al., 2015; Kakoschke et al., 2017a). The aim of this study was to assess the effectiveness of a novel training paradigm combining elements of these tasks on explicit and implicit food liking for both healthy and unhealthy foods. Participants were trained to make responses when healthy foods appeared on screen, and withhold responses when unhealthy foods appeared as dictated by the colour of a fixation cross. Healthy and unhealthy foods were then replaced by pleasant and unpleasant stimuli, respectively. Analyses indicated no effect of the training task on increasing explicit or implicit liking of healthy foods, nor on decreasing explicit or implicit liking of unhealthy foods.

Despite the lack of evidence to support the effects of training on explicit (H1) or implicit (H2) liking, we found strong evidence for learning during the training task (H3). Participants were significantly faster at responding to healthy food stimuli in go trials compared to non-food stimuli, and were also more successful at withholding responses to unhealthy food stimuli in no-go trials compared to non-food stimuli. This is in line with a number of studies that have shown evidence of learning in GNG training (Aulbach et al., 2021; Lawrence et al., 2015b; Sedgmond et al., 2020; Sedgmond et al., 2019), however, in all of these designs the food stimuli has either preceded the no-go signal or the two have been presented simultaneously. Similarly, when cueing a response in either GNG training or CAT the go signal typically follows the onset of the stimulus at either a fixed time point (Aulbach et al., 2021) or after a variable delay (Zoltak et al., 2017). In our design the go and no-go cues preceded the food stimuli suggesting that a delay is not necessary for a training effect to be observed. However, it may explain why we found no change in liking. Research has indicated that in CAT specifically, the motor response alone is not sufficient for a change in preference or choice to occur; the delay must be present as it allows sustained attention to the stimuli which is thought to drive the change (Bakkour et al., 2016; Zoltak et al., 2017).

Exploratory analyses were carried out to investigate the importance of the stimuli used in the task. Research has suggested that in EC, the conditioned stimuli – in this case the food stimuli - need to be neutral in order to observe an effect (Hofmann et al., 2010). However GNG training and CAT typically use stimuli that possess high reward value, with some research suggesting that the effects cannot be replicated with neutral stimuli (Chen et al., 2019). Due to these findings, we used two stimulus sets for unhealthy foods specifically; one consisting of foods that had been rated as highly liked, and one consisting of neutrally rated foods. We split the data based on these stimulus sets but still found no effect of stimulus type on explicit or implicit liking suggesting that these differences in stimulus valence was unlikely to be driving the overall null effect of training. This corresponds with more recent research that has shown effects of EC when appetitive foods are used (Hollands et al., 2011). Further research is necessary to understand the importance of stimulus value in GNG training.

A potential limitation of the stimuli used, however, may be the lack of personalisation. While the two stimulus sets were based on pilot data, the importance of individual preferences in food liking may be an important factor in the efficacy of training tasks such as this. For example, most studies using CAT have selected stimuli based on participant’s explicit attitudes towards the foods determined using measures of attractiveness (Chen et al., 2016) or how much they would be willing to pay for each item (Schonberg et al., 2014; Veling et al., 2017a; Zoltak et al., 2017) prior to the training, allowing for a value to be attached to the stimuli. Research investigating behaviour change interventions has also stressed the importance of personalisation (Dennison et al., 2013; Gorton et al., 2011), but findings are unclear. In a GNG training task where participants had the option to personalise their food stimuli, there was no difference in a measure of food frequency following training for those who had customised their task compared to those who had not (Aulbach et al., 2021). In addition, personalisation has not been necessary to observe effects on food choice (Porter et al., 2018) or food consumption (Lawrence et al., 2015a). Personalisation of food stimuli is also rare in EC studies typically using the same stimuli across participants (Walsh & Kiviniemi, 2014), though some have also taken pilot data into consideration (Hensels & Baines, 2016; Hollands et al., 2011). It could be that while personalisation is not necessary to observe training effects, for studies aiming to promote

long-term behaviour change, tailored apps may enhance engagement (Tang et al., 2015) and reduce the risk of training feeling impersonal (Ni Mhurchu et al., 2014).

A tailored approach could have been beneficial in selecting the stimuli in the EC element. Again, while stimuli were selected from pilot data it could be argued that in the case of the unpleasant stimuli, they were not aversive for all participants. Studies reporting an effect of EC on health-related behaviours have used stimuli such as obese body shapes (Dwyer et al., 2007; Lascelles et al., 2003; Lebens et al., 2011) and potential health consequences of being obese (Hollands et al., 2011). Some of the stimuli used in this study included litter and pollution which while unpleasant to some, may not have produced the desired outcomes, potentially being too subtle. Furthermore, the use of aversive stimuli may have made the link between the food stimuli and the EC stimuli more apparent. Contingency awareness has been frequently debated in EC studies with suggestions that awareness of the stimulus pairings results in larger effects (Hofmann et al., 2010) and can be crucial to observing the effect (Kattner, 2012). Arguably a food paired with a particular body shape, health consequence, or even a negative facial expression (Hensels & Baines, 2016; Porter et al., 2018) would have made the link clearer. Though we did try to capture awareness in this study, our use of an open-ended question resulted in responses from only 20% of participants, making it difficult to fully evaluate awareness in this case.

While many CAT, GNG training and EC studies have shown effects on food choice (Porter et al., 2018; Schonberg et al., 2014; Walsh & Kiviniemi, 2014) the link between the choice behaviour and liking needs further exploration. While the decrease in food choice observed in GNG training has been explained by a reduction in explicit food evaluations (Chen et al., 2018; Veling et al., 2013a), the increase of choice observed in CAT is typically related to monetary value rather than food evaluations (Schonberg et al., 2014; Zoltak et al., 2017). In EC studies measures of food choice are typically used alongside measures of implicit attitudes, although, the relationship is less clear. Some studies have shown an effect on implicit attitudes but not food choice (Hensels & Baines, 2016) whereas others have found an effect on food choice but a less clear effect on implicit attitudes (Hollands et al., 2011). Food liking is known to be a key driver of food consumption as well as food choice, but it is possible that some of the changes in behaviour being observed are

independent of a change in liking.

In conclusion, the current study failed to show an effect of a novel training task on explicit or implicit food liking. Considerations were given to the stimuli used as well as the order in which participants completed the outcome measures, however, neither of these factors consistently offered an explanation for the findings. To better understand the mechanisms and potential role of cognitive control training in food-related behaviour change, more consistency is needed in study designs and outcome measures. Subtle differences between aspects such as stimulus timings, duration of training and different measurements may be sufficient to influence the efficacy of training tasks (see Chapter 6 for further discussion).

Chapter 5

Investigating the role of evaluative conditioning on implicit and explicit food preferences

5.1 Introduction

Our behaviour is strongly determined by our evaluations of the stimuli around us (Strack & Deutsch, 2004). The mechanisms behind these evaluations has been a vital question in psychology (Havermans & Jansen, 2007) not only to better understand the acquisition of these preferences, but also to understand whether they can be influenced, and if so, how (Hofmann et al., 2010).

EC is considered a basic mechanism by which we can acquire our likes and dislikes; many phobias and fears can be attached to previously neutral stimuli following negative experiences (Lascelles et al., 2003). As a training paradigm, EC typically refers to the repeated pairing of a conditioned stimulus with an unconditioned stimulus that holds either positive or negative affect. The simple co-occurrence of the stimuli can result in the transfer of valence from the unconditioned stimulus to the conditioned stimulus (Jones et al., 2010). Typically a conditioned stimulus will be rated more positively after being paired with a positive unconditioned stimulus, and more negatively after being paired with a negative unconditioned stimulus (Baeyens et al., 1998). As such, EC has been used in research with the primary goal of either increasing or decreasing the attractiveness of specific stimuli.

EC has been implemented in different areas of health psychology with the aim of reducing behaviours associated with adverse health effects such as excessive soda and alcohol consumption. For example, simply pairing images of alcoholic beverages with unpleasant unconditioned stimuli has been shown to increase negative attitudes toward the drinks from pre-to post-training (Houben et al., 2010a), decrease craving (Houben et al., 2010b) and also significantly decrease consumption when compared to a control group (Houben et al., 2010a; Houben et al., 2010b; Tello et al., 2018). Similarly, pairing images of soft drinks with unconditioned stimuli thought to evoke disgust resulted in a decrease in real-world consumption of the drinks (Shaw et al., 2016).

Similar studies have also considered the potential role of EC in changing attitudes towards foods. In one of the first studies to investigate the effect of EC on food preferences, images of various food items were paired with images depicting one of three different body types; obese, normal-weight, and thin (Lascelles et al., 2003). Results indicated that explicit liking of the foods paired with the obese images decreased from pre-to post training, and the difference in liking was significantly different when compared to foods that had been paired with the normal and thin body types. In a later study, pictures of foods considered to be neutral (primarily vegetables) were paired with images of different body types (Dwyer et al., 2007). Explicit liking of the foods was measured before and after training and revealed that foods paired with images of obese body types were rated more negatively from pre-to post, while foods that had been paired with neutral body types either remained unchanged or were rated slightly higher.

While both of these studies looked at the effect of EC on explicit liking, the potential effects on implicit liking has also been investigated. Once again using images of body types as unconditioned stimuli, pictures of fruit were paired with body types that had previously been rated positively, and pictures of high-fat snack foods were paired with negatively rated body types (Lebens et al., 2011). Implicit attitudes were measured using both a positive and negative single category IAT and a significant effect of training was found with participants displaying decreased positive associations, and increased negative association with high-fat foods in comparison to control participants. Similar findings were observed after healthy foods were paired with a picture of a happy face. Participants had a stronger preference for healthy foods than participants who had seen the healthy

foods paired with an angry face (Hensels & Baines, 2016).

Further evidence indicates that EC can also influence food choice. Using images of the potential health consequences of obesity, Hollands et al. (2011) found that participants not only had a stronger preference for fruits after seeing images of snack foods paired with images such as arterial disease and obesity, but they were also more likely to choose a fruit than a snack food item in a subsequent food choice task. Further support suggests that the unconditioned stimuli don't need to evoke such strong responses in order for training to have an effect. Walsh and Kiviniemi (2014) paired images of fruit with positive, negative or neutral pictures or words. Following the training, participants received a food choice task in which they could select a piece of fruit or a granola bar for consumption. They found a significant effect of the conditioning paradigm: participants who had seen fruits paired with the positive stimuli were more likely to select a fruit than those who had seen fruits paired with negative or neutral stimuli.

The mechanisms underlying the EC effect are widely debated. Although the overall result of the stimulus pairings seems to be either an increase or decrease in evaluation of stimuli, the role and contested importance of factors such as extinction, contingency awareness and valence of the conditioned stimulus (whether neutral, liked or disliked prior to conditioning) make understanding the mechanisms more challenging. For example, Jones et al. (2010) noted that all of the models attempting to explain the EC effect are incompatible with at least one of these factors. However, most models agree that the effects seen are based on the formation of associations simply by the pairings. For example, Jones et al. (2010) proposed the implicit misattribution model which suggests that the response associated with the unconditioned stimulus is misattributed to the conditioned stimulus, resulting in the changed evaluation, crucially without any awareness. Similarly, the referential account of EC suggests that following the stimulus pairings, the conditioned stimulus initiates a visual representation of the unconditioned stimulus it had been paired with which then drives the evaluation, and that this evaluation is dependent solely on the co-occurrence of the stimuli (Havermans & Jansen, 2007).

While the mechanisms are still not clear, the results seem promising. Research has suggested that EC can affect both explicit and implicit attitudes towards food which are known to be key drivers in behaviour. Here we investigated the effects of EC on both

explicit and implicit liking across two experiments.

5.2 Experiment 1

The purpose of Experiment 1 was to investigate the effects of EC on both implicit and explicit liking of healthy and unhealthy foods. Using a within-subjects design participants initially completed a measure of explicit food liking before being exposed to an EC task in which healthy foods were paired with pleasant and neutral stimuli, and unhealthy foods were paired with unpleasant and neutral stimuli. Participants then repeated the measure of explicit liking as well as an APP to measure implicit liking. Based on findings from previous research, we expected explicit liking of healthy foods paired with pleasant stimuli to increase from pre-to post training in comparison healthy foods paired with neutral stimuli (H1a) while liking of unhealthy foods paired with unpleasant stimuli was expected to decrease from pre-to post training in comparison to unhealthy foods paired with neutral stimuli (H1b). For implicit liking, we expected correct RTs for healthy foods that had been paired with pleasant stimuli in the EC task to be faster when paired with a positive target (H2a) and slower when paired with a negative target (H2b) in comparison to the healthy foods that had been paired with neutral stimuli in the EC task. For unhealthy foods we predicted that correct RTs for those foods paired with unpleasant stimuli in the EC task to be faster when paired with negative targets (H2c) and slower when paired with positive targets (H2d) in comparison to the unhealthy foods that had been paired with neutral stimuli.

The pre-registered protocol is available online (<https://osf.io/4qpkh/>).

5.2.1 Hypotheses

Primary hypotheses

H1. Effects of EC on explicit liking

H1a. Participants will show a greater increase in explicit liking of healthy foods paired with pleasant stimuli from pre-post conditioning (hpd) compared to healthy foods paired with neutral stimuli (hnd). Explicit liking: $hpd > hnd$

H1b. Participants will show a greater decrease in explicit liking of unhealthy foods

paired with unpleasant stimuli from pre-post conditioning (uud) compared to unhealthy foods paired with neutral stimuli (und). Explicit liking: $uud < und$

H2. Effects of EC on implicit liking.

H2a. Correct RTs will be faster in positive target trials for healthy foods paired with pleasant stimuli (php) compared to healthy foods paired with neutral stimuli (nhp). RT: $php < nhp$

H2b. Correct RTs will be slower in negative target trials for healthy foods paired with pleasant stimuli (phn) compared to healthy foods paired with neutral stimuli (nhn). RT: $phn > nhn$

H2c. Correct RTs will be faster in negative target trials for unhealthy foods paired with unpleasant stimuli (uun) compared to unhealthy foods paired with neutral stimuli (nun). RT: $uun < nun$

H2d. Correct RTs will be slower in positive target trials for unhealthy foods paired with unpleasant stimuli (uup) compared to unhealthy foods paired with neutral stimuli (nup). RT: $uup > nup$

5.2.2 Methods

Participants

A total of 132 participants (103 females, age: $M = 19.83$, $SE = 0.19$) were recruited from the experimental management system at Cardiff University and were reimbursed with course credits. Participants were aged 18 years or over and had a body mass index of at least 18.5. Participants were excluded if they had any history of an eating disorder. All participants provided informed consent and were debriefed at the end of the study. The study was approved by the School of Psychology Research Ethics Committee, Cardiff University.

Sampling plan

Experiment 1 was conducted as part of four final-year dissertation projects. As a result, while taking into account time constraints and availability of course credits, a power analysis determined that 100 participants would achieve 90% power to detect a small-

medium effect size of Cohen's $d_z = 0.3$ using a paired-samples t-test with an alpha level of 0.05 (acquired using G*Power; Faul et al., 2007).

Procedure

Participants were informed that they were taking part in a study investigating the role of personality on food preferences. The study began with a VAS measuring participants' current level of hunger before moving onto the explicit measure of food liking. Participants then completed the EC task which consisted of 5 blocks of 48 trials before repeating the measure of explicit liking in addition to the implicit liking measure. Lastly, participants completed three measures of socioeconomic status, a questionnaire on their intention to eat healthily, and the Dutch Eating Behavior Questionnaire (DEBQ; van Strien et al., 1986). These measures in addition to the measure of hunger were included as part of four final year student projects and will not be discussed further (see Appendix D for a summary of results).

Conditioned stimuli

A total of 48 pictures of foods were used as conditioned stimuli; 8 healthy and 8 unhealthy foods, each with 3 exemplars. Food stimuli were selected from a pre-existing database (Restrain, 2019). Healthy food stimuli were defined as having no more than 100kcal per 100g and unhealthy foods were defined as having at least 300kcal per 100g. All stimuli were against a white background.

Unconditioned stimuli

A total of 48 unconditioned stimuli were presented in the experiment; 4 pleasant, 4 unpleasant, and 8 neutral, all of which had 3 exemplars. The pleasant and unpleasant stimuli were selected based on pilot data to ensure that the pleasant stimuli had been rated as 'extremely pleasant', and the unpleasant stimuli as 'extremely unpleasant'. The neutral stimuli included stationery and household items.

Explicit food liking

Participants were presented with the 16 foods from the conditioned stimuli; 8 healthy and 8 unhealthy. Each image appeared individually in the centre of the screen in a randomised order with a 200-point VAS underneath. Participants were asked to imagine that they were tasting each of the foods and to then indicate how much they like the taste, ranging from ‘not at all’ (0) to ‘very much’ (200).

Implicit food liking

To measure implicit food liking an APP was used with 16 primes and 16 targets. The primes were the 8 healthy and 8 unhealthy conditioned stimuli and the targets were 8 positive and 8 negative words. Participants were instructed that a picture would appear briefly on the screen before being replaced by a word. They were instructed to categorise the word as positive or negative as quickly and as accurately as possible by pressing either ‘c’ or ‘m’ on the keyboard (key presses were counterbalanced across participants). Each prime appeared on the screen for 250ms before an ITI of 250ms. The target then appeared on the screen for 2500ms, or until the participant made a response. Each food was presented twice with both a positive and negative target as 1 block of 32 trials [Figure 5.1].

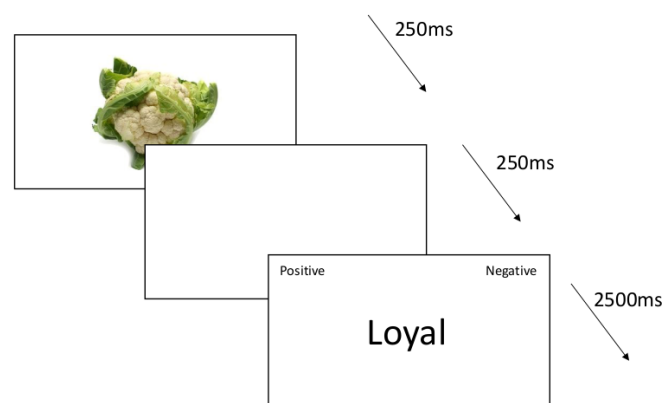


Figure 5.1: The APP was used to measure implicit liking of 16 foods. Participants were instructed to categorise a target word as either positive or negative as quickly and as accurately as possible. Reaction times were recorded and compared for healthy-positive, healthy-negative, unhealthy-positive, and unhealthy-negative pairings.

EC task

A picture-picture EC task was used in which pictures of food were used as conditioned stimuli and pictures rated as either pleasant or unpleasant were used as unconditioned stimuli. Each trial began with the appearance of a black fixation cross in the centre of the screen for 500ms. A conditioned stimulus would then appear on the left or right hand side of the screen for 1000ms before being replaced by an unconditioned stimulus for 500ms. There was then an inter-trial interval lasting 1500ms. To limit awareness of the study, participants were informed that on a subset of the trials (8%), the fixation cross would turn green, indicating to participants that they would need to identify the location of the conditioned stimulus ('c' for left, 'm' for right). Each block displayed each of the 16 food stimuli. For the healthy food pictures, 4 were paired with pleasant unconditioned stimuli and 4 with neutral unconditioned stimuli. For the unhealthy foods, 4 were paired with unpleasant unconditioned stimuli and 4 with the remaining neutral unconditioned stimuli [Figure 5.2]. All exemplars of the conditioned and unconditioned stimuli were presented once in each block without repetition.

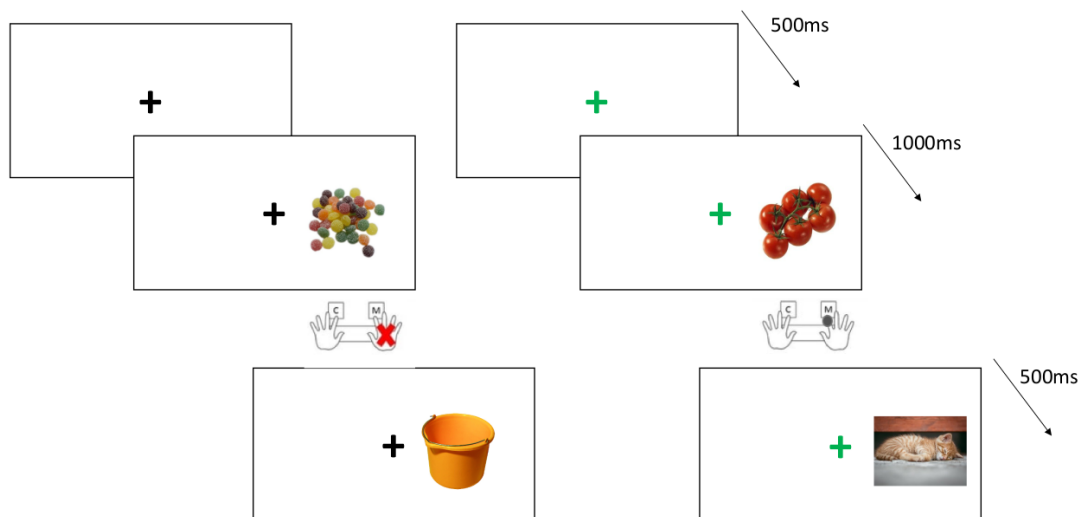


Figure 5.2: During the EC task participants were instructed to respond to the stimulus immediately following a fixation cross only if the fixation cross was green. Pictures of healthy and unhealthy foods were presented for 1000ms before being replaced by an unconditioned stimulus for 500ms.

Hunger

Participants completed a VAS measuring how hungry they were at the time of participation, ranging from 0 ('not at all hungry') to 100 ('very hungry').

Socioeconomic status

Participants completed three measures of socioeconomic status: the family affluence scale (Currie et al., 1997) and a further two questionnaires relating to the education level attained by the individual's caregiver/s, and a measure of subjective social class measured on a 5-point likert scale; "at the right end of the scale are the families that are most well-off, with the most money and the highest social standing. At the left end of the scale are the families that are least well-off, with the least money and the lowest social standing. Please indicate on the scale, where you think your family ranks relative to other families in the society".

Intention to eat healthily

To investigate whether an individual's intention to engage in healthy eating behaviour was associated with the efficacy of the EC task, participants were presented with four statements alongside a 7-point likert scale measuring from strongly disagree (1) to strongly agree (7). Statements were based on the individual's intention to eat healthily today, this week, over the coming weeks, and over the coming months.

Dutch eating behavior questionnaire

Participants completed the 33-item Dutch Eating Behavior Questionnaire (DEBQ; van Strien et al., 1986) to investigate whether eating behaviours such as dietary restraint or emotional eating were related to the effectiveness of EC.

5.2.3 Exclusion criteria

Participants were excluded from the analyses and replaced if any of the following criteria were met:

- Failure to comply with the study's eligibility requirements including:

- Not having a current/ history of eating disorders
- The participant exercised their right to withdraw from the study or their right to withdraw data
- Any unforeseen errors resulting in the loss of any data or inability to complete the entire session

APP data were also checked for RTs and responses to determine missing or incorrect data. Trials with RTs of $< 350\text{ms}$ or $> 1000\text{ms}$ were removed before the final analyses in addition to any trials with incorrect responses. Participant data were removed from analyses if more than 20% of trials were missing or had been removed based on RTs and response made. Explicit liking responses were also checked to ensure that no more than 20% of responses had been missed.

5.2.4 Results

Data exclusions

Based on exclusion criteria, data from 29 participants were excluded from analyses based on performance on the measure of implicit liking leaving a final sample of 103.

Primary analyses

All primary analyses have been summarised in Table 5.1.

Effects of EC on explicit liking (H1)

A paired samples t-test was conducted to investigate whether explicit liking of healthy foods paired with pleasant stimuli in the EC task increased from pre-to post training in comparison to healthy foods paired with neutral stimuli. Contrary to our hypotheses, not only was there an overall decrease in explicit liking of all healthy foods following training, but those paired with pleasant stimuli showed a greater decrease ($M = -3.88$, $SE = 1.97$) than those paired with neutral stimuli ($M = -1.15$, $SE = 1.3$). No significant difference was found between the two conditions, indicating strong evidence for H0 (**H1a**: $B_{JZS} = 0.05$, $t(102) = -1.36$, $p = 0.91$, $dz = -0.13$).

Hypothesis		B_{10}	t	p	dz	Evidence interpretation
H1	Explicit liking					
H1a	hpd > hnd	0.05	-1.36	0.91	-0.13	Strong evidence for H0
H1b	uud < und	0.1	0.08	0.53	0.01	Moderate evidence for H0
H2	Implicit liking					
H2a	php < nhp	0.79	-1.67	< 0.05	-0.17	Anecdotal evidence for H0
H2b	phn > nhn	0.05	-1.39	0.92	-0.14	Strong evidence for H0
H2c	uun < nun	0.11	-0.03	0.49	-0.03	Moderate evidence for H0
H2d	uup > nup	0.11	-0.05	0.52	-0.01	Moderate evidence for H0

Table 5.1: Outcomes of the primary hypothesis tests for Experiment 1. In all cases, the evidence favoured the null hypothesis (H0) over the corresponding alternative hypothesis. *Note.* hpd = healthy pleasant difference, hnd = healthy neutral difference, uud = unhealthy unpleasant difference, und = unhealthy neutral difference, php = pleasant healthy positive, nhp = neutral healthy positive, phn = pleasant healthy negative, nhn = neutral healthy negative, uun = unpleasant unhealthy negative, nun = neutral unhealthy negative, uup = unpleasant unhealthy positive, nup = neutral unhealthy positive.

It was also hypothesised that there would be a greater decrease in explicit liking of unhealthy foods paired with unpleasant stimuli from pre-to post training in comparison to unhealthy foods paired with neutral stimuli. Although there was an overall decrease in explicit liking of unhealthy foods, this decrease was greater in those paired with neutral stimuli ($M = -1.1$, $SE = 1.15$) than those paired with unpleasant stimuli ($M = -0.98$, $SE = 1.53$). Again, there was no significant difference between the two conditions (**H2a**: $B_{JZS} = 0.1$, $t(102) = 0.08$, $p = 0.53$, $dz = 0.01$) indicating moderate evidence for H0. [Figure 5.3].

Effects of EC on implicit liking (H2)

RTs in positive target trials were significant faster for healthy foods paired with pleasant stimuli ($M = 517$, $SE = 7.34$) compared to healthy foods paired with neutral stimuli ($M = 531$, $SE = 8.56$; **H2a**: $B_{JZS} = 0.79$, $t(102) = -1.67$, $p < 0.05$, $dz = -0.17$) though still indicating anecdotal evidence for H0. There was no significant difference in the RTs

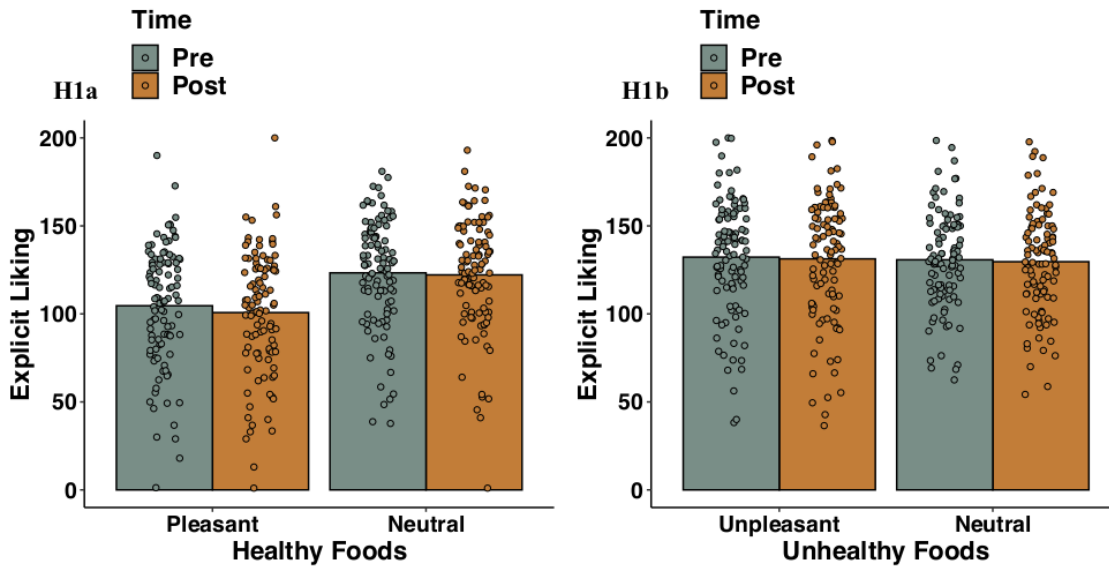


Figure 5.3: Mean explicit liking of healthy and unhealthy foods based on stimulus pairings and time. Individual data points highlight the variability of food liking across participants. Evidence was found against the effect of EC on increasing liking of healthy foods (H1a) and decreasing liking of unhealthy foods (H1b).

between pleasant ($M = 527, SE = 7.75$) and neutral pairings ($M = 538, SE = 7.45$) in negative target trials (**H2b**: $B_{JZS} = 0.05, t(102) = -1.39, p = 0.92, dz = -0.14$) indicating strong evidence for H0.

There was no significant difference in RTs in negative target trials for unhealthy foods paired with unpleasant stimuli ($M = 528, SE = 6.83$) compared to unhealthy foods paired with neutral stimuli ($M = 528, SE = 6.29$; **H2c**: $B_{JZS} = 0.11, t(102) = -0.03, p = 0.49, dz = -0.003$), nor was there a significant difference in RTs in positive target trials for unpleasant pairings ($M = 512, SE = 6.71$) compared to neutral pairings ($M = 513, SE = 7.01$; **H2d**: $B_{JZS} = 0.11, t(102) = -0.05, p = 0.52, dz = -0.01$), providing moderate evidence for H0 for both H2c and H2d. [Figure 5.4].

Exploratory analyses

Baseline liking

Baseline liking of the food stimuli used was analysed to check whether there were any differences between liking of healthy foods paired with pleasant stimuli and liking of healthy foods paired with neutral stimuli. We found a significant difference in baseline liking of healthy foods; those paired with neutral stimuli received significantly higher baseline rat-

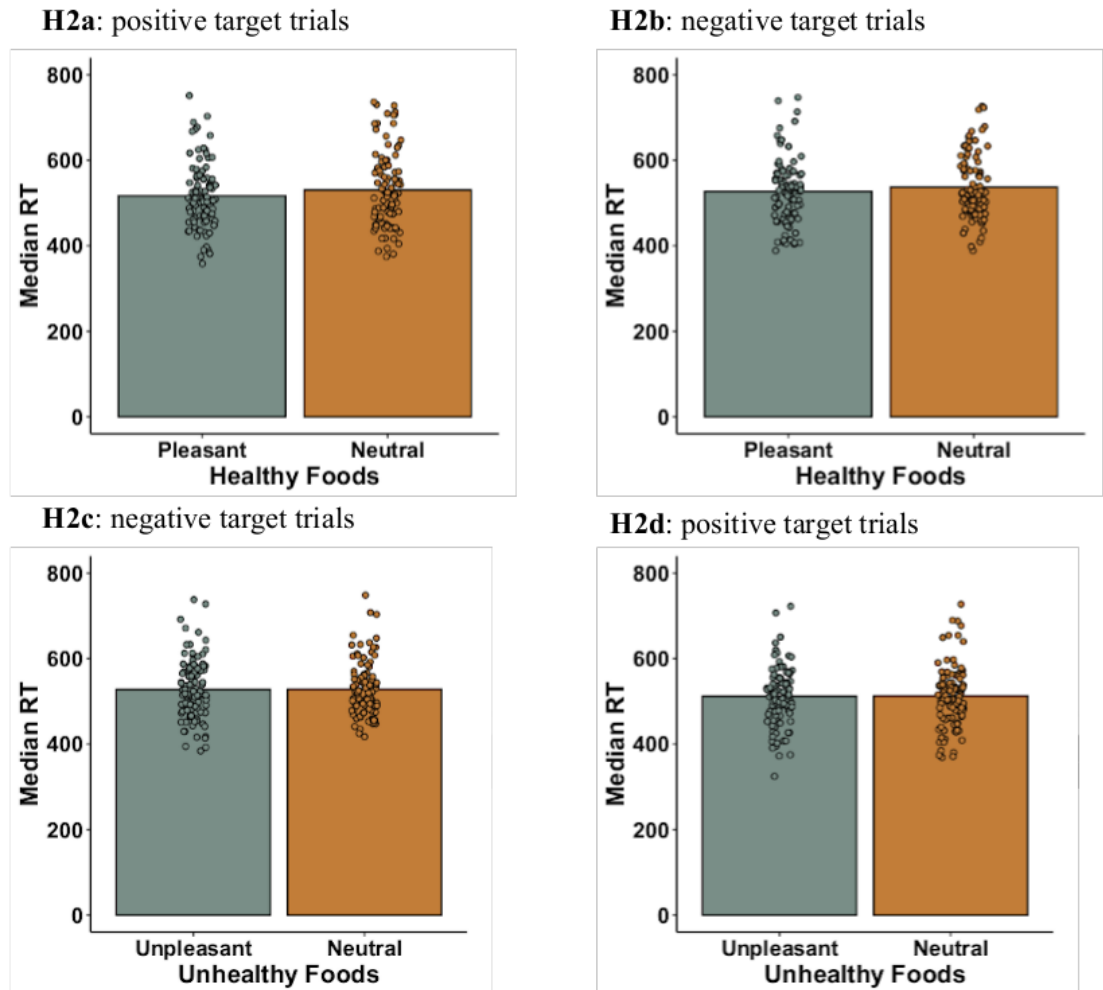


Figure 5.4: Median RT and individual data points based on food type, stimulus pairing, and trial type using the APP. No effect of EC was found on implicit liking.

ings of explicit liking ($M = 123.3$, $SE = 3.06$) compared to those paired with pleasant stimuli ($M = 104.6$, $SE = 3.38$; $B_{JZS} = 2.780e+6$, $t(102) = -6.45$, $p < .001$, $dz = -0.64$). Similar analyses also investigated whether baseline liking of unhealthy foods paired with unpleasant or neutral stimuli differed. There was no significant difference in the baseline liking of unhealthy foods paired with unpleasant stimuli ($M = 132.3$, $SE = 3.27$), and those paired with neutral stimuli ($M = 130.8$, $SE = 2.73$; $B_{JZS} = 0.14$, $t(102) = 0.68$, $p = 0.5$, $dz = 0.07$).

Effects of EC on the positivity bias

Exploratory analyses were also conducted to explore potential effects of EC on the positivity bias. Bias scores were calculated for median RTs on correct trials, percentage errors and inverse efficiency.

For median RT, positive target trials were subtracted from negative targets trials to produce a bias score which was then compared for healthy foods paired with pleasant stimuli and healthy foods paired with neutral stimuli. If pairing foods with pleasant stimuli had made them more positive we would expect slower RTs for negative words and faster RTs for positive words compared to those paired with the neutral stimuli; however we found no reliable evidence for this pattern ($B_{JZS} = 0.14$, $t(102) = 0.27$, $p = 0.4$, $dz = 0.03$). Median RT was also calculated for unhealthy foods with the opposite assumption; that if pairing the foods with unpleasant stimuli had made them more negative we would see slower RTs for positive words and faster RTs for negative words compared to those that had been paired with neutral stimuli. We also found no evidence of this ($B_{JZS} = 0.11$, $t(102) = 0.01$, $p = 0.5$, $dz = 0.001$), with both analyses providing moderate evidence for H0.

To investigate the effect of conditioning on error rates, bias scores were again calculated by subtracting positive target trials from negative target trials. We found no evidence for an effect of conditioning on the size of the positivity bias in error rates for healthy foods ($B_{JZS} = 0.17$, $t(102) = 0.52$, $p = 0.3$, $dz = 0.05$) or unhealthy foods ($B_{JZS} = 0.06$, $t(102) = 1.09$, $p = 0.86$, $dz = 0.11$) suggesting that the stimulus pairings did not influence error rates.

Finally, inverse efficiency was calculated by dividing median RT by the proportion of correct responses. If pairing healthy foods with pleasant stimuli had made them more positive we would expect to see a reduction in inverse efficiency to positive words and an increase in inverse efficiency to negative words; however, we did not observe reliable evidence for this outcome ($B_{JZS} = 0.14$, $t(102) = 0.3$, $p = 0.38$, $dz = 0.03$), nor did we find evidence in unhealthy foods ($B_{JZS} = 0.1$, $t(102) = 0.09$, $p = 0.53$, $dz = 0.01$).

5.2.5 Discussion

Contrary to our hypotheses, in this first experiment we found no effect of EC on explicit or implicit food liking. Unlike Lascelles et al. (2003) and Dwyer et al. (2007) we found no reduction in the liking of unhealthy foods paired with unpleasant stimuli (H1b), nor did we find an increase in the liking of healthy foods paired with pleasant stimuli (H1a) as found by Lascelles et al. (2003). Our findings on implicit liking of healthy foods (H2a

& H2b) were also inconsistent with previous research that has found increased positive associations following EC (Hensels & Baines, 2016), as were our findings on the implicit liking of unhealthy foods (H2c & H2d). We found no evidence of the increased negative associations that previous research has supported (Lebens et al., 2011).

One potential limitation of this experiment is evident from the analyses of baseline liking. Although food stimuli were selected from a pre-existing database, baseline liking hadn't been considered and as a result there was a significant difference in liking of healthy foods paired with pleasant stimuli compared with those foods paired with neutral stimuli. While this cannot explain the decrease observed in explicit liking across all healthy foods, food stimuli were subsequently changed for Experiment 2.

5.3 Experiment 2

The purpose of Experiment 2 was to investigate the effects of EC on both implicit and explicit liking of healthy and unhealthy foods. Using an online experimental design, several changes were made to improve upon Experiment 1. Due to the findings that healthy foods paired with neutral stimuli were rated higher than healthy foods paired with pleasant stimuli at baseline, pilot data was used to determine explicit liking of foods in the database. Presentation time of the unconditioned stimuli was also reduced in line with other research and the number of blocks in the EC task were reduced from 5 to 4 to maximise engagement due to the online nature of Experiment 2. Finally, the measures of explicit and implicit liking were counterbalanced to explore any potential effects of the order in which participants completed the outcome measures in the exploratory analyses. As in Experiment 1, participants completed a measure of explicit food liking prior to the same EC task in Experiment 1. Participants then repeated the measure of explicit liking as well as a measure of implicit liking (counterbalanced). For explicit liking, we expected to see an increase in liking of healthy foods paired with pleasant stimuli from pre-to post training in comparison to healthy foods paired with neutral stimuli (H1a) and a decrease in liking of unhealthy foods paired with unpleasant stimuli from pre-to post training in comparison to unhealthy foods paired with neutral stimuli (H1b). Implicit liking was determined based on correct RTs. We expected RTs towards healthy foods

paired with pleasant stimuli to be faster in positive target trials and slower in negative target trials when compared to healthy foods paired with neutral stimuli (H2a & H2b). We also expected RTs towards unhealthy foods paired with unpleasant stimuli to be faster in negative target trials and slower in positive target trials in comparison to unhealthy foods paired with neutral stimuli (H2c & H2d). The methods and stimuli used in Experiment 2 were the same as Experiment 1 unless stated otherwise.

5.3.1 Hypotheses

Primary hypotheses

H1. Effects of EC on explicit liking

H1a. Participants will show a greater increase in explicit liking of healthy foods paired with pleasant stimuli from pre-post conditioning (hpd) compared to healthy foods paired with neutral stimuli (hnd). Explicit liking: $hpd > hnd$

H1b. Participants will show a greater decrease in explicit liking of unhealthy foods paired with unpleasant stimuli from pre-post conditioning (uud) compared to unhealthy foods paired with neutral stimuli (und). Explicit liking: $uud < und$

H2. Effects of EC on implicit liking.

H2a. RTs will be faster in positive target trials for healthy foods paired with pleasant stimuli compared to healthy foods paired with neutral stimuli. RT: $php < nhp$

H2b. RTs will be slower in negative target trials for healthy foods paired with pleasant stimuli compared to healthy foods paired with neutral stimuli. RT: $phn > nhn$

H2c. RTs will be faster in negative target trials for unhealthy foods paired with unpleasant stimuli compared to unhealthy foods paired with neutral stimuli. RT: $uun < nun$

H2d. RTs will be slower in positive target trials for unhealthy foods paired with unpleasant stimuli compared to unhealthy foods paired with neutral stimuli. RT: $uup > nup$

5.3.2 Methods

Participants

A total of 232 participants (127 males, age: $M = 28.01$, $SE = 0.48$) were recruited using Prolific (www.prolific.co) and received monetary compensation at a rate of £6.93 per hour. Inclusion and exclusion criteria was identical to Experiment 1.

Sampling plan

A SSD was used to estimate the required sample size based on set parameters. In line with Experiment 1, an effect size of $d_z = 0.3$ was used for the SSD based on a paired-sample t-test for H1 and H2. The default scale parameter of $\sqrt[2]{2}$ for the half-Cauchy distribution was used (Rouder et al., 2009) with an upper boundary of 6 and a power of .90. A final sample size of 200 was determined to achieve 93% power.

Procedure

The procedure was identical to that of Experiment 1 aside from the following changes. The number of blocks was reduced to 4 in order to maximise participant engagement with the task and reduce the study duration as the experiment was being conducted online. The order in which participants completed the measures of explicit and implicit liking was also counterbalanced.

Conditioned stimuli

A total of 48 food stimuli were used as conditioned stimuli; 8 healthy and 8 unhealthy foods, each with 3 exemplars. Due to concerns with baseline liking in Experiment 1, foods were still selected from the same database, but pilot data was collected to determine explicit liking in advance to prevent any grouping of similarly rated foods.

EC task

The EC task was identical to Experiment 1, however the duration of the unconditioned stimulus presentation was reduced from 500ms to 250ms to reduce participant awareness.

5.3.3 Results

Data exclusions

Using the same exclusion criteria as in Experiment 1 (see section 5.2.3), 32 participants were excluded from data analyses based on performance on the implicit liking task resulting in a final sample of 200.

Primary analyses

All primary analyses have been summarised in Table 5.2.

Hypothesis		B_{10}	t	p	dz	Evidence interpretation
H1	Explicit liking					
H1a	hpd > hnd	0.1	2.93	0.39	0.02	Moderate evidence for H0
H1b	uud < und	0.03	1.76	0.96	0.12	Very strong evidence for H0
H2	Implicit liking					
H2a	php < nhp	0.98	-1.95	0.03	-0.14	Anecdotal evidence for H0
H2b	phn > nhn	0.76	1.82	0.04	0.13	Anecdotal evidence for H0
H2c	uun < nun	13.45	-3.04	0.001	-0.22	Strong evidence for H0
H2d	uup > nup	0.11	0.38	0.35	0.03	Moderate evidence for H0

Table 5.2: Outcomes of the primary hypothesis tests for Experiment 2. *Note.* hpd = healthy pleasant difference, hnd = healthy neutral difference, uud = unhealthy unpleasant difference, und = unhealthy neutral difference, php = pleasant healthy positive, nhp = neutral healthy positive, phn = pleasant healthy negative, nhn = neutral healthy negative, uun = unpleasant unhealthy negative, nun = neutral unhealthy negative, uup = unpleasant unhealthy positive, nup = neutral unhealthy positive.

Effects of EC on explicit liking (H1)

Consistent with the findings of Experiment 1, we found a reduction in the explicit liking of healthy foods paired with both pleasant ($M = -0.64$, $SE = 1.4$) and neutral ($M = -1.08$, $SE = 1.32$) stimuli following training with results indicating moderate evidence for H0 (**H1a**: $B_{JZS} = 0.1$, $t(199) = 0.29$, $p = 0.39$, $dz = 0.02$).

Once again, there was an overall reduction in explicit liking of unhealthy foods following training, although this reduction was greater for neutral pairings ($M = -4.56$, $SE = 1.22$) compared to unpleasant pairings ($M = -2.51$, $SE = 1.17$). Analysis indicated very strong evidence for H0 (**H1b**: $B_{JZS} = 0.03$, $t(199) = 1.76$, $p = 0.96$, $dz = 0.12$). [Figure 5.5].

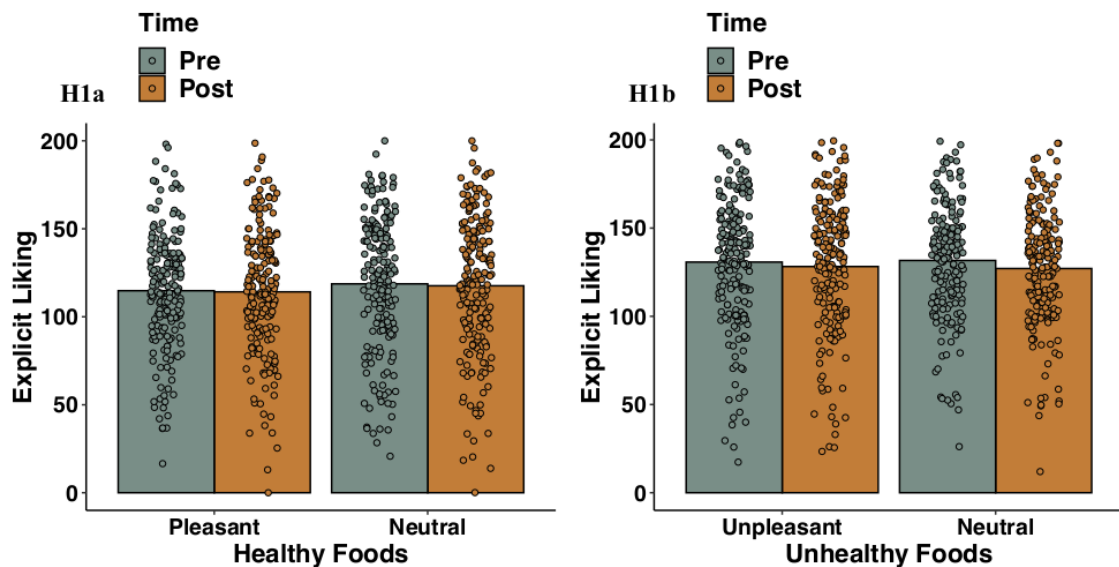


Figure 5.5: Mean explicit liking of healthy and unhealthy foods based on stimulus pairings and time. Individual data points highlight the variability of food liking across participants. Analyses revealed moderate and very strong evidence against the effect of EC on explicit liking of healthy (H1a) and unhealthy foods (H1b) respectively.

Effect of EC on implicit liking of healthy foods (H2a & H2b)

To investigate the effect of training on implicit liking of healthy foods, RTs were compared for pleasant and neutral pairings. As predicted, RTs were significantly quicker in positive target trials for healthy foods that had been paired with pleasant stimuli ($M = 590$, $SE = 7.38$) compared to those paired with neutral stimuli ($M = 604$, $SE = 7.78$; **H2a**: $B_{JZS} = 0.98$, $t(199) = -1.95$, $p = 0.03$, $dz = -0.14$) though still indicating anecdotal evidence for H0. Participants were also significantly slower at responding to healthy foods that had been paired with pleasant stimuli ($M = 618$, $SE = 7.79$) in negative target trials compared to those paired with the neutral stimuli ($M = 607$, $SE = 7.39$; **H2b**: $B_{JZS} = 0.76$, $t(199) = 1.82$, $p = 0.04$, $dz = 0.13$) again indicating anecdotal evidence for H0.

Effect of EC on implicit liking of unhealthy foods (H2c & H2d)

RTs in negative target trials were significantly faster for unhealthy foods paired with unpleasant stimuli ($M = 587$, $SE = 7.35$) compared to those paired with neutral stimuli ($M = 604$, $SE = 7.24$) supporting our predictions in H2c and providing strong evidence for H1 (**H2c**: $B_{JZS} = 13.45$, $t(199) = -3.04$, $p = 0.001$, $dz = -0.22$). However for the positive target trials there was no significant difference in RTs for the unpleasant paired foods ($M = 614$, $SE = 7.46$) compared to the neutral paired foods ($M = 612$, $SE = 7.4$; **H2d**: $B_{JZS} = 0.11$, $t(199) = 0.38$, $p = 0.35$, $dz = 0.03$) indicating moderate evidence for H0. [Figure 5.6].

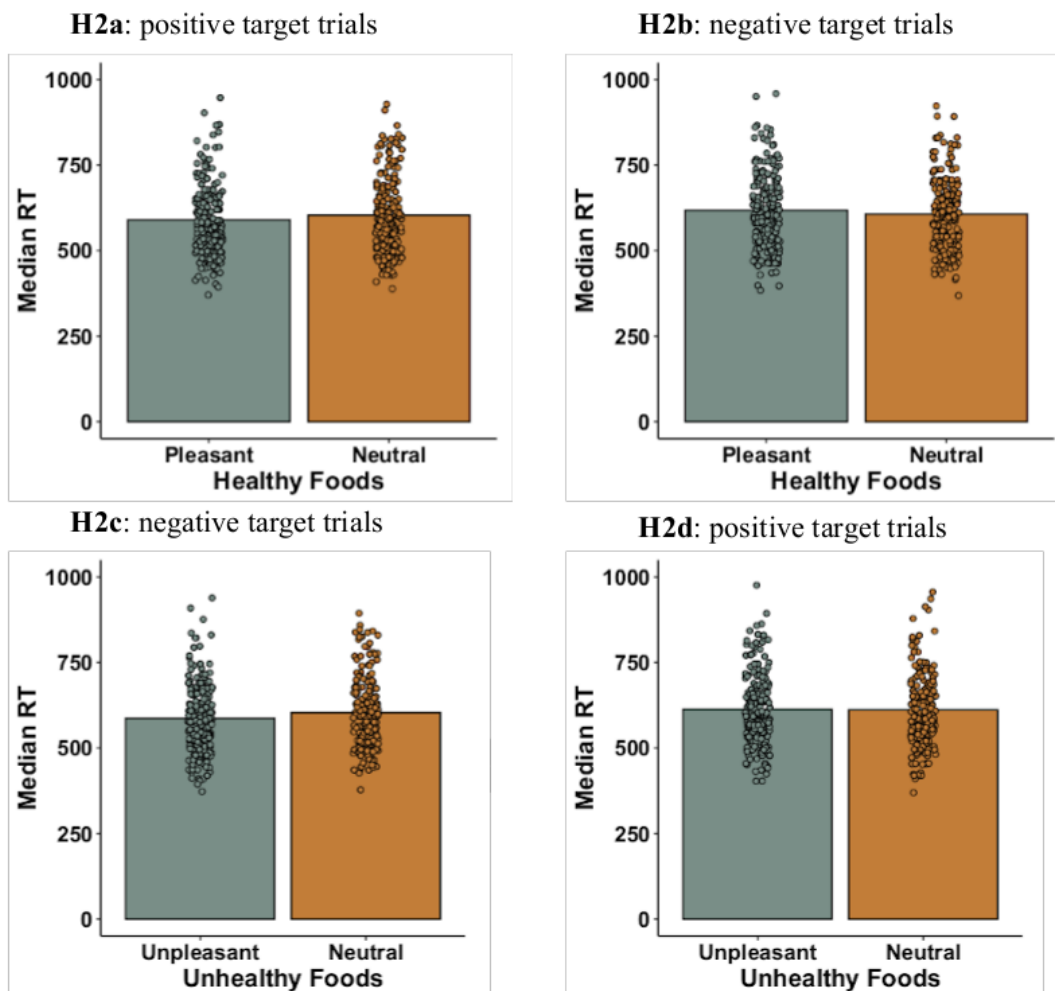


Figure 5.6: Median RT and individual data points based on food type, stimulus pairing, and trial type using the APP. Analyses revealed anecdotal to strong evidence against the effect of EC on implicit food liking.

Exploratory analyses

Baseline liking

There was no significant difference in baseline liking of healthy foods paired with pleasant stimuli ($M = 114.8$, $SE = 2.32$) compared with healthy foods paired with neutral stimuli ($M = 118.7$, $SE = 2.67$; $B_{JZS} = 0.36$, $t(199) = -1.77$, $p = 0.08$, $dz = 0.13$). There was also no significant difference in baseline liking of unhealthy foods paired with unpleasant stimuli ($M = 130.7$, $SE = 2.55$) compared with unhealthy foods paired with neutral stimuli ($M = 131.6$, $SE = 2.25$; $B_{JZS} = 0.09$, $t(199) = -0.52$, $p = 0.6$, $dz = -0.04$).

Order effects

To investigate whether the order in which participants completed the outcome measures influenced the efficacy of the training, data was split by those who completed the explicit liking measure first and those who completed the implicit liking measure first.

Effect of EC on explicit liking of healthy foods (H1a)

For participants who completed the implicit liking measure first, there was no significant difference between liking of healthy foods paired with pleasant stimuli compared to those paired with neutral stimuli ($B_{JZS} = 0.12$, $t(99) = 0.07$, $p = 0.47$, $dz = 0.01$). As seen in the primary analyses there was a reduction in liking of the pleasant paired healthy foods ($M = -2.51$, $SE = 2.36$) and the neutral paired healthy foods ($M = -2.69$, $SE = 2.31$). However, participants who completed the explicit liking measure first showed an increase in both healthy foods paired with pleasant stimuli ($M = 1.12$, $SE = 1.5$), and those paired with neutral stim ($M = 0.52$, $SE = 1.28$), though this difference was not significant ($B_{JZS} = 0.16$, $t(99) = 0.4$, $p = 0.35$, $dz = 0.04$) and in both cases provides moderate evidence for H0.

Effect of EC on explicit liking of unhealthy foods (H1b)

Regardless of the order in which participants completed the liking measures, an overall decrease in liking of unhealthy foods was observed. There was no significant difference in explicit liking of unhealthy foods paired with unpleasant stimuli compared to neutral

stimuli from pre to post training for participants who completed the implicit liking measure first ($B_{JZS} = 0.06$, $t(99) = 0.86$, $p = 0.8$, $dz = 0.09$), or those who completed the explicit liking measure first ($B_{JZS} = 0.05$, $t(99) = 1.6$, $p = 0.94$, $dz = 0.16$), providing strong evidence for H0 in both analyses.

Effect of EC on implicit liking of healthy foods (H2a & H2b)

Participants who completed the implicit liking measure first displayed significantly quicker RTs for healthy foods that had been paired with pleasant stimuli in positive target trials ($B_{JZS} = 6.81$, $t(99) = -2.7$, $p = 0.004$, $dz = -0.27$) providing moderate evidence for H1 however this difference was not observed in participants who completed the explicit liking measure first ($B_{JZS} = 0.13$, $t(99) = -0.17$, $p = 0.44$, $dz = -0.02$). For the presentation of healthy foods in negative target trials there was no significant difference in RTs for those who completed the implicit measure first ($B_{JZS} = 0.32$, $t(99) = 1.04$, $p = 0.15$, $dz = 0.1$), or those who completed the explicit measure first ($B_{JZS} = 0.6$, $t(99) = 1.5$, $p = 0.07$, $dz = 0.15$), indicating moderate and anecdotal evidence for H0 respectively.

Effect of EC on implicit liking of unhealthy foods (H2c & H2d)

Further differences were observed in the RTs for unhealthy foods. In negative target trials, RTs for foods that had been paired with unpleasant stimuli ($M = 592$, $SE = 10.24$) were significantly quicker than those paired with neutral stimuli ($M = 612$, $SE = 10.13$) in participants who completed the implicit measure first ($B_{JZS} = 6.39$, $t(99) = -2.68$, $p = 0.004$, $dz = -0.27$). This difference was not observed in participants who completed the explicit task first ($B_{JZS} = 0.77$, $t(99) = -1.65$, $p = 0.05$, $dz = -0.16$) suggesting that the difference observed in the primary analyses was driven by only one group. In contrast, in positive target trials there was no difference in RTs for foods that had been paired with unpleasant compared to neutral stimuli in participants who completed the implicit measure first ($B_{JZS} = 0.04$, $t(99) = -1.66$, $p = 0.95$, $dz = -0.17$). However, there was a significant difference in the explicit first group, with quicker RTs for foods that had been paired with neutral stimuli ($M = 596$, $SE = 9.81$) than those paired with unpleasant stimuli ($M = 613$, $SE = 11.53$; $B_{JZS} = 2.52$, $t(99) = 2.27$, $p = 0.01$, $dz = 0.23$).

Positivity bias

As in Experiment 1, additional exploratory analyses were conducted to investigate the potential effects of EC on the positivity bias. Bias scores were calculated for median RT, percentage errors and inverse efficiency (see exploratory analyses of Experiment 1 for details). For healthy foods we found moderate evidence of conditioning on median RTs ($B_{JZS} = 5.84$, $t(199) = 2.73$, $p = 0.003$, $dz = 0.19$) and inverse efficiency ($B_{JZS} = 5.46$, $t(199) = 2.71$, $p = 0.004$, $dz = 0.19$) suggesting that the pairing healthy foods with pleasant stimuli made them more positive. Analysis of percentage errors found moderate evidence for H0 suggesting that conditioning did not influence error rates ($B_{JZS} = 0.05$, $t(199) = -0.54$, $p = 0.71$, $dz = -0.04$).

For unhealthy foods there was anecdotal evidence of conditioning on median RT ($B_{JZS} = 2.11$, $t(199) = -2.31$, $p = 0.01$, $dz = -0.16$) and inverse efficiency ($B_{JZS} = 1.93$, $t(199) = -2.27$, $p = 0.01$, $dz = -0.16$). Similarly to the healthy foods, analysis of percentage errors indicated moderate evidence for H0 ($B_{JZS} = 0.06$, $t(199) = 0.3$, $p = 0.62$, $dz = 0.02$).

5.3.4 Discussion

As in Experiment 1, we failed to support previous research findings and found no evidence for an effect of evaluative conditioning on explicit liking for healthy or unhealthy foods (Dwyer et al., 2007; Lascelles et al., 2003). However the results for implicit liking were less clear. Although analyses for H2a, H2b and H2d all provided evidence for H0, there was strong evidence for H2c with faster reaction times in negative target trials for unhealthy foods paired with unpleasant stimuli compared to unhealthy foods paired with neutral stimuli, consistent with research showing an increase in negative attitudes following EC (Lebens et al., 2011). Exploratory analyses also indicated that the order in which outcome measures are completed may have an effect on the results observed. While participants who completed the explicit measure first showed an overall increase in explicit liking of healthy foods, those who completed the implicit measure first showed an overall decrease in explicit liking of healthy foods. Further differences were found for implicit liking. The implications of the findings are further considered in the General Discussion.

5.4 General Discussion (Chapter 5 only)

The aim of these experiments was to investigate whether EC could increase implicit and explicit liking of healthy foods, and decrease implicit and explicit liking of unhealthy foods. Contrary to our hypotheses and previous literature demonstrating these effects (Dwyer et al., 2007; Hensels & Baines, 2016; Lascelles et al., 2003; Lebens et al., 2011), across two experiments we found no effect of EC on explicit liking (H1), and only some indication of an effect on implicit liking (H2). In Experiment 1 all analyses for H2 indicated anecdotal to strong evidence for H0, while in Experiment 2, analyses for H2a, H2b and H2d revealed anecdotal to moderate evidence for H0. However there was strong evidence for faster RTs in negative target trials for unhealthy foods paired with unpleasant stimuli in comparison to neutral stimuli (H2c).

In both experiments we also conducted exploratory analyses on the positivity bias. Analyses of median reaction time and inverse efficiency for healthy foods revealed no effect of conditioning on the positivity bias in Experiment 1, but moderate evidence in Experiment 2. Analyses of median RTs and inverse efficiency for unhealthy foods similarly revealed no evidence in Experiment 1, but anecdotal evidence in Experiment 2. None of the analyses on error rates in showed any evidence for the positivity bias.

In Experiment 2 we also investigated the potential role of order effects on our findings and found that while participants who completed the implicit task first showed a decrease in explicit liking of healthy foods, those who completed the explicit task first showed an increase in explicit liking of healthy foods. Although the APP has been shown to be a reliable measure of implicit attitudes towards foods (Tzavella et al., 2020), it is possible that its use directly before an explicit measure of food liking may have indirectly altered these food evaluations. On the other hand, if this were the case, we would have expected to observe similar findings in Experiment 1 where all participants completed the explicit task first, but an overall reduction in liking of healthy foods was observed.

Analyses investigating the role of order effects on implicit liking were less clear. There was moderate evidence for H2a - which predicted faster RTs in positive target trials for healthy foods paired with pleasant stimuli - in participants who completed the implicit measure first, but moderate evidence for H0 in those who completed the explicit measure first. There was no reliable difference between groups for H2b which predicted slower RTs

in negative target trials for healthy foods paired with pleasant stimuli. For H2c, which predicted faster RTs in negative target trials for unhealthy foods paired with unpleasant stimuli, there was moderate evidence in the subgroup who completed the implicit measure first, but anecdotal evidence for H0 in the subgroup who completed the explicit measure first. Finally for H2d, which predicted slower RTs in positive target trials for unhealthy foods paired with unpleasant stimuli, there was anecdotal evidence in participants who completed the explicit measure first but strong evidence for H0 in those who completed the implicit measure first. While these results do not point to a clear mechanism or explanation as to why these results were observed, they do highlight the importance for the consideration of order effects in research that utilises more than one outcome measure.

While our lack of overall evidence for an effect of EC on either explicit or implicit liking is inconsistent with existing literature, it could be explained by the conditioned stimuli that were used. In a meta-analysis Hofmann et al. (2010) explored the role of moderators in EC studies to investigate whether the effects are dependent upon procedural characteristics, one of which was conditioned stimulus selection. While they found that results did not differ depending on whether conditioned stimuli had been assigned at a group level or selected individually based on preferences, critically, the stimuli needed to be evaluated as neutral in order to observe an effect. In both of the current experiments, participants rated baseline liking on a 200-point VAS where 100 would have indicated a neutral point on the scale. Mean liking for healthy foods was 116 and 117 for Experiment 1 and 2, respectively, and for unhealthy foods was 131 in both experiments, making the foods relatively neutral. However further exploration revealed that the range in ratings for healthy foods was 167 (min = 20, max = 186) in Experiment 1 and 155 in in Experiment 2 (min = 22, max = 177). Similarly the range for unhealthy foods was 149 (min = 50, max = 199) in Experiment 1 and 172 (min = 22, max = 194) in Experiment 2. Despite the evidence from Hofmann et al. (2010), future research may still benefit from personalising stimuli to take into account the importance of individual preferences.

The importance of personalisation in unconditioned stimulus selection was also investigated in the same meta-analysis and revealed that the effects of EC are greater when the unconditioned stimuli have been personalised to participants based on their preferences. This is likely due to individual differences in what we perceive as pleasant and unpleasant;

our likes and dislikes are extremely individual and though the unconditioned stimuli we used were selected based on pilot data for both experiments, we cannot assume that they had the desired effect across all participants. However, just how pleasant and aversive stimuli need to be is unclear. Significant effects of evaluative conditioning on implicit liking of healthy food have been observed after healthy foods are paired with a happy face (Hensels & Baines, 2016). While a happy face may not receive a consistently high rating of pleasantness, it could be argued that the pairings of healthy foods with happy faces (and unhealthy foods with angry faces) simplified the pairings and might have made the relationship between the conditioned and unconditioned stimuli clearer to participants.

There is evidence to suggest that the effects of EC can be enhanced if participants are aware of the stimulus pairings (Hofmann et al., 2010). Some research has even found that the effects can only occur when participants are able to verbalise the contingency (Purkis & Lipp, 2001). However, the literature surrounding the importance of contingency awareness in EC is mixed. In addition to the evidence suggesting contingency awareness will enhance the effects, some evidence has claimed that the awareness can actually interfere (Field, 2000; Jones et al., 2010). There is also evidence suggesting that awareness of the stimulus pairings is unrelated to the effect of EC (Jones et al., 2010) which is in line with some evidence investigating the role of EC in food preferences specifically, with claims that awareness did not moderate the effect of EC (Hensels & Baines, 2016; Walsh & Kiviniemi, 2014). We did not test for awareness of stimulus pairings in either experiment but future studies may benefit from directly measuring and also manipulating contingency awareness to better understand its role in the EC effect.

Across 2 experiments we investigated the effect of an EC task on implicit and explicit food liking. Our findings do not support previous evidence for the role of EC in changing food preferences, but future research may benefit from giving more consideration to both the conditioned and unconditioned stimuli used in experiments, as well as collecting participant feedback. EC has shown promise for making changes to behaviour (Hollands et al., 2011; Shaw et al., 2016; Tello et al., 2018), and furthermore such effects may be resistant to extinction (De Houwer et al., 2001) highlighting their potential for long-term behaviour change.

Chapter 6

General Discussion

The aim of this thesis was to investigate the potential role of both non-invasive brain stimulation and cognitive control training in modifying automatic responses to food cues. Chapter 2 investigated the role of tDCS when administered alongside inhibition training in reducing food consumption and food craving, while Chapter 3 used HD-tDCS alongside the same training with the aim of reducing food craving and desire to eat. Chapters 4 and 5 focussed on the role of behavioural training in targeting these behaviours. Chapter 4 sought to combine elements of 3 different types of behavioural training to develop a novel task with the goal of modifying the value of food as measured using explicit and implicit food liking, while Chapter 5 looked to achieve the same effects using an EC paradigm. This chapter will provide a summary of the key findings in this thesis, and critically evaluate the use of neuromodulation and behavioural training in changing dietary related behaviours. General directions and considerations for future research in this field will also be outlined.

6.1 The role of brain stimulation in behaviour change

6.1.1 Summary of findings

Chapters 2 and 3 explored the potential role of non-invasive brain stimulation in modifying food-related behaviours following cue-induced craving when used alongside response inhibition training. We found no evidence to suggest that tDCS can be used to reduce food craving, food consumption or desire to eat.

Chapter 2 sought to replicate findings that had demonstrated an effect of tDCS on either food craving or food consumption (Fregni et al., 2008; Goldman et al., 2011; Lapenta et al., 2014) using a larger-than-typical sample size while also pre-registering hypotheses and analysis plans. We hoped to also extend upon these findings by combining the stimulation with a food-related inhibition training task. In a between-subjects design, participants received either active or sham stimulation for 20 minutes and the effects on state food craving and ad-libitum food consumption were measured. We found no evidence for an effect of active tDCS on reducing either food craving or consumption. Exploratory analyses did reveal evidence of learning in the training task; participants were faster at responding to healthy foods compared to filler images in go trials and more successful at inhibiting to unhealthy foods compared to filler images, providing strong and very strong evidence respectively for an effect of training.

In Chapter 3 several changes were made to the study design, most notably the stimulation. Though there was evidence that conventional tDCS could reduce food-related behaviours, concerns had been raised regarding the focality of the technique. As a result we used HD-tDCS to investigate whether a more focal technique with similar parameters (the intensity had to be reduced from 2mA to 1.5mA to address participant discomfort) would allow us to replicate previous findings. In a within-subjects design participants received both active and sham stimulation across two separate sessions at least one week apart. In both sessions participants completed a measure of state food craving before and after stimulation as in Chapter 2. Participants also completed a measure of desire to eat before and after stimulation in which they ate 6 different foods and were asked to rate their desire to continue eating each food. We also included a measure of trait craving to investigate whether the effects of stimulation on food-related behaviours are specific to high food cravers.

The findings of Chapter 3 once again revealed no significant effect of stimulation on reducing food craving or desire to eat the foods used in the training task. Exploratory analyses using trait craving as a moderator did not affect the primary findings. Consistent with Chapter 2, we found evidence of learning in the training task; participants were faster at responding to healthy foods and were more successful at stopping to unhealthy foods in comparison to filler images (moderate evidence for both findings).

6.1.2 Limitations and future directions

Despite the conflicting research that has been produced from the tDCS and food literature, the interest in using the technique in an attempt to modify food-related behaviours is still evident. However recent research, published since the studies conducted in Chapters 2 and 3, has still produced contradictory evidence for the use of the technique in this research area. While some research has failed to replicate previously observed effects (Beaumont et al., 2021; Stevens et al., 2021), other findings have been mixed (Amo Usanos et al., 2020).

In a sample of overweight and obese participants, Amo Usanos et al. (2020) examined the effect of a 4 week intervention on food craving, desire to eat, and body weight. Participants received a total of 8 stimulation sessions in the first 2 weeks of the intervention, and were also prescribed a calorie-controlled diet from weeks 2-4. Although participants who had received active stimulation demonstrated a larger reduction in body weight compared to those receiving sham stimulation, the remaining results were less conclusive. There was no significant effect of tDCS on food craving, but there was a reduction in desire to eat following sham stimulation. Similarly, two later studies also failed to find an effect on food craving (Beaumont et al., 2021; Stevens et al., 2021). Also using a sample of overweight and obese participants, Stevens et al. (2021) failed to find an effect of stimulation on food craving or food consumption. Similarly, Beaumont et al. (2021) found moderate evidence against the effects of tDCS on food craving, and also anecdotal evidence against the effects on implicit and explicit food reward. The authors included this measure due to the neural differences that are often observed between normal weight and obese participants in studies investigating the reward value of food, stating the importance of looking beyond the typical measures of craving used, however no significant effects were observed.

As detailed in the discussion of Chapters 2 and 3, there is evidence to suggest that the effects of tDCS may be trait dependent. For example, as noted previously, the majority of studies showing an effect of tDCS within the food domain have recruited participants exhibiting some form of trait susceptibility to overconsume food (Burgess et al., 2016; Fregni et al., 2008; Goldman et al., 2011; Lapenta et al., 2014; Ljubisavljevic et al., 2016). For example, Burgess et al. (2016) found a significant effect of tDCS on obese participants who met the diagnostic criteria for binge eating disorder with participants exhibiting a

decrease in both state craving and food consumption following stimulation. However a later study by the same group failed to replicate these findings in an obese sample who did not meet the criteria for binge eating (Ray et al., 2017). While attempts were made to include measures of trait characteristics such as dietary restraint (Chapter 2) and trait craving (Chapter 3) in this thesis, the populations we recruited from were not targeted for these traits, and as a result instances were low.

Experiments have now started to include trait measures to examine whether the effects of tDCS can only be observed in those with these characteristics. Beaumont et al. (2021) and Stevens et al. (2021) both carried out additional analyses while controlling for behaviour trait scores though neither found a moderating effect. However it should be noted that the sample used in Beaumont et al. (2021) displayed normal trait profiles with no participants meeting the cut-off score for trait craving and Stevens et al. (2021) did not report whether participants in their study met the criteria for their measure of subthreshold binge eating disorder. Amo Usanos et al. (2020) also included a measure of trait craving in their study however they did not control for this measure in any analyses and did not report the number of participants who met the cut-off score for trait craving.

It seems reasonable to suggest that potentiating activity in the DLPFC may not elicit any changes in healthy participants or those who do not exhibit hypo-activity in this region. While differences in DLPFC activity have been observed in normal weight individuals compared to those with obesity (Alonso-Alonso & Pascual-Leone, 2007; Brooks et al., 2013a; Brooks et al., 2013b), it would be interesting to understand how trait characteristics affect these neural differences.

Future research may also benefit from considerations of outcome measures in tDCS research. The majority of studies have used food craving and desire to eat to measure the efficacy of food stimulation, but to our knowledge, the effect of tDCS on food choice has not been examined. Researchers developing behavioural training aimed at changing dietary behaviours have stated that while training may not be sufficient to change preferences, its role in food choice could be as useful in an environment where these choices are so ubiquitous (Zoltak et al., 2017). It is possible that the same could be true of tDCS. Evidence from increased activity of the DLPFC has been linked to self-regulation in the form of food choice (Hare et al., 2009) and dietary success (Weygandt et al., 2013), nei-

ther of which are reliant on food preferences. Therefore exploration of its role in eating related decision making may be more successful, and particularly useful in the obesogenic environment.

6.2 The role of behavioural training in behaviour change

6.2.1 Summary of findings

In Chapter 4 a novel training task was developed to investigate whether combining elements of GNG, CAT and EC could change explicit and implicit liking. This study was originally designed to incorporate a training element of the AAT however due to the COVID-19 pandemic and the move to online data collection, the programmed experiment needed several modifications to allow us to successfully run it online (including the removal of a stimulus personalisation feature).

Analyses revealed no effect of the training task on either explicit or implicit liking, with moderate to strong evidence for H0. Exploratory analyses investigated whether the stimuli used or the order in which participants had completed the outcome measures influenced the results. We found no stimuli-specific effects, and only one significant finding based on the order of outcome measures. Participants who completed the implicit measure first displayed faster RTs for healthy untrained foods in negative trials than healthy trained foods providing moderate evidence for H2b. When this data was re-analysed to also incorporate the stimuli used, there was strong evidence for H2b in participants who had completed the implicit measure first but only with neutral foods. Once again we found evidence of learning from the training task. Analyses indicated strong evidence for the effect of learning for healthy foods with faster RTs on go-trials for healthy foods compared to filler images. We also found extreme evidence for the effect of learning on unhealthy foods, with participants more successful as inhibiting to unhealthy foods compared to filler images.

In Chapter 5, the role of EC on implicit and explicit food liking was explored across two experiments. In Experiment 1, participants completed an EC task in which healthy

foods were paired with pleasant stimuli and unhealthy foods were paired with unpleasant stimuli with the aim of increasing and decreasing liking respectively. In Experiment 2, the same task was used in an online setting with changes to the conditioned stimuli to address issues with baseline liking observed in Experiment 1. In both experiments we found anecdotal to very strong evidence for H0 across all primary hypotheses. Order effects were also explored in Experiment 2. No order effects were found for explicit liking with analyses providing moderate to strong evidence for H0. However the findings for implicit liking were less clear. Participants who completed the implicit measure first had faster RTs for healthy foods that had been paired with pleasant stimuli for the positive target trials (moderate evidence) and faster RTs for unhealthy foods that had been paired with unpleasant stimuli in negative target trials. Finally, participants who completed the explicit measure first exhibited faster RTs for unhealthy foods that had been paired with neutral stimuli in positive target trials compared to foods paired with unpleasant stimuli.

This thesis found little evidence to suggest that either of the behavioural training tasks used could increase liking of healthy foods or decrease liking of unhealthy foods, unless additional considerations were taken into account such as the order in which outcome measures are completed. The only consistent finding came from the use of GNG training in Chapters 2, 3 and 4, which across all three experiments showed a consistent effect on learning. It seems that while participants learn the associations between stimuli and responses, this learning does not translate into attitudes towards the foods.

6.2.2 Limitations and future directions

Task parameters

The behavioural tasks used across all four chapters assessed the effects of single-session protocols on immediate behaviour change in either a laboratory or online setting. While learning may occur after a single-session protocol, translations to behaviour change may be dependent on factors such as duration of training, number of training session, and validity of behavioural measurements. As the ultimate goal in using these training tasks is to make long-term behaviour change, it is important to consider the role of task parameters such as single versus multi-session effects on real-world, as well as lab-based behaviour.

Laboratory measures of eating behaviour such as ad-libitum food consumption and

self-serving of food have been used to measure the efficacy of food-specific ICT (Adams et al., 2017; Blackburne et al., 2016; Folkvord et al., 2016; Houben, 2011; Houben & Jansen, 2015; van Koningsbruggen et al., 2014; Lawrence et al., 2015a; Lawrence et al., 2015b). Despite meta-analyses reporting that training can significantly influence eating behaviour (Allom et al., 2015; Jones et al., 2016), it is important to assess whether these training effects apply to real-world behaviour change, and if so, how long the effects may last.

Behaviour change in real-world settings tends to be based on changes in body weight and self-reported eating consumption. For example Veling et al. (2014) assessed the effect of a four-week GNG intervention on body weight in a group of normal-weight participants and found a significant reduction in the training group compared to a control group. The findings were replicated in an overweight and obese sample who exhibited a reduction in self-reported weight and self-reported food intake following one week of training (Lawrence et al., 2015a). Crucially, these effects persisted for up to 6 months. Further long-term effects of GNG training have been observed in multi-session protocols (Aulbach et al., 2021; Blackburne et al., 2016). While Blackburne et al. (2016) found no effect of training on ad-libitum food intake in the laboratory, participants reported a significant increase in healthy food consumption at follow-up. Similarly, in a recent study participants could choose how frequently they completed their training (Aulbach et al., 2021). Follow-up between 30 and 90 days after initial baseline measures had been collected revealed a positive relationship between frequency of training and behaviour change. Participants who completed more training sessions showed a reduced intake of unhealthy foods, and an increased intake of healthy foods. These findings suggest that there is potential for long-term effects of food-specific ICT on real-world behaviour change, though it should be noted that most studies have relied on self-report measurements. It is possible that effects observed are due to demand characteristics if participants are aware of study aims.

As a relatively new training task, studies using CAT have assessed the immediate effects of training on food choice in laboratory settings (Bakkour et al., 2016; Veling et al., 2017a; Zoltak et al., 2017), and to our knowledge, the effects of CAT on real-world behaviour change is yet to be explored. However the training does show promise for long-term maintenance of the effects. For example, Schonberg et al. (2014) invited participants back to the lab between 1 and 2 months after a single training session to complete the

binary choice task again and revealed that the preference for go stimuli was still evident. Bakkour et al. (2018) also found the effects of CAT were still present 1 month after training, however this was enhanced when training had been spaced over two days. While the effects of multi-session protocols are yet to be investigated, these findings along with the potential for CAT to be used to increase choices for healthy foods shows promise for behaviour change in real-world settings.

Similarly to CAT, to our knowledge, no studies have used EC to explore long-term effects or the influence on real-world behaviour. Studies that have used EC have explored the effects on immediate measures of food preference (Hensels & Baines, 2016; Hollands et al., 2011; Lascelles et al., 2003; Lebens et al., 2011; Shaw et al., 2016; Walsh & Kiviniemi, 2014). Future research would benefit from exploring whether changes in food preference last beyond the day of exposure, and whether multi-session protocols using the same stimulus-pairings could influence food choice.

Personalisation of stimuli

When designing these behavioural tasks, consideration should be given to the importance of personalisation. Despite plans to personalise stimuli based on individual preferences in Chapter 4, due to programming constraints we were unable to implement this element of the design. When focusing specifically on reducing the liking of unhealthy foods it is important to consider that not all unhealthy food stimuli will elicit an attentional or approach bias. Therefore training an individual to avoid or not respond to a food that does not elicit a reward response is unlikely to influence behaviour (Forman et al., 2018; Jones et al., 2018).

Some studies have addressed this issue by recruiting specific samples. For example many studies have specifically recruited chocolate cravers (Houben & Jansen, 2015) or checked baseline liking of chocolate (Schumacher et al., 2016) before assessing the effects of training on chocolate consumption specifically. CAT also selects stimuli in the task based on an initial measure of value (e.g. Veling et al., 2017). However the importance of personalisation still requires more exploration. In a recent study assessing the effects of GNG training, Aulbach et al. (2021) found no difference in food intake for those who had personalised their stimuli compared to those who had not. However they did report that

the use of personalisation led to increased engagement with the training task. Personalising stimuli may enhance attention to the training task which could then translate into improved adherence (Forman et al., 2018).

Target population

A common problem in psychological research is the over reliance on convenience sampling, which means samples are often drawn from WEIRD (Western, Educated, Industrialised, Rich, Democratic), undergraduate populations (Henrich et al., 2010). Though an attempt was made in Chapters 2 and 3 to recruit beyond the student population, the majority of participants in these studies were undergraduate students, many of whom were also studying psychology. Although we did assess for whether participants had guessed the aims of the two studies, this is still something that requires further attention as psychology students are likely to become familiar with many of the paradigms that are used in our research. In Chapter 4 and Experiment 2 of Chapter 5 we recruited an online sample to bring in a more diverse sample. However demographic details reveal the age, average BMI, and ethnicity was very similar to our lab-based studies. When designing research studies, it is important to keep in mind which population is being targeted. It is a common problem that inferences are drawn despite target populations rarely being tested (Simmons & DeVile, 2017).

While some studies using ICT have screened for specific traits (Adams et al., 2017) or specifically recruited based on weight (Blackburne et al., 2016; Lawrence et al., 2015a), many studies have tested the effects in normal-weight participants, often consisting of university students (van Koningsbruggen et al., 2014; Lawrence et al., 2015b; Veling et al., 2011; Veling et al., 2013a; Veling et al., 2014). Furthermore, studies investigating the effects of CAT and EC have also only investigated the effects in healthy participants. If we are not targeting individuals who have strong approach or attentional biases, or those with deficits in inhibitory control, we may be unlikely to see any additive effects of training. For example, research has indicated that the SST was only effective in those with poor inhibitory control (Houben, 2011). While it is often necessary to test the feasibility of new tasks in a convenient sample, if this type of sampling continues, making assumptions about the applicability of training becomes difficult.

This lack of diversity is also problematic when generalising findings to difference ethnic or racial groups which are rarely reported in psychological research (DeJesus et al., 2019). In this thesis ethnicity was only recorded in Chapter 4 and Chapter 5, and data revealed that over 80% of participants were white. This is an issue across all domains in psychology, but particularly in cognitive psychology. A recent study analysing 50 years worth of publications found that there have been almost no publications in cognitive psychology that highlighted race (Roberts et al., 2020), despite evidence that cognitive processes can vary based on factors such as racial diversity (see Roberts et al., 2020 for an overview). Based on evidence that shows variation in levels of obesity between different racial (CDC, 2020) and ethnic groups (Liu et al., 2021), it is imperative that research not only records all demographic information, but that attempts are made to recruit a diverse population. We can not continue to conduct psychological research on the assumption that it is a one size fits all approach when we have sufficient evidence to suggest otherwise.

Targeting the reflective system

The experiments in this thesis focused specifically on interventions that aim to change associations that underlie impulsive processes. However research has suggested that as problematic health behaviours are caused by the interplay between two systems, interventions that aim to improve the capacity of reflective processes may also be beneficial (Hofmann et al., 2008).

Implementation intentions, or if-then planning have been shown to facilitate health behaviour predominantly by increasing consumption of healthy foods, though attempts to reduce unhealthy food behaviours have also been made (see Adriaanse et al., 2011 for a review). Implementation intentions pair intentions with specific plans for achieving individual goals, while also taking into account situational cues (Gollwitzer, 2014). For example, an implementation intention to reduce consumption of chocolate would specify a situation where chocolate consumption could occur (e.g. “If someone offers me chocolate”), with a specific goal-directed action to prevent this (e.g. “I will eat something healthier”). This training addresses the conflict between behavioural schema generated by the impulsive system, and the goals of the reflective system.

In addition to assessing the effects of ICT on body weight, Veling et al. (2014) also

investigated the potential efficacy of implementation intentions. Participants were instructed to make an intention specific to their dieting goals (e.g. “if I am tempted by an unhealthy food, I will think of my diet”). They found that simply being reminded of dieting led to a reduction in weight that was mediated by the strength of the diet goal; a greater facilitation in weight loss was observed in participants with stronger goals.

A recent systematic review and meta-analysis examined 23 studies that had used implementation intentions to modify dietary behaviour (Adriaanse et al., 2011). A small effect on reducing the consumption of unhealthy foods was reported, along with a medium effect on encouraging the consumption of healthy foods, with research findings indicating that the intervention can be used to increase fruit and vegetable consumption in both the short- and long-term . This is supported by evidence that introducing healthy behaviours is easier than reducing unhealthy behaviours (Holland et al., 2006). Further research has found that diet reminders can also increase healthy food choices (Papies & Veling, 2013). Diet reminders were incorporated into menus in a restaurant and were found to significantly influence choice for healthy foods in those who were dieting.

While implementation intentions show promise when used in isolation, it has been suggested that interventions targeting both the impulsive and reflective system may be even more beneficial in determining health behaviour (Friese et al., 2011). As effects are stronger in changing healthy behaviours, combining implementation intentions along with CAT with a focus on cueing participants towards healthy foods could further enhance the effects.

The role of interoception

Alternative methods of dietary behaviour change have focused on the importance of interoceptive sensitivity. Interoception refers to the ability to perceive the physiological state of the body, and it has been suggested that a predisposition to overconsumption of food may be caused by a reduced interoceptive awareness (Simmons & DeVille, 2017). Measures of interoception in the laboratory often use heartbeat perception to determine awareness. Herbert and Pollatos (2014) asked participants to relay the number of heartbeats they had counted to assess sensitivity and found a reduction of interoceptive awareness in overweight and obese participants when compared to normal weight participants and posited

that this reduction could transfer to sensitivity to hunger and satiety signals. Research has suggested that an increase in body weight may be associated with a hypersensitivity to hunger signals, and a hyposensitivity to satiety signals (Simmons & DeVille, 2017). This has been further supported by research showing that interoceptive sensitivity negatively predicted BMI (Herbert et al., 2013). Moreover, interoceptive sensitivity was also positively related to intuitive eating, which is dependent upon the ability to recognise physiological cues of hunger and satiety.

Intuitive eating has become an increasingly popular alternative to dieting as it encourages food consumption based on bodily sensations. It has been argued that all humans are born with a mechanism that allows for the determination of sufficient food intake, but that this innate ability is often overcome by alternative factors such as social influence, emotion, and various other cues (Herbert et al., 2013). While the link between weight and interoceptive awareness is unclear, it could be that consumption of ultra-processed and energy dense foods has led to a reduction in awareness. However, training individuals to become more attuned to their physiology may allow for consumption based on hunger and satiety which is likely to reduce the likelihood of overindulgence (Birch et al., 2003).

6.3 Barriers for behaviour change

While behavioural training via both the impulsive and reflective systems, as well as brain stimulation show promise in changing behaviour such as food choice, they are entirely dependent upon the ability to make these changes. Potential barriers to behaviour change such as access to foods need to be considered to ensure that changes in lab-based behaviour are possible in different environments.

In the UK, over 8 million people are affected by food insecurity (Taylor & Loopstra, 2016) defined by the paucity of nutritionally dense foods. Food insecurity has been associated with both poor diet quality (Keenan et al., 2021) and obesity (Franklin et al., 2012; Nettle et al., 2017). Individuals with the highest consumption rates of ultra-processed foods are most likely to live in deprived areas and experience food insecurity (Rauber et al., 2021), and the highest rates of obesity are among those with the most severe insecurity (see Franklin et al., 2012 for a review). Furthermore, food inequity means that

the poorest 10% of UK households would need to spend 74% of their disposable income on food to meet current guidelines (Broken Plate, 2020). Recent research has also identified that cost is the biggest factor in determining food choice, with many individuals claiming that the ability to afford food is a continuous issue (Puddephatt et al., 2020). Furthermore, calorie for calorie, ultra-processed foods can cost a third of the price of healthier alternatives (Broken Plate, 2021). As a result food choices are often made based on affordability rather than factors relating to health or nutrition.

While discovering mechanisms that may be able to influence dietary behaviour such as food choice is important, it is vital to remember the population for whom we are designing these interventions. Even if behavioural training or neuromodulation can successfully influence deficient cognitive mechanisms and influence food choice, those in most need of changes to their diet may not have the capacity to make the changes necessary. Interventions that aim to facilitate healthier behaviours need to take these factors into consideration and strive for more tailored approaches to behaviour change.

6.4 Open science

Throughout this thesis I have critically evaluated the findings from both neuromodulation and cognitive control training studies. Despite the literature suggesting a role of both methods in modifying automatic associations to food cues, the evidence is often (though not always) from underpowered studies with small effects and mixed results. As discussed in Chapter 1, we are currently facing a reproducibility crisis in psychology where positive findings are unable to be replicated. My own research has produced predominantly null findings across a series of highly powered studies; I have found evidence against the effects of tDCS and behavioural training on implicit and explicit measures of food liking, food craving and food consumption, with positive effects only revealed during exploratory analyses.

Open research practices offer a solution for this problem (Munafò et al., 2017) and were implemented throughout this thesis. All hypotheses, methods and analyses were pre-planned prior to data collection, and following study completion all materials were shared on the Open Science Framework. Additionally, power analyses were calculated for

all experiments to ensure samples were adequate to detect a true effect. While there are concerns regarding the feasibility of open research practices, particularly for early career researchers (Allen & Mehler, 2019; Maizey & Tzavella, 2019), I believe that study preregistration should be carried out as a minimum for all future research. Clear aims, methods and analysis plans should be declared before data collection, along with justification for sample size. Throughout my PhD I have experienced the benefits of these practices not only in my own research, but also when working with undergraduate students who benefited from the careful planning of their research. Several institutions are now paving the way by introducing undergraduate students to open research practices via mandatory study preregistration for dissertation projects as well as consortium projects, both of which are teaching students the importance of scientific rigour. While this is promising, more work needs to be done to promote and encourage the adoption of these practices in order to benefit future research.

6.5 Conclusion

The aim of this thesis was to investigate the role of neuromodulation and cognitive control training on changing drivers of food consumption such as liking, craving, and desire to eat, as well as food consumption itself. Across two studies I found no evidence for an effect of conventional or HD-tDCS in modifying food craving, desire to eat, or food consumption when used alongside inhibition training. Findings from mine and other studies indicate that neuromodulation may only be additive in those who display dysregulation of prefrontal activity, as determined by trait characteristics. Future research may also benefit from determining the difference between stimulation of the left versus the right prefrontal cortex.

Results in this thesis also found no evidence for the effect of a novel training task, or EC on implicit or explicit food liking. Despite promising findings from studies using ICT, CAT, and EC in isolation, combining elements from each task failed to influence food preferences. The importance of task parameters and sample characteristics needs to be considered in future research if these interventions are to have an impact on long-term dietary behaviours.

Appendix A

Supplementary information for Chapter 2

A.1 Bayesian stopping rule

In our pre-registered protocol we aimed to determine our sample size using a Bayesian inferential stopping rule for the main effect of total calorie intake between tDCS groups. We initially collected data for 20 participants and then planned to continue with data collection until the Bayes factor provided substantial evidence for either the experimental hypothesis (H_1 ; $B > 3$) or the null hypothesis (H_0 ; $B < 0.33$). Based on recent recommendations for early research we adjusted our threshold to achieve a Bayes factor of either > 6 (substantial evidence for H_1) or < 0.16 (substantial evidence for H_0 ; Schönbrodt et al., 2017). Using Bayesian hypothesis testing allows for a flexible stopping rule on data collection without correcting for the elevation of Type I error, as would be required under a conventional frequentist approach (Dienes, 2011, 2014).

To calculate an expected difference for total calorie intake between groups (the Bayesian prior), we used data available at the time of the pre-registered protocol. At the time, the only publication reporting an effect of tDCS on calorie consumption was Fregni et al. (2008) who showed a difference of 110 calories between sham and anodal right/ cathodal left tDCS of DLPFC¹ Following Dienes (2011) we applied a half-normal distribution with a mean value of 0 and a standard deviation that corresponded to the expected difference. For the sample mean and standard error, a between-subjects t-test was performed for the effect of tDCS condition (active or sham) on total food intake. The mean difference

¹Since publishing our pre-registered protocol, Lapenta et al. (2014) reported a reduction in calorie intake following active tDCS (anodal right/ cathodal left tDCS of DLPFC) and we are currently awaiting figures from the authors.

and standard error of the difference for this comparison were entered into Dienes' online calculator².

A.2 Participant debrief

At the end of the study, participants were asked a series of questions. To probe for awareness of the study aims, participants were asked 1) whether they were aware of the aim of the study, 2) whether they noticed anything in particular about the training task, 3) whether they thought the signals were distributed evenly, randomly or grouped, and 4) whether their performance on the training task had any influence on the questionnaires, the snack buffet, or speeded GNG task. They were then asked if they had participated in any related studies, if they were currently dieting, if they had any history of eating disorders, and at what time they last ate to allow for exclusions based on these criteria. Checks for these factors were made prior to testing but were asked again during the debrief for clarification.

A.3 Outliers and exclusions

Reason for exclusion	tDCS condition	
	Sham	Active
GNG Training		
Mean RT (> 3SDs group mean)	1	0
% no-signal errors (> 15%)	1	0
Comission errors (> 3SDs group mean)	2	3
Speeded GNG task		
Mean RT (> 3SDs group mean)	0	0
% no-signal errors (> 15%)	2	1
Comission errors (> 3SDs group mean)	0	2
Dieting or eating disorder	0	1
Debrief comments	1	1

Table A.1: Reasons for participant exclusions. *Note.* Exclusions for performance on the speeded GNG task were only excluded from response inhibition analyses.

²http://www.lifesci.sussex.ac.uk/home/Zoltan_Dienes/inference/bayes_factor.swf

A.4 Additional analyses

A.4.1 Predictors of food intake

Consistent with our pre-registered analyses we also explored whether any of the following variables were associated with total food consumption: age, BMI, RS, hours since food, hunger, fullness, desire to eat, positive affect, negative affect and baseline G-FCQ-S score. BMI was the only variable found to be significantly associated with food consumption [Appendix A: Table A.2]. In our pre-registration we stated that any significant variables would be included as covariates in our primary ANOVAs.

	<i>p</i>
Age	0.54
BMI	0.02
RS	0.09
Hours since food	0.75
Hunger	0.41
Fullness	0.64
Desire to eat	0.33
Positive affect	0.31
Negative affect	0.61
G-FCQ-S (baseline)	0.31

Table A.2: Relationship between group characteristics and total food consumption. *Note.* Model $R^2 = 0.13$, $F(10,160) = 2.36$, $p = 0.01$

A.4.2 Food consumption

A 2x2x2 mixed ANCOVA (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factors: *food type* [healthy or unhealthy] and *food novelty* [old or new]; covariate: BMI) revealed no significant main effects of tDCS ($B_{JZS}=0.17$, $F(1,168) = 0.98$, $p = 0.32$, $\eta p^2 = 0.01$), food novelty ($B_{JZS} = 1.304e+27$, $F(1,168) = 0.2$, $p = 0.65$, $\eta p^2=0.001$) or BMI ($B_{JZS} = 0.36$, $F(1,168) = 2.93$, $p < 0.09$, $\eta p^2=0.02$). The interactions between food type and tDCS ($B_{JZS} = 0.11$, $F(1,168) = 0.56$, $p = 0.46$, $\eta p^2 = 0.003$), food novelty and tDCS ($B_{JZS}=0.11$, $F(1,168) = 0.004$, $p = 0.95$, $\eta p^2 < 0.001$), and food type and food novelty ($B_{JZS}=5.43$, $F(1,168) = 3.11$, $p = 0.08$, $\eta p^2 = 0.02$) were also non-significant, as was the three-way interactions between food type, food novelty and tDCS ($B_{JZS} = 0.19$, $F(1,168) = 0.05$, $p = 0.83$, $\eta p^2 < 0.001$). There was a significant

main effect of food type ($B_{JZS} = 1.438e+20$, $F(1,168) = 9.81$, $p = 0.002$, $\eta p^2 = 0.06$).

A.4.3 Food craving

A 2x2 mixed ANCOVA for total state craving scores (between-subjects factor: tDCS condition [active or sham]; within-subjects factor: time [pre or post stimulation]; covariate: BMI) revealed no main effect of tDCS ($B_{JZS} = 0.48$, $F(1,168) = 1.31$, $p = 0.25$, $\eta p^2 = 0.01$), time ($B_{JZS} = 6.813e+12$, $F(1,168) = 0.17$, $p = 0.68$, $\eta p^2 = 0.001$), or BMI ($B_{JZS} = 0.3$, $F(1,168) = 0.16$, $p = 0.69$, $\eta p^2 = 0.001$). Furthermore there was no significant interaction between time and tDCS ($B_{JZS} = 0.24$, $F(1,168) = 1.18$, $p = 0.28$, $\eta p^2 = 0.01$).

A.4.4 Response inhibition

A 2x4 mixed ANCOVA on percent of successful no-go responses in the speeded task (between-subjects factor: tDCS condition [active or sham]; within-subjects factor: stimulus type [unhealthy old, unhealthy new, healthy, filler]; covariate: BMI) revealed no main effect of tDCS ($F(1,163) = 0.79$, $p = 0.377$, $\eta p^2 = 0.01$; $B_{JZS} = 0.36$), stimulus type ($B_{JZS} = 248301.9$, $F(1,163) = 1.12$, $p = 0.34$, $\eta p^2 = 0.01$), or BMI ($B_{JZS} = 0.4$, $F(1,163) = 1.1$, $p = 0.3$, $\eta p^2 = 0.01$). The interaction between stimulus type and tDCS ($B_{JZS} = 1.18$, $F(1,163) = 1.63$, $p = 0.18$, $\eta p^2 = 0.01$) was also non-significant).

A.4.5 Sweet versus savoury foods

Some of the literature investigating the effects of tDCS on food craving and food consumption has indicated a possible influence of food type. For example, Kekic et al., (2014) found a significant effect of tDCS on craving in sweet foods, but this result was not replicated in savoury foods.

In addition to the sweet vs savoury analysis, we further split the foods and conducted a 2x2 ANOVA (between-subjects factor: *tDCS condition* [active or sham]; within-subjects factor: *food type* [unhealthy sweet and unhealthy savoury]). This revealed no main effect of food type ($B_{JZS} = 0.38$, $F(1,170) = 2.35$, $p = 0.13$, $\eta p^2 = 0.01$) or tDCS ($B_{JZS} = 0.19$, $F(1,170) = 0.49$, $p = 0.48$, $\eta p^2 = 0.003$), and no interaction between the two ($B_{JZS} = 0.49$, $F(1,170) = 2.31$, $p = 0.13$, $\eta p^2 = 0.01$).

A.4.6 Individual foods

To explore whether there were any significant differences between individual foods, we analysed each food from the buffet individually. The only food item that resulted in a significant difference between groups was grapes, with participants who received active stimulation consuming significantly more than those who received sham stimulation [Table A.3]

	Sham	Active	B_{JZS}	t	p	d
Chocolate	182.12 (16)	174.48 (14.78)	0.18	0.35	0.73	0.05
Carrots	12.18 (1.35)	13.18 (1.51)	0.19	0.49	0.62	0.08
Cheese bites	109.5 (11.31)	131.63 (13.48)	0.34	1.25	0.21	0.19
Bread sticks	24 (3.35)	21.55 (2.72)	0.19	0.57	0.57	0.09
Biscuits	76.42 (9.14)	74.18 (9.41)	0.17	0.17	0.87	0.03
Grapes	63.71 (5.07)	88.57 (6.75)	8.18	2.92	0.004	0.45
Crisps	99.61 (8.99)	116.82 (9.81)	0.36	1.29	0.2	0.2
Rice cakes	10.09 (1.25)	10.78 (1.4)	0.18	0.37	0.72	0.06

Table A.3: Food consumption data for individual food items in kCal for tDCS condition (SE within parentheses).

A.4.7 Debrief

After completion of the study, participants were probed for awareness of the stimulus mappings during the training task. They were considered aware if any comments were made regarding unhealthy foods being associated with signals. Overall awareness was quite low with only 9.88% of participants noticing anything specific about the task. Within conditions, 14.29% of those in the sham group were aware, and 5.68% in the active group. A chi-square test revealed no significant difference between groups ($B_{JZS} = 0.65$, $\chi^2(1) = 3.57$, $p = 0.06$, $\phi = 0.14$)

Participants were also asked whether they believed the training had any influence on the questionnaires, snack buffet, or the speeded Go/No-Go task. Across both groups 35.47% reported an influence; 39.29% in the sham condition and 31.82% in the active condition ($B_{JZS} = 0.3$), $\chi^2(1) = 1.05$, $p = 0.31$, $\phi = 0.08$. Influence was then split into 3 categories: task, hunger, and mood. Task related to any comments participants made regarding the training having improved their performance on the speeded Go/No-Go task due to, for example, practice effects. Hunger related to any comments about

increased appetite or consumption after the training task, and mood related any comments regarding motivation, alertness or fatigue. 13.37% reported a positive effect of training on speeded performance, 19.77% reported an effect of training on increased hunger, and 1.16% reported an effect of mood. A chi-square test was conducted for each category but was not significant for task ($B_{JZS} = 0.27$, $\chi^2(1) = 1.54$, $p = 0.22$, $\phi = 0.1$), hunger ($B_{JZS} = 0.15$, $\chi^2(1) = 0.02$, $p = 0.88$, $\phi = 0.01$), or mood ($B_{JZS} = 0.09$, $\chi^2(1) = 1.93$, $p = 0.17$, $\phi = 0.11$).

A.5 Output of Bayesian comparison of total calories consumed in sham vs. active tDCS conditions using an informative prior

The screenshot shows a web-based calculator for calculating Bayes factors. It includes several input fields and a 'Go!' button. Below the inputs, the results for the likelihoods and the Bayes factor are displayed.

Question	Answer
Is the distribution of $p(\text{population value} \text{theory})$ uniform?	<input type="radio"/> yes <input checked="" type="radio"/> no
What is the sample standard error?	44.69661
What is the sample mean?	-53.55608
What is the mean of $p(\text{population value} \text{theory})$?	0
What is the standard deviation of $p(\text{population value} \text{theory})$?	110
Is the distribution one-tailed or two-tailed? (1/2)	1
Go!	
The likelihood of the obtained data given your theory is	0.0008
The likelihood of the obtained data given the null is	0.0044
The Bayes factor is	0.19

A.6 Full ANOVA outputs

Despite analyses indicating no main effects of, or interactions with tDCS, here all main effects and interactions are reported.

A.6.1 Effects on food consumption (H1)

A 2x2x2 mixed ANOVA (between-subjects factor: tDCS condition [active or sham]; within-subjects factors: food type [healthy or unhealthy] and food novelty [old or new]) revealed significant main effects of food type and food novelty indicating that participants ate significantly more calories from unhealthy food than healthy food ($B_{JZS} = 1.636e+20$, $F(1,170) = 642.4$, $p < 0.001$, $\eta p^2 = 0.79$), and significantly more calories from old foods than novel foods ($B_{JZS} = 1.818e+27$, $F(1,170) = 217.93$, $p < 0.001$, $\eta p^2 = 0.56$; see Supplementary Table 5 for food consumption data). There was also a significant interaction between food type and food novelty ($B_{JZS} = 5.28$, $F(1,170) = 263.61$, $p < 0.001$, $\eta p^2 = 0.61$), with pairwise comparisons indicating a significant difference between old and new foods for healthy ($p < 0.001$) but not unhealthy foods ($p = 0.31$).

A.6.2 Exploratory food consumption analyses

A 2x2 mixed ANOVA for healthy food consumption in grams (between-subjects factor: tDCS condition [active or sham]; within-subjects factor: food novelty [old or new]) revealed a main effect of novelty ($B_{JZS} = 8.993e+54$, $F(1,170) = 364.81$; $p < 0.001$, $\eta p^2 = 0.67$) with greater consumption of old foods compared to new foods.

A.6.3 Effects on food craving (H2)

A 2x2 mixed ANOVA for total state craving scores (between-subjects factor: tDCS condition [active or sham]; within-subjects factor: time [pre or post stimulation]) revealed a significant main effect of time with craving scores increasing after exposure to food images in the training task ($B_{JZS} = 6.753e+12$, $F(1,170) = 79.96$, $p < 0.001$, $\eta p^2 = 0.32$).

		Weight provided (g)	kCals per 100g	Fat per 100g
Healthy foods	Rice cakes (mini)	≈57	388	3
	<i>Plain rice cakes</i>			
	Carrot batons	≈279	42	0.3
	<i>Pre-cut carrots</i>			
Unhealthy foods	Grapes	≈387	70	0.1
	<i>Green grapes</i>			
	Crisps	≈76	550	36.3
	<i>Ready salted crisps</i>			
Novel healthy food	Chocolate	≈269	554	34.2
	<i>Cadbury 'Bista Wispa'</i>			
	Biscuits (mini)	≈158	484	21.4
	<i>Fox's mini malted milk</i>			
Novel unhealthy food	Breadsticks (mini)	≈110	404	7.4
	<i>Mini breadsticks</i>			
	Cheese bites	≈172	536	29.2
	<i>Asda's cheese bites</i>			

Table A.4: Nutritional information and weights for the foods presented in the snack buffet. Note. Similar products were used where other products were discontinued.

	Sham	Active	B_{JZS}	t	p	d
Gender (% female)	79%	77%				
Age	21.1 (0.45)	20.51 (0.28)	0.3	1.13	0.26	0.17
BMI	22.52 (0.38)	23.24 (0.41)	0.35	1.28	0.2	0.2
RS	7.82 (0.49)	8.09 (0.49)	0.18	0.39	0.7	0.06
Hours since food	5.87 (0.51)	6.09 (0.5)	0.17	0.31	0.76	0.05
Hunger (baseline)	5.04 (0.21)	5.19 (0.19)	0.19	0.51	0.61	0.08
Hunger (post-pre)	-1.47 (0.16)	-1.23 (0.15)	0.28	1.07	0.29	0.16
Fullness (baseline)	1.38 (0.17)	1.64 (0.16)	0.31	1.16	0.25	0.18
Fullness (post-pre)	-0.35 (0.1)	-0.52 (0.12)	0.31	1.16	0.25	0.18
Desire to eat (baseline)	5.47 (0.25)	5.6 (0.23)	0.18	0.39	0.7	0.06
Desire to eat (post-pre)	-1.44 (0.19)	-1.23 (0.16)	0.23	0.85	0.4	0.13
Positive affect (baseline)	28.45 (0.64)	27.17 (0.71)	0.38	1.34	0.18	0.21
Positive affect (post-pre)	-3.43 (0.55)	-4.66 (0.54)	0.52	1.58	0.12	0.24
Negative affect (baseline)	12.84 (0.32)	12.2 (0.31)	0.43	1.44	0.15	0.22
Negative affect (post-pre)	-1.11 (0.29)	-0.5 (0.28)	0.47	1.51	0.13	0.23
G-FCQ-S (baseline)	46.33 (1.31)	45.41 (1.3)	0.19	0.5	0.62	0.08
G-FCQ-S (post-pre)	5.7 (0.85)	4.62 (0.78)	0.25	0.94	0.35	0.14
G-FCQ-S_DE (baseline)	9.98 (0.36)	10 (0.32)	0.17	0.05	0.96	0.01
G-FCQ-S_PR (baseline)	9.23 (0.36)	9.08 (0.3)	0.17	0.32	0.75	0.05
G-FCQ-S_NR (baseline)	9.95 (0.3)	9.78 (0.29)	0.18	0.4	0.69	0.06
G-FCQ-S_OP (baseline)	7.02 (0.29)	6.78 (0.3)	0.19	0.58	0.56	0.09
G-FCQ-S_PS (baseline)	10.16 (0.3)	9.76 (0.31)	0.24	0.92	0.36	0.14

Table A.5: Group characteristics and between-group significance tests (SE within parentheses). Note. RS = Restraint Scale; G-FCQ-S = General Food Craving Questionnaire – State Version; G-FCQ-S_DE = desire to eat; G-FCQ-S_PR = anticipation to positive reinforcement; G-FCQ-S_NR = anticipation to negative reinforcement; G-FCQ-S_OP = obsessive preoccupation; G-FCQ-S_PS = craving as a physiological state.

Appendix B

Supplementary information for Chapter 3

		Weight provided	Weight consumed	kCals per 100g	Fat per 100g
Healthy foods	Rice cakes (mini)	9g	1g	362	1.4
	<i>Plain rice cakes</i>				
	Carrot batons	31g	4g	43	0.4
	<i>Pre-cut carrots</i>				
	Grapes	42g	6g	66	0.1
	<i>Green grapes</i>				
Unhealthy foods	Crisps	20g	3g	544	33.2
	<i>Ready salted crisps</i>				
	Chocolate	15g	2g	535	30
	<i>Cadbury giant buttons</i>				
	Biscuits	24g	4g	485	21
	<i>Shortcake biscuits</i>				

Table B.1: The selection of foods that were presented in the training task and desire to eat measure.

Appendix C

Supplementary information for Chapter 4

C.1 Pilot studies

The aim of the pilot studies was initially to ensure that the images used in the training task would be suitable. In the original protocol, food and evaluative conditioning stimuli were going to be personalised based on preferences, therefore the aim of the pilot was to ensure that the chosen stimuli allowed individual preferences to be met. However, due to the change in task design, pilot data were instead used to determine which of the stimuli would be most suitable to be used in the training task.

C.1.1 Food stimuli

A total of 18 foods were depicted in the training task; 6 neutral healthy foods, 6 neutral unhealthy foods, and 6 high-value unhealthy foods, each of which had 3 exemplars. Pilot data allowed us to identify suitable foods for each category. Participants had been asked to rate a series of food items on a 200-point visual analogue scale. Neutral foods were categorised as those with ratings between -50 and 50, and high-value foods were categorised as those with a rating of 75 or more. Table C.1 details each of the foods used and the average rating collapsed across participants. All food stimuli can be accessed here: <https://osf.io/yg9k8/>

Neutral healthy foods	Average rating	Neutral unhealthy foods	Average rating	High-value unhealthy foods	Average rating
Celery	-5.82 (5.29)	Flapjack	29.45 (3.23)	Cookie	98.95 (0.45)
Cauliflower	5 (4.92)	White chocolate	1.14 (6.25)	Croissant	98.95 (0.42)
Carrots	26.41 (3.16)	Ice-cream	31.91 (4.3)	Milk chocolate	98.64 (0.54)
Cucumber	15.95 (4.37)	Lemon tart	33.41 (3.46)	Ring doughnut	99.14 (0.37)
Lettuce	9.96 (3.4)	Jam biscuit	29.36 (3.53)	Crisps	98.91 (0.39)
Broccoli	8.59 (4.61)	Jelly beans	34.68 (3.2)	Brownie	98.68 (0.52)

Table C.1: All food items used in the training task. *Note.* SE within parentheses

C.1.2 Evaluative conditioning stimuli

Evaluative conditioning stimuli were also selected based on ratings on a 200-point visual analogue scale. Pleasant stimuli required an average rating of 75 or over while unpleasant stimuli required an average rating of -75 or below. A total of 6 evaluative conditioning pictures were selected based on ratings, each with 3 exemplars.

Pleasant stimuli	Average rating	Unpleasant stimuli	Average rating
Beach and sea	98.27 (0.97)	Dirty bathroom	-98.73 (0.96)
Meadow	96.18 (1.22)	Waste piles	-96.82 (1.32)
Mountains	96.09 (1.07)	Litter	-97.68 (1.17)

Table C.2: All evaluative conditioning stimuli used in the training task. *Note.* SE within parentheses

C.2 Order of outcome measure and stimulus type

As discussed in section 4.5.5, further analyses were conducted to determine the effect of both order of outcome measure as well as the foods used on H1 and H2. All analyses are detailed below.

C.2.1 Explicit first, high-value stimulus set

H1a. $B_{JZS} = 0.07$, $t(199) = -0.13$, $p = 0.55$, $dz = -0.01$

H1b. $B_{JZS} = 0.04$, $t(199) = 0.95$, $p = 0.83$, $dz = 0.07$

H2a. $B_{JZS} = 0.13$, $t(199) = -0.56$, $p = 0.29$, $dz = -0.04$

H2b. $B_{JZS} = 0.12$, $t(199) = 0.49$, $p = 0.31$, $dz = 0.04$

H2c. $B_{JZS} = 0.07$, $t(199) = 0.26$, $p = 0.6$, $dz = 0.02$

H2d. $B_{JZS} = 0.07$, $t(199) = -0.27$, $p = 0.61$, $dz = -0.02$

C.2.2 Implicit first, high-value stimulus set

H1a. $B_{JZS} = 0.1$, $t(199) = 0.25$, $p = 0.4$, $dz = 0.02$

H1b. $B_{JZS} = 0.11$, $t(199) = -0.37$, $p = 0.36$, $dz = -0.03$

H2a. $B_{JZS} = 0.44$, $t(199) = -1.49$, $p = 0.07$, $dz = -0.11$

H2b. $B_{JZS} = 0.23$, $t(199) = 1.04$, $p = 0.15$, $dz = 0.07$

H2c. $B_{JZS} = 0.08$, $t(199) = 0.04$, $p = 0.52$, $dz = 0.003$

H2d. $B_{JZS} = 0.12$, $t(199) = 0.44$, $p = 0.33$, $dz = 0.03$

C.2.3 Explicit first, neutral stimulus set

H1a. $B_{JZS} = 0.1$, $t(199) = 0.27$, $p = 0.4$, $dz = 0.02$

H1b. $B_{JZS} = 0.05$, $t(199) = 0.86$, $p = 0.8$, $dz = 0.06$

H2a. $B_{JZS} = 0.06$, $t(199) = 0.3$, $p = 0.62$, $dz = 0.02$

H2b. $B_{JZS} = 0.03$, $t(199) = -1.47$, $p = 0.93$, $dz = -0.1$

H2c. $B_{JZS} = 0.09$, $t(199) = -0.15$, $p = 0.44$, $dz = -0.01$

H2d. $B_{JZS} = 0.04$, $t(199) = -1.34$, $p = 0.91$, $dz = -0.1$

C.2.4 Implicit first, neutral stimulus set

H1a. $B_{JZS} = 0.47$, $t(199) = 1.53$, $p = 0.6$, $dz = 0.11$

H1b. $B_{JZS} = 0.39$, $t(199) = -1.42$, $p = 0.08$, $dz = -0.1$

H2a. $B_{JZS} = 0.01$, $t(199) = 4.74$, $p = 0.99$, $dz = 0.34$

H2b. $B_{JZS} = 14.47$, $t(199) = 3.06$, $p = 0.001$, $dz = 0.22$

H2c. $B_{JZS} = 0.03$, $t(199) = 1.93$, $p = 0.97$, $dz = 0.14$

H2d. $B_{JZS} = 0.02$, $t(199) = -3.38$, $p = 0.99$, $dz = -0.24$

C.3 Exploratory robustness checks on H2

Further exploratory robustness checks were carried out on H2 using median RT, percentage errors, and inverse efficiency calculated using both mean and median RT. All analysed revealed anecdotal to moderate evidence for H0. All analyses are detailed below.

C.3.1 Median RT

H2a. $B_{JZS} = 0.02$, $t(799) = 1.66$, $p = 0.95$, $dz = 0.06$

H2b. $B_{JZS} = 0.28$, $t(799) = 1.63$, $p = 0.05$, $dz = 0.06$

H2c. $B_{JZS} = 0.02$, $t(799) = 0.77$, $p = 0.78$, $dz = 0.03$

H2d. $B_{JZS} = 0.02$, $t(799) = -1.37$, $p = 0.91$, $dz = -0.05$

C.3.2 Percentage errors

H2a. $B_{JZS} = 0.02$, $t(799) = 1.74$, $p = 0.96$, $dz = 0.06$

H2b. $B_{JZS} = 0.11$, $t(799) = 0.98$, $p = 0.17$, $dz = 0.03$

H2c. $B_{JZS} = 0.04$, $t(799) = 1.62$, $p = 0.5$, $dz = 5.737\text{e-}12$

H2d. $B_{JZS} = 0.01$, $t(799) = -3.04$, $p = 0.99$, $dz = -0.11$

C.3.3 Inverse efficiency (mean RT)

Inverse efficiency was calculated to combine RT and accuracy into one variable. Mean RT was divided by the proportion of correct responses.

H2a. $B_{JZS} = 0.02$, $t(799) = 1.48$, $p = 0.93$, $dz = 0.05$

H2b. $B_{JZS} = 0.36$, $t(799) = 1.77$, $p = 0.04$, $dz = 0.06$

H2c. $B_{JZS} = 0.02$, $t(799) = 0.98$, $p = 0.84$, $dz = 0.04$

H2d. $B_{JZS} = 0.01$, $t(799) = -2.57$, $p = 0.99$, $dz = -0.09$

C.3.4 Inverse efficiency (median RT)

Inverse efficiency was also calculated using median RT which was divided by the proportion of correct responses.

H2a. $B_{JZS} = 0.01$, $t(799) = 1.81$, $p = 0.97$, $dz = 0.06$

H2b. $B_{JZS} = 0.35$, $t(799) = 1.77$, $p = 0.04$, $dz = 0.06$

H2c. $B_{JZS} = 0.02$, $t(799) = 0.78$, $p = 0.78$, $dz = 0.03$

H2d. $B_{JZS} = 0.02$, $t(799) = -1.66$, $p = 0.95$, $dz = -0.06$

C.4 Moderators

To investigate whether BMI, hunger, or dieting status had an effect on the training task, each of the primary analyses were analysed again with the moderators using a linear mixed effects analysis in R (R core team, 2016) with the lme4 package (Bates et al., 2015). *p*-values were calculated from degrees of freedom estimated using Satterthwaite’s method (Kuznetsova, Brockhoff & Christensen, 2016).

C.4.1 Effect of BMI

Of the 800 participants, BMI data was recorded for 767. BMI was used to categorise participants as underweight ($N = 45$), normal ($N = 472$), overweight ($N = 151$) or obese ($N = 99$). Analyses indicated no main effects or interactions between training or BMI on explicit liking for H1 (all F s < 1.88 , all p s > 0.09). There were also no main effects or interactions between training and BMI on implicit liking for H2 (all F s < 3.17 , all p s > 0.07).

C.4.2 Effect of hunger

Due to the varying levels of hunger reported from participants, we also wanted to investigate whether participant hunger had an effect on the effect of training. For H1b through to H2d there were no main effects or interactions between hunger and training on liking (all F s < 3.61 , all p s > 0.05).

C.4.3 Effect of dieting

A final series of analyses were conducted using dieting status as a moderator. There were no main effects or interactions between dieting status and training on liking for any hypotheses (all F s < 2.40 , all p s > 0.12).

Appendix D

Supplementary information for Chapter 5

D.1 Student project

D.1.1 Hunger

Overview

It was hypothesised that the effects of EC on implicit and explicit liking of healthy foods would be greater as hunger increased, and that hunger would also impact the effect of EC on unhealthy foods though a direction was not stated.

Results

Hunger was not correlated with changes in explicit or implicit liking following EC.

D.1.2 Socioeconomic status

Overview

Based on previous research indicating that a lower SES is associated with a reduced liking of healthy foods, it was hypothesised that participants with a higher SES would have higher baseline liking of healthy foods compared to those with a lower SES. It was also predicted that the healthy-pleasant pairings in the EC task would have a stronger effect on participants with a lower SES.

Results

There was no difference in baseline liking of healthy foods as a result of SES nor was there a moderating effect of SES on EC for either explicit or implicit liking.

D.1.3 Intention to eat healthily

Overview

It was proposed that the intention to eat healthily would increase the effects of EC due to the relevance of the training to personal goals. It was hypothesised that the effects of training would be stronger in those with stronger goal intentions to eat healthily.

Results

Analyses revealed no correlation between intention to eat healthily and a change in explicit liking. Similar results were found for implicit liking though there was a significant positive correlation between intention to eat healthily and a change in the implicit liking of unhealthy foods paired with unpleasant stimuli ($r(100) = 0.3, p = 0.002$).

D.1.4 Dietary restraint

Hypotheses

It was hypothesised that the effects of EC on both explicit and implicit liking would be greater in restrained eaters compared to unrestrained eaters.

Results

Participants were categorised as restrained or unrestrained using a median-split. A series of ANOVAs revealed no moderating effect of dietary restraint on the effects of EC on liking.

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