Cognitive Bias Modification for Unhealthy Food Behaviours

Thesis submitted in accordance with the requirements of the University of Liverpool

for the degree of Doctor of Philosophy by

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DECLARATION

This thesis is the result of my own work. The material contained in the thesis has not been presented, nor is currently being presented, either wholly or in part for any other degree or qualification.

Abstract

Cognitive Bias Modification (CBM) paradigms are hypothesised to reduce unhealthy food behaviours (and potentially weight) through the completion of non-invasive computerised tasks. Despite their potential, inconsistent task designs and study outcomes across the literature raise questions in relation to true training efficacy. The overall aim of this thesis was to investigate two specific CBM paradigms (cue-inhibitory control training (cue-ICT) and evaluative conditioning (EC)) to evaluate their impact in terms of behavioural change and identify mechanisms of effect while also addressing limitations of the current literature base. Factors associated with training outcomes (including cue-inhibition contingencies, belief in training and proxy measures of change) were also investigated to attempt to explain inconsistent training outcomes and accurately evaluate the efficacy of CBM training paradigms.

The results from chapter 3 demonstrated that neither cue-ICT or EC administered in the lab had a significant influence on ad-libitum food consumption or implicit food preference. While there was a significant difference in explicit preferences between conditions, this was between the active cue-ICT and EC training groups rather than the active or passive control groups. The studies contained within chapter 4 demonstrated that systematically varying the cue-inhibition contingencies (cue-ICT) and critical pairing percentages (EC) experienced during online training had no influence on training outcomes, with no significant differences found at any task percentage for unhealthy food value for either cue-ICT and EC. There was some evidence to suggest EC may influence explicit choice, with healthier choices made in the 100% unhealthy food-negative image group compared to the control (50%) group.

As these studies provided limited evidence to support the use of CBM in food contexts, chapter 5 examined the role of individual level variables (belief) in training

outcomes across two online studies. The results revealed that active CBM only appeared to be effective at reducing unhealthy food value when a manipulation message describing the CBM technique (either cue-ICT or EC) in a positive way was presented prior to training completion. For EC these effects were still evident one week after training. The final experimental chapter (chapter 6) used an EMA design to examine the extent to which commonly used measures of food preference and value were related to real world food consumption. While these measures are commonly used as indicators of CBM training effectiveness, the results provided limited evidence to suggest that these measures are related to real world food behaviours, with only unhealthy food value predicting consumption over the study period.

Overall, the results of this thesis provide limited evidence to support the use of CBM as a standalone intervention strategy for unhealthy food behaviours, with factors external to training (i.e., belief in training effectiveness) appearing to have a substantial influence on training efficacy. Future research is needed to further identify the role of individual differences within CBM contexts and validate alternative measures of food preference and value that can accurately predict real world food behaviours.

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Chapter 1. General Introduction

1.1. Prevalence and risks associated with overweight and obesity

Overweight (defined as a body mass index (BMI) of ≥ 25 and < 30) and obesity (defined as a BMI ≥ 30) are significant global health concerns caused by excess calorie intake over prolonged periods of time (Skidmore & Yarnell, 2004). While historically a greater problem in high-income countries, the prevalence of overweight and obesity has increased worldwide, with increases in obesity observed alongside decreases in underweight (NCD Risk Factor Collaboration, 2021). In 2016, 1.9 billion adults globally were living with overweight (and 650 million of these were living with obesity: World Health Organisation, 2021). Statistical models also predict substantial increases in worldwide obesity prevalence by 2030 based on current trajectories (Ampofo & Boateng, 2020). In the UK, 2018 data revealed that 28% of adults were categorised as obese (NHS Digital, 2020), with predictions suggesting this percentage will increase to 36% by 2030, resulting in the UK having the highest rates of obesity in Europe (Ampofo & Boateng, 2020).

Health conditions related to overweight and obesity result in additional costs to healthcare services, with expenditure not only attributable to hospitalisations (with 10 780 hospitalisations in the UK directly related to obesity in 2019 (NHS Digital, 2021)) but to the wider context of obesity management and treatment (e.g., GP appointments, medication, bariatric surgery)), with the NHS spending over an estimated £6.1 billion on overweight and obesity related ill health in 2014/15 across the UK (Public Health England, 2017). Excess weight is associated with increased risk for a number of health conditions including cardiovascular diseases (Khan et al., 2018; Koliaki et al., 2019), diabetes (Al-Goblan et al., 2014) and some types of cancer (Gallagher & LeRoith, 2015). During the recent covid-19 pandemic, individuals with overweight or obesity who contracted the disease were more likely to require hospitalisation and mechanical ventilation during treatment (Alberca et al., 2020), with obesity a significant predictor of post-infection mortality (Pettit et al., 2020). Obesity can also substantially influence quality of life, with individuals with obesity likely to suffer from functional mobility issues (Forhan & Gill, 2013) in addition to increased risk of mental health issues and lower self-esteem (Sarwer & Polonsky, 2018).

The global rise in overweight and obesity has been at least partly attributed to increasingly obesogenic environments, where the consumption of low-cost, energy-dense highly palatable unhealthy foods is both widely available and heavily promoted (Lake & Townshend, 2006; Swinburn & Egger, 2002; Swinburn et al., 2011). However, despite similar environmental exposure, not all individuals struggle with weight management. This may indicate that individual differences are implicated in the regulation of responses to environmental cues associated with increased calorie intake, and this being true, make the identification of these individual differences of critical importance for future psychological interventions to address unhealthy food consumption.

1.2. Dual process models in eating behaviour contexts

Individual variability in psychological responses to food cues may be explained by theories of dual processing, which propose that food-related decisions (and subsequently consumption) are driven by implicit and reflective processes (Hofmann et al., 2008, Strack & Deutsch, 2004).

Implicit processes are hypothesised to be based on 'associative clusters', which are stored in long term memory and activated by either perceptual or imagined stimuli (e.g., an 'unhealthy food' cluster may be activated when unhealthy food stimuli are encountered or imagined) (Hofmann et al., 2009; Strack & Deutsch, 2004). Associative clusters link concepts, outcomes (in terms of positive or negative affect) and behaviours based on previous experiences, with the activation of any part of the cluster activating the additional linked elements (e.g., after repeated exposure to chocolate, clusters may be formed linking chocolate (concept) with positive affect (hedonically driven outcome) when consumed (behaviour), resulting in an individual linking the behaviour (eating chocolate) to positive affect, and responding to/approaching the cue accordingly (see figure 1.1)) (Hofmann et al., 2009; Strack & Deutsch, 2004). These clusters are formed over time, are thought to be formed independently of conscious awareness, and allow for rapid behavioural decisions to be made (without placing demands on cognitive resources) in response to environmental (or homeostatic) cues (Hofmann et al., 2008), potentially overriding conscious behavioural intentions (e.g., to not consume unhealthy food items) (Jones et al., 2018).

This is in contrast to reflective processes, which are based on conscious and deliberate evaluations of behavioural choices and are linked to higher-order executive functions (EFs). EFs refer to a group of related, top-down mental processes that are required for self-control and behaviour management (Diamond, 2013). EFs provide an increased level of control over both decisions and behaviours and allow for reasoned judgements and evaluations to be made, supporting the execution of goal-directed behaviours (Hofmann et al., 2009). Importantly, EFs also allow individuals to override or inhibit learned or dominant responses to stimuli through inhibitory control (Diamond, 2013), which can support longer-term strategic health goals (e.g., not consuming an unhealthy food item despite availability of the item, see figure 1.1) (Jones et al., 2018). While this increased control can be advantageous, reflective processes are much slower (relative to implicit processes) and place high demand on cognitive resources (Strack & Deutsch, 2004). Researchers also believe that these processes have a limited capacity, determined by both situational and dispositional factors: when capacity is limited (or chronically reduced), individuals can fail to identify discrepancies between goals and behaviours, or fail to inhibit non-goal aligned responses (Hofmann et al., 2008).

Dual process models frame food behaviours as the outcome of conflict between implicit and reflective processes, with the relatively 'stronger' process determining the behavioural response (e.g., weaker reflective processes would be easily overruled by stronger implicit processes when exposed to food-related cues). This may help to explain disparities between longer-term health goals (e.g., weight loss) and immediate consumption behaviours (e.g., eating unhealthy foods) (Jones et al., 2018), with relative process strength determining behavioural outcomes (and responses to food cues). There is evidence to support the application of dual process models to eating behaviours, with work by Nederkoorn et al., (2010) discovering that weight gain was predicted by an interactive effect of strong implicit preferences for snack foods and poor inhibitory control capacity (as a proxy for Executive Functioning). Additionally, work by Brockmeyer et al., (2016) discovered that participants who had high levels of inhibitory control and scored lower on unhealthy food liking were most successful in a weight loss intervention, and work by Houben et al., (2014) revealed that there was an association between high BMI and decreased inhibitory ability towards unhealthy food images (although recent work has found associations between obesity and cognitive factors to be small in terms of statistical effect size (Robinson et al., 2020)).

1.3. Cognitive Bias Modification

While theories of dual processing may help to explain individual differences in terms of responses to food cues, they have also resulted in the development of targeted interventions, under the umbrella term of Cognitive Bias Modification (CBM). CBM training paradigms support behavioural change by targeting implicit and reflective processes to either strengthen/improve self-control abilities, or weaken the associations that underlie automatic processes (Friese et al., 2011; Wiers et al., 2013), with CBM paradigms providing a lower-cost alternative to face to face psychological interventions (Jones et al., 2018).

CBM approaches have been utilised across various psychopathologies including anxiety (e.g., Beard et al., 2011) and depression (e.g., Vrijsen et al., 2018) to reduce clinical

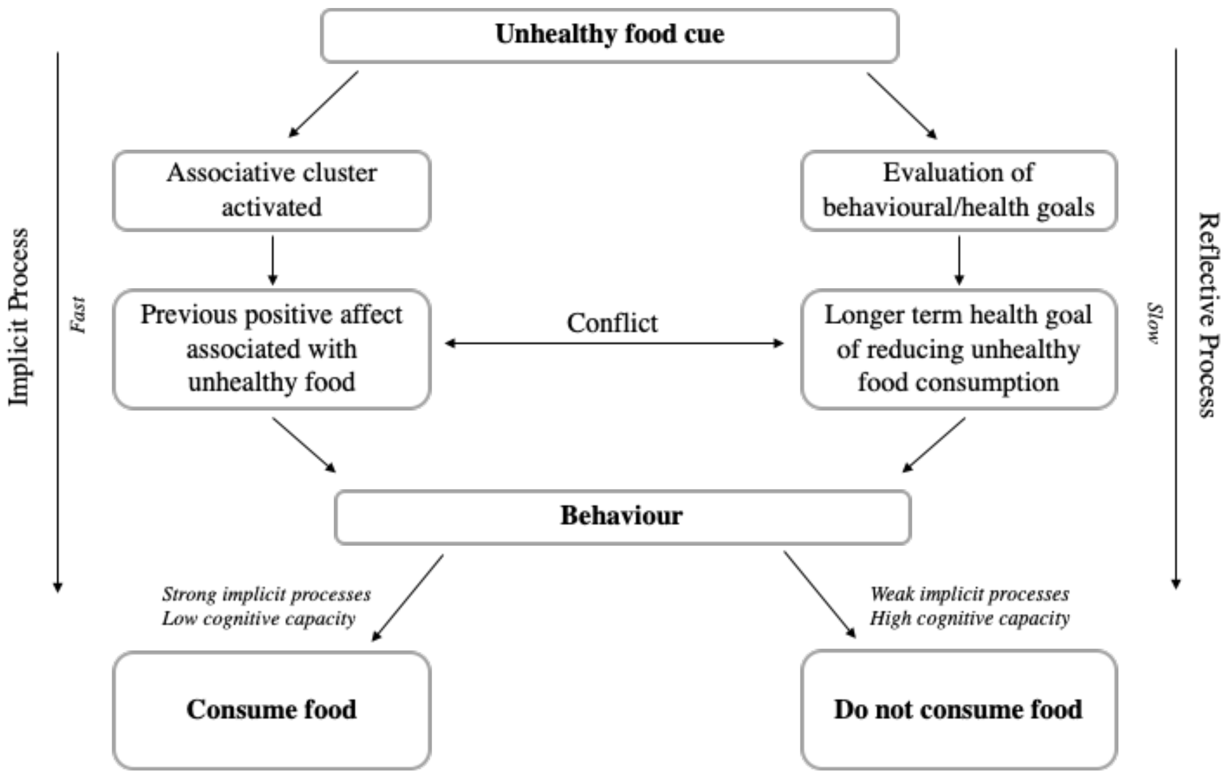


Figure 1.1. Implicit and reflective determinants of behaviour as applied to unhealthy food consumption

symptoms, however, recent review work has discovered that while the benefits from CBM training within these contexts are typically consistent (albeit small), effect size heterogeneity and a high risk of bias across studies raises questions in relation to the overall effectiveness of training (Fodor et al., 2020). CBM has also been applied to appetitive contexts, where training has led to reduced alcohol consumption (e.g., Houben et al., 2011), however, a Bayesian meta-analysis on individual participant data discovered that while there is some evidence to suggest training influences actual cognitive biases, the credible intervals associated with the effects were wide (0.06 – 0.41), and there was no evidence to suggest that training had any influence on alcohol use *behaviour* (Boffo et al., 2019).

While the term CBM training covers a wide variety of psychological approaches (e.g., attempting to increase inhibitory control capacity through general inhibitory control training (Guerrieri et al., 2009)), two specific training paradigms targeting the associations that underlie automatic processes are detailed below.

1.3.1. Cue-specific Inhibitory Control Training

Cue-specific Inhibitory Control Training (cue-ICT) is a CBM paradigm that trains participants to form associations between the engagement of inhibitory control and exposure to specific stimuli (e.g., unhealthy food-cues), without specifically increasing overall inhibitory capacity (Jones et al., 2018). It works by modifying one of two tasks which are used to measure inhibitory control capacity; the go/no-go task or the stop signal task. The Go/No-go task involves participants withholding responses to specific stimuli on the majority of (if not all) trials where these images are presented, and responding to images of unrelated stimuli items. This is in contrast to the stop signal task, where participants are required to make rapid responses to stimuli until a signal (e.g., an audio tone) is provided on a minority of trials where they are required to inhibit their response.

In an appetitive context, cue-ICT tasks typically involve the presentation of images of unhealthy food items (and filler images), and participants complete an inhibitory control task where they are prompted to withhold responses to unhealthy food images on the majority of (if not all) trials where these images are presented (see figure 1.2).

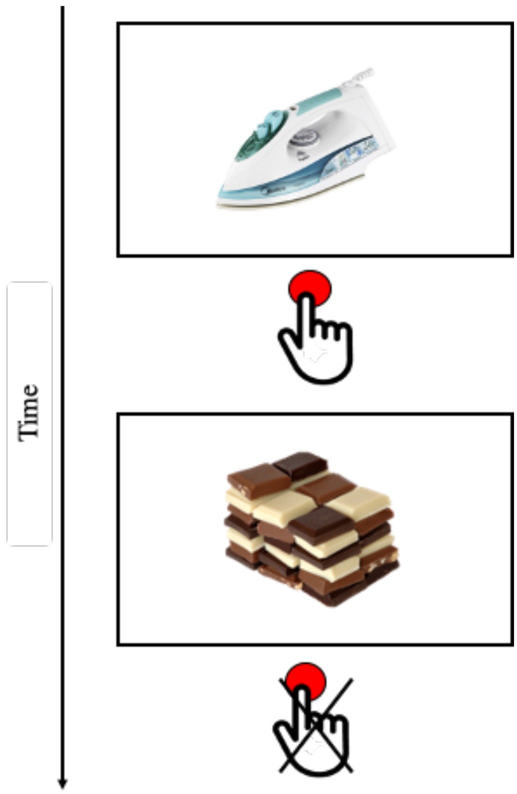


Figure 1.2. A schematic of a typical cue-ICT trial. In a go/no-go task, participants provide a response to the filler images and withhold responses to unhealthy food images.

While cue-ICT paradigms have been applied to various health behaviours (including alcohol intake (e.g., Di Lemma & Field, 2017) and smoking (e.g., Scholten et al., 2019)), food consumption is one of the most popular applications of cue-ICT. Meta analytic work by Jones et al., (2016) revealed that a single session of cue-ICT resulted in a robust (albeit small (*SMD* = .36, 95% CIs [0.24, 0.47])) reduction in food and alcohol consumption in the laboratory supporting the findings of an earlier meta-analysis which also concluded that inhibitory control training positively influenced health behaviours (Allom et al., 2016). More recently, Oomen et al., (2018) discovered that 6 online cue-ICT sessions resulted in significantly less snack food consumption in an ad libitum taste test (when compared to a control group trained towards non-food stimuli) ($\eta p^2 = .11$), and work by Chen et al., (2018a) discovered that in both healthy weight and individuals with obesity, completing go/no-go training resulted in higher evaluation ratings for 'go' food items in comparison to 'no-go' items, supporting earlier work that discovered withholding responses to appetitive stimuli resulted in decreased evaluations for these items (Chen et al., 2016).

Despite these promising findings, not all studies report positive post-training outcomes. Work by Bongers et al., (2018) revealed that adding Go/No-go training to cue-exposure treatment did not result in any significant differences in chocolate (or snack food) consumption (compared to a sham training group) and Adams et al., (2017, study 1) found that when using a stop signal task paradigm, participants in the unhealthy food-stop group did not differ in terms of implicit preference for chocolate or ad libitum snack food consumption compared to a double response group. Recent work by Carbine et al., (2021) found that training had no influence on weight loss or caloric intake over a 12 week period, and work by Tzavella et al., (2021) discovered that while participants were less likely to select a 'no-go' food during a choice task after training, they were not more likely to select 'go' foods, and there were no significant changes to food liking.

Given the inconsistencies in relation to training efficacy, Carbine and Larson (2019) conducted a p-curve analysis for food related ICT to evaluate evidence in support of the presence of a true underlying training effect. P-curve analyses examine the distribution of significant p values within the literature and compare these to the expected distributions of p values were there no effect, a true effect, or selective reporting in relation to the specific phenomena being studied (Simonsohn et al., 2014). For cue-ICT, the analyses resulted in 'U' shaped distributions, providing some evidence to support evidential value (i.e., a true underlying effect) but also some evidence to support selective reporting / p-hacking (with increased prevalence of p values closer to .05 than .025) (Carbine & Larson, 2019).

While an updated analysis provided increased support for evidential value (Veling et al., 2020), the prevalence of p values close to the threshold for statistical significance is still an important consideration given the inconsistencies in training outcomes across studies. There are a number of possible explanations for the inconsistencies. One potential explanation may be related to statistical power: while the ICT effect size is hypothesised to be small (Jones et al., 2016), not all studies within the literature are appropriately powered to detect such effects (Carbine & Larson, 2019), which makes it difficult to draw definitive conclusions in relation to cue-ICT effectiveness and highlights the need for well-powered investigations.

Alternatively, these ambiguous findings may be related to a lack of pre-registration across studies: while not an issue solely unique to CBM literature, pre-registration supports transparency within scientific research, and helps to ensure that analysis decisions and research findings can be independently evaluated by readers while discouraging questionable scientific practices such as HARKing, selective reporting and optional stopping (Lakens, 2019). By pre-registering specific hypotheses and data collection/analysis plans prior to study commencement, researchers can improve the credibility of research findings (Nosek et al., 2018), which for cue-ICT studies would reduce the risks associated with selective reporting and help to ascertain the true impact of training on food behaviours.

An additional consideration in relation to mixed cue-ICT research outcomes relates to variations in task design. Although most cue-ICT paradigms involve the completion of similar tasks (i.e., inhibit responses to target (unhealthy food) images)), there is no consistent paradigm universally adopted across studies. While there appears to be between task differences (e.g., with larger effect sizes for go/no-go tasks compared to stop-signal tasks (potentially related to the proportion of successful inhibitions) (Jones et al., 2016)) there are also substantial presentation differences *within* the same type of experimental task. For example, there are variations in the proportion of trials where participants are required to inhibit responses to unhealthy food cues between Go/No-go training studies: while some studies employ a 100% cue-inhibition contingency (i.e., inhibit responses each time the target stimuli (unhealthy food) is presented (e.g., Houben & Jansen, 2015)), some researchers adopt a lower cue-inhibition contingency (e.g., 90% (Kakoschke et al., 2017)), and there are also variations in the actual number of critical trials (where participants are required to inhibit responses to target stimuli) within training paradigms, with proportions ranging between 25% (e.g., Adams et al., 2017) and 50% (e.g., Porter et al., 2018) of total trials, further complicating comparisons. Additionally, the type of stimuli used within experimental trials can vary substantially, with some studies using images unrelated to food as 'go' trials (e.g., van Koningsbruggen et al., 2014; Veling et al., 2013a) and others using healthy food images (e.g., Lawrence et al., 2015a; Stice et al., 2017). These discrepancies may help to explain some of the mixed outcomes from food cue-ICT, however, this lack of standardisation causes problems when attempting to evaluate the potential for training in relation to food consumption behaviours (as the impact of these task variations on behaviour change is rarely studied).

One final consideration relates to the design of control groups within cue-ICT studies. While most studies do ensure that some form of comparison group is incorporated within the experimental design, these are not necessarily 'active' control groups, and often consist of reversed experimental contingencies (i.e., respond to 100% of unhealthy foods), which may over-inflate between-group differences as participants are being trained *towards* unhealthy food stimuli, potentially increasing consumption and appeal for these items (Jones et al., 2016). The inclusion of active control conditions (where participants respond to and inhibit responses to equal numbers of unhealthy food and 'comparison' stimuli) is essential to ensure appropriate comparisons are made and training potential is evaluated objectively (Jones et al., 2018).

1.3.2. Evaluative Conditioning

Evaluative conditioning (EC) is a second CBM approach that attempts to influence behaviour by pairing a stimulus item (e.g., an unhealthy food item) with a second stimulus that is positively or negatively valenced to influence evaluations for the original item (De Houwer, 2007; Hofmann et al., 2010). When targeting food behaviours, a typical EC task would involve the presentation of unhealthy food cues paired with a negatively valenced stimulus (e.g., an image of a negative health outcome) over a series of experimental trials (see figure 1.3).

Similarly to cue-ICT, EC procedures have been applied to numerous health contexts including alcohol consumption (Houben et al., 2010) and physical activity (Conroy & Kim, 2020) in addition to food choice and consumption. There is evidence to support the application of EC paradigms to eating behaviours, with early work by Hollands et al., (2011) discovering that exposing participants to pairs of images depicting unhealthy snack foods and aversive body images resulted in participants choosing fruit over unhealthy snacks more frequently (in comparison to the control group). Further work by Haynes et al. (2015b) discovered that participants with poorer inhibitory control consumed fewer snack foods in an ad libitum taste test post EC training, and Wang et al., (2017) revealed that a single EC session resulted in less favourable explicit and implicit attitudes towards chocolate.

Although these findings suggest that EC has the potential to influence food related attitudes and behaviours, there are some inconsistencies in relation to training outcomes. While Lebens et al., (2011) discovered that participants in the experimental condition had more negative implicit attitudes towards snack foods, there were no behavioural differences observed in a virtual shopping task. Hensels and Baines (2016) discovered that while participants completing an EC task displayed increased implicit preference for healthy foods, there were no significant differences between groups in relation to explicit food choices, and work by Hollands and Marteau (2016) found that although participants exposed to negative images during training chose fruit more frequently than snacks in an explicit choice task, this appeared to be a consequence of exposure to aversive images rather than the pairing of negative images and unhealthy food images (as the interaction between food type and image type was not significant).

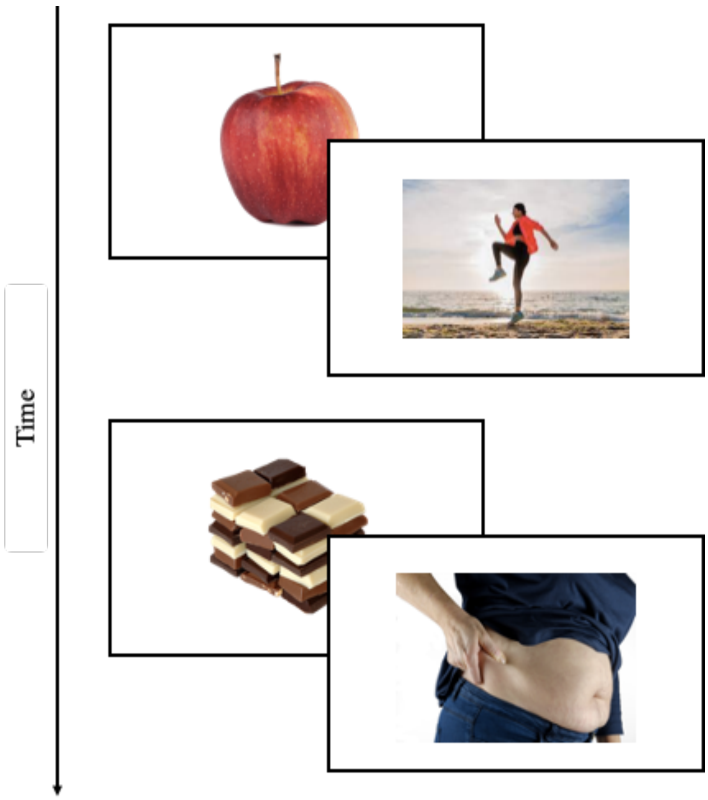


Figure 1.3. A schematic of typical EC trials. In the top image, a healthy food image is followed by a positive health outcome image, and in the bottom image, an unhealthy food image is followed by a negative health outcome image.

These mixed findings make it difficult to draw conclusions related to the efficacy of EC within eating behaviour contexts, however, not unlike the ICT literature there are inconsistencies between studies that may help to explain some of this variation in behavioural outcomes. While most food-specific EC studies use unhealthy food stimuli as the target stimuli (with the aim of reducing preference/consumption for this food category), the format that this takes can vary between study, with some researchers opting to use image-based stimuli (e.g., Hollands & Marteau, 2016; Lebens et al., 2011; Wang et al., 2017) while others utilise text stimuli within training paradigms (e.g., the word 'chocolate') (e.g., Bui & Fazio, 2016; Haynes et al., 2015b; Zerhouni et al., 2019).

A further complication relates to the nature of the valenced stimuli used within training: while some researchers use context specific health outcome images (e.g., Hollands et al., 2011; Hollands & Marteau, 2016; Lebens et al., 2011), others use images from the International Affective Picture System (IAPS) (Lang et al., 2008) (e.g., Haynes et al., 2015b; Zerhouni et al., 2019) while others use images of faces with happy and angry expressions (e.g., Hensels & Baines, 2016). While it is suggested that feature matching (where logical associations can be made between stimuli pairs) within EC training can have a positive influence on training outcomes (e.g., Jones et al., 2010), these differences in stimuli type between studies make it difficult to directly compare paradigms (and outcomes).

A further consideration in relation to EC training design concerns control groups. Similarly to cue-ICT, researchers often employ reversed image pairings (i.e., pairing positively valenced stimuli with unhealthy food cues) for comparison groups, however, this risks inflating between group differences (as participants are being trained with unhealthy food – positive stimuli pairs, potentially increasing preferences for these items) (Jones et al., 2018). There are also inconsistencies in relation to study design, with some researchers adopting mixed designs (allowing for changes in preference/value to be measured pre and post intervention (e.g., Hollands & Marteau, 2016)), and others adopting a solely between subjects design (with preference/value only measured after training completion), which can make it difficult to ascertain the true impact of training participation (although repeated measurements may not always be feasible due to resource limitations or task practicality). Finally, there is variation in the actual number of critical trials (unhealthy food cue – negative stimuli) presented within EC training, with the number of trials ranging from as low as 24 (e.g., Hensels & Baines, 2016) to 100 (e.g., Hollands & Marteau, 2016). Meta-analytic work has tentatively suggested that the EC effect is stronger when the number of critical trials increases (Hofmann et al., 2010), however, the lack of standardisation (or identification of an optimum design) in this area makes it difficult to draw robust conclusions.

1.4. Hypothesised mechanisms of action

Although there is evidence to support the use of CBM in eating behaviour contexts, there is a lack of consensus in relation to the mechanisms through which training exerts its effects. Although cue-ICT and EC are distinct CBM paradigms, as both attempt to influence the associations that are hypothesised to underlie automatic processes, there are similarities in their hypothesised mechanisms of action, as outlined below.

1.4.1. Devaluation

One hypothesised mechanism of action for CBM effects, devaluation, is derived from early work on Behavioural Stimulus Interaction (BSI) theory (Veling et al., 2008). BSI theory states that appetitive stimuli which are evaluated positively by individuals (i.e., unhealthy food items) automatically elicit approach tendencies. When these cues are not congruent with this approach response – due to the need to inhibit on the tasks, a response conflict is created. To resolve this conflict, the initially positively evaluated stimuli item is *devalued* (i.e., negative affect is attached to the item), reducing appeal for the stimuli. For CBM in food contexts, it is argued that this reduction in appetitive value reduces approach and consumption behaviours for food items, providing an explanation for positive training outcomes (Veling et al., 2017).

There is evidence to support this hypothesised mechanism of action across both cue-ICT and EC literature. Work by Veling et al., (2013b) discovered that the effect of a go/no-go task on food choice was mediated by food evaluation, with the decreased evaluation of no-go foods responsible for the observed mediation. Across two pre-registered experiments, Chen et al., (2018b) found that no-go foods were consistently less liked by participants post go/no-go training (in comparison to 'go' and novel foods not used in training), and pilot work by Stice et al., (2017) discovered that intervention group participants reported reduced high calorie food evaluations (in terms of palatability) post training. Evaluation changes post training have also been observed within EC training paradigms, with Hollands et al., (2011) revealing that implicit preferences for snack foods were reduced for individuals with strong or moderate baseline preferences for snacks (after intervention completion), and work by Hensels and Baines (2016) discovered a significant indirect effect of training on food choice mediated by implicit food evaluations.

Despite these findings, not all studies have found evidence to support a devaluation hypothesis. Adams et al., (2017, study 1) discovered that training had no significant influence on implicit preferences for chocolate, and work by Hollands and Marteau (2016) also discovered that training had no significant influence on implicit preferences towards fruit stimuli. Meta analytic work (Jones et al., 2016) failed to detect an overall effect of training on stimuli devaluation, and suggested that the *type* of value measure used (i.e., implicit vs explicit measures of preference) may influence the perceived devaluation effect. This further complicates attempts to identify mechanisms of effect, but supports the findings of studies where changes to explicit preferences are not mirrored by implicit preference measures or vice versa (e.g., Hollands et al., 2011; Tzavella et al., 2021). It is also argued (Veling et al., 2017) that while there is evidence to support the existence of devaluation within CBM literature, there is not sufficient evidence to conclude that this is the mechanism that underlies CBM effects, as not all changes in stimuli evaluations result in changes to food consumption (e.g., Adams et al., 2021). This further adds to the uncertainty in relation to true training (and potential intervention) effectiveness and raises questions in relation to exactly what is being modified during CBM training.

1.4.2. Memory formation/Association based accounts

While devaluation is hypothesised to be the most likely explanation for CBM effects (Veling et al., 2017), alternative explanations for behaviour change exist, including accounts based on memory formation and *associative learning*. These theories suggest that positive post training behavioural outcomes may be a result of 'links' formed between target stimuli items (i.e., unhealthy foods) and avoid responses (or positively/negatively valenced images in the case of EC) (De Houwer, 2014; De Houwer et al., 2001; Verbruggen et al., 2014a). It is proposed that these associations (as reinforced through CBM paradigms) influence decisions in the real world, resulting in 'automatic' approach or avoid behaviours when exposed to target stimuli (driving the decision to consume or not consume unhealthy food).

In support of these theories, work by Best et al., (2016) provided evidence to suggest that participants are able to learn direct associations between stimuli items and stop responses, and research by Houben and Jansen (2015) discovered that after completing a go/no-go training task, participants in the chocolate no-go condition were significantly less likely to associate chocolate with a 'go' response in comparison to participants in the chocolate go condition. Previous work has demonstrated that within CBM tasks, participant reaction time decreases as the required task response becomes more consistent (indicating associations are forming between signals and responses) (Bowditch et al., 2016; Stice et al. 2016), and the proportion of successful inhibitions is a significant predictor of behavioural outcomes for food related cue-ICT (Jones et al., 2016) further highlighting the role of stimulus associations in successful training outcomes. Changes to stimulus associations have also been reported within EC studies, with work by Lebens et al., (2011) discovering increased negative and decreased positive associations with snack foods in CBM training groups.

Although it is generally accepted that these associations develop during CBM training (Veling et al., 2017), the actual contribution of associations in relation to training effects is unclear. Associations are not consistently linked with positive behavioural outcomes, with work by Lawrence et al., (2015b) discovering that while there was evidence of associative learning (between food cues and stop responses), there was no significant correlation between this learning and food consumption in a taste test, and Lebens et al., (2011) found no evidence to support behavioural changes post training (despite the successful development of associations between target stimuli and negative images). It is argued that behaviour change observed within cue-ICT paradigms is driven by the *act* of not responding rather than the formation of associations, with previous work discovering that instructing participants to memorise associations between stimuli had no significant influence on training outcomes (Chen et al., 2016), however, the role of associations within CBM paradigms is relatively understudied, with few studies directly investigating this potential mechanism of action (despite the associations between contingency awareness and training outcomes (e.g., Zerhouni et al., 2019)).

1.5. Additional factors influencing training outcomes

While methodological concerns and inconsistencies may explain some variability in CBM outcomes, a key prediction of dual process models is that individuals vary in terms of their responses to food stimuli based on the relative strength of their implicit and reflective processes. This would imply that individual differences could also have a substantial influence on CBM in terms of training outcomes and longer-term behavioural change. While there are numerous participant level variables investigated within food CBM contexts, several factors implicated in the perceived outcome of training are outlined below.

1.5.1. Individual variability

To ascertain the influence of training on food behaviours, many researchers utilise paradigms targeting one specific type of food (e.g., chocolate (Houben & Jansen, 2015; Wang et al., 2017)). While practically this allows for direct and specific comparisons between experimental groups (and lower financial costs where ad libitum taste tests are utilised within research designs), in real life, participants are unlikely to solely (over)consume one specific food item (Roefs et al., 2019), limiting the applicability of results to real world contexts. While some researchers have specifically recruited and screened participants with preferences for the target stimuli presented within training (e.g., Bongers et al., 2018), this strategy is not consistently applied, with some studies recruiting participants who self-identify as individuals who like to consume the item (e.g., Houben & Jansen, 2015) and others not assessing preference for the item prior to study completion (e.g., Wang et al., 2017). While it is suggested that the personalisation (i.e., selecting foods specifically appealing to the individual participant) of CBM paradigms may improve the potential influence of training (Jones et al., 2018), not all studies collect pre and post training measures of preference. This makes it difficult to isolate training effects from naturally occurring individual differences in appeal, even where participants are assumed to initially have preferences for specific food items.

An additional consideration relates to individual variability in *responses* to unhealthy food cues. While it is assumed that on a group level, participants display deficits in reflective/implicit processes (Franken & van de Wetering, 2015), there is considerable variation between individuals, and many studies do not attempt to specifically recruit (or identify) individuals who might benefit most from training (i.e., participants who do not have pre-existing negative evaluations of unhealthy foods may not benefit from an EC intervention attempting to influence stimuli evaluation as their evaluations are already more negative (Jones et al., 2018)). While there is evidence to suggest that individuals with overweight and obesity have severe impairments in many inhibitory components (including response inhibition and motor impulsiveness (Spitoni et al., 2017)), there are also questions in relation to causality, as it is not possible to determine whether inhibitory control deficits are the cause or the consequence of food behaviours linked to overweight and obesity (Franken & van de Wetering, 2015).

A final concern relates to participant motivation and subsequent task engagement. There is considerable heterogeneity in terms of the samples recruited for CBM research, with some researchers recruiting participants with specific eating behaviours (such as restrained or uncontrolled eaters (e.g., Houben & Jansen, 2011; Oomen et al., 2018)) or participants who are hoping to reduce their food consumption (or lose weight) (e.g., Haynes et al., 2015b; Forman et al., 2016), which may have implications in terms of motivation to engage with experimental tasks and subsequently experimental outcomes (with previous work linking low effort responding to increased risk of type 1 errors (Huang et al., 2015)) (Jones et al., 2016). Although the investigation of individual traits is interesting from a knowledge perspective, there are issues in relation to the overall evaluation of CBM paradigm effectiveness. While it is suggested that the recruitment and engagement of specific participants may increase the therapeutic potential of CBM paradigms (Jones et al., 2018), this lack of consistency in participant recruitment across the literature complicates attempts to interpret and review the use of CBM to reduce unhealthy food consumption. It may be that CBM is only effective for specific individuals with specific traits, motivations, and/or food behaviours, however, without a standardised approach, it is difficult to examine these factors as potential predictors of training outcomes.

1.5.2. Aim awareness and training beliefs

An additional consideration relates to participants' knowledge and understanding in terms of awareness of experimental aims, beliefs regarding training and expectancies in relation to training. Meta-analytic work has identified contingency awareness (participants' ability to recognise and identify task pairings throughout training) as an important moderator of EC effects, with substantially larger training effects observed within contingency aware participants (d = .60 in aware participants compared to d = .20 in unaware participants (Hofmann et al., 2010)). Although EC effects have been observed independently of contingency awareness (e.g., Lebens et al., 2011), work by Zerhouni et al., (2019) found that contingency awareness was a significant predictor of explicit evaluations for unhealthy foods (although this was only the case for participants in the control group), and work by Benedict et al., (2019) revealed that participants completing EC paradigms are susceptible to misinformation manipulations, with misinformation moderating both explicit memory for stimuli and attitudes towards stimuli. While contingency awareness is not as commonly assessed within cue-ICT paradigms, work in the alcohol domain has revealed that some participants were able to identify experimental aims after training (Di Lemma & Field, 2017), and work by Kemps et al., (2013) discovered that after completing a modified implicit association task (IAT), 41% of participants were able to correctly recognise the repeated presentation of chocolate images and 'approach' or 'avoid' words (although these groups did not differ significantly in terms of approach bias or craving, potentially due to the analysis being underpowered).

Participants being able to identify and describe experimental aims and contingencies raises questions in relation to the role of beliefs and expectancies on training paradigms, as it is possible that this heightened awareness may influence training outcomes. While there is limited work investigating the role of beliefs and expectancies within CBM contexts, research by Best et al., (2016) revealed that participants expecting to withhold their response to specific stimuli (stimuli previously associated with a 'stop' signal) were slower to respond to these images in subsequent trials where a response was required (suggesting that the anticipation of specific responses influenced reaction times), and work by Tzavella et al., (2021) also found evidence to support contingency learning (with a higher proportion of successful inhibitions for no-go foods). Boot et al., (2013) highlighted the role of expectancies within intervention work and stated that while the use of active control groups ensures that appropriate comparisons are made between groups, to fully (and objectively) assess intervention effectiveness, researchers need to ensure that both experimental and control groups have the same expectations in terms of improvements/behavioural change. Outside of food contexts, Beard et al., (2011) discovered that CBM training expectancy was correlated with changes in social anxiety assessment (with greater change observed in individuals who had high expectations for training), and work by Smith et al., (2018) revealed that in a clinically depressed sample, participants with high expectancy (in terms of treatment success) experienced less post treatment depressive symptoms than those who had low expectancy. These findings suggest that expectations may play an important role in CBM outcomes, and further research is needed to identify their relation to successful intervention outcomes within food CBM contexts.

1.6. Measures of CBM behaviour change

While the precise mechanisms through which CBM paradigms influence behaviour are not clear, there are useful frameworks to assess intervention success using Experimental Medicine (EM) methods. EM uses an inductive approach to theory development and focuses on the development of interventions that specifically address the precise mechanisms that underlie target behaviours (Field et al., 2021). Sheeran et al., (2017) proposed a specific framework for health behaviour change interventions, and outlined four steps to develop successful interventions, with the first step (path A) being the identification of factors that are linked to behaviour and are potentially modifiable (and can be used as targets for interventions). The second step (path B) focuses on the validation of these factors by developing measures and evaluating the extent to which these factors are linked to behavioural change. The third step (path C) focuses on the development of intervention strategies to influence the previously validated factor, and the final step (path D) involves the completion of randomised controlled trials to determine whether behaviour is successfully changed through the effect of the intervention of the specified target. By following these frameworks, researchers can ensure that interventions are theory based and are implemented (and evaluated) effectively (Field et al., 2021) (see figure 1.4).

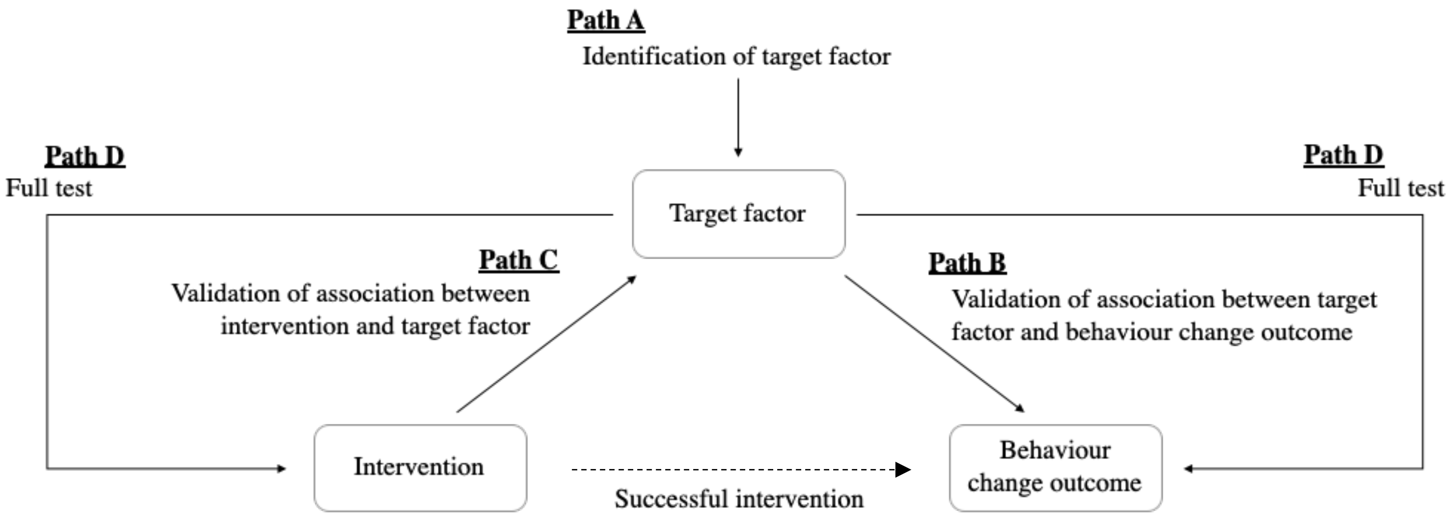


Figure 1.4. The experimental medicine framework as applied to laboratory studies of food intake (adapted from Sheeran et al., 2017)

Across CBM literature, the targeted outcome variable can vary substantially depending on the research protocol used. Although the general aim of CBM within food contexts is to reduce unhealthy food consumption and/or weight, the measurement of these variables is complicated (and often difficult) within research. The measurement of weight change can be problematic due to issues related to accuracy (particularly where participants self-report weight (Maukonen et al., 2018)), the potential psychological consequences of weighing participants (e.g., Benn et al., 2016; Mintz et al., 2013), and the additional requirement for researchers to follow up with participants after the study period (as weight changes will not be immediate) which may result in greater levels of participant attrition, reduced statistical power and potential sample bias (Barry, 2005).

In terms of food consumption, ad libitum taste tests can be utilised in laboratory contexts, where participants are presented with food items and their consumption of these items is recorded (using either weight (grams) or energy (kcal/KJ)) (Blundell et al., 2010).

While these measures allow for the precise measurement of eating behaviours (and can be tailored to the specific study as required), the highly controlled experimental environment in which these measures are administered results in heightened participant awareness (resulting in reduced energy intake (Robinson et al., 2015)). While previous work has indicated that the ad libitum taste test is a valid measure of food intake (Robinson et al., 2017), recent research has demonstrated that effects observed in the lab may be smaller in comparison to real world consumption (Gough et al., 2021). It is suggested that this may explain poor translations in terms of intervention outcomes between lab-based assessments and real world effectiveness (Field et al., 2021), and for CBM, this might help to explain disparities between lab measures of behaviour and longer term eating behaviours (e.g., recent work revealing no significant differences in real world food consumption or weight loss after cue-ICT (Adams et al., 2021) despite previous meta analytic work (Jones et al., 2016) revealing robust reductions in food consumption post training in the laboratory).

While measures of consumption and weight are used as outcomes within CBM research, many researchers choose to use alternative measures of eating behaviours, including the measurement of self-reported food value, food preferences and motivation to eat. Although numerous measures exist, frequently utilised measures include hedonic food value ratings (where participants are presented with various food images asked to score images on a scale for appeal (e.g., Chen et al., 2018a; 2018b; Lawrence et al., 2015a)), explicit preference (also referred to as forced choice) tasks (where participants are presented with a variety of images (or food items in some lab studies) and asked to indicate which item they would most like to consume at that time (e.g., Hollands & Marteau, 2016; Kakoschke et al., 2018; Veling et al., 2013a)), or implicit association tasks (IAT: where response latencies to various food cues are used to infer preferences for specific categories of foods (e.g., healthy or unhealthy foods) (e.g., Hensels & Baines, 2016; Lebens et al., 2011; Nederkoorn et al., 2010). Although these measures can be easier to administer to participants, more cost effective (as participants do not have to attend a lab/food does not have to be purchased for use in the study) and can be completed within one experimental session, researchers have raised concerns in relation to the use of measures that do not directly measure behaviour within psychological research (Baumeister et al., 2007), and work by Klein and Hilbig (2019) suggested that the use of hypothetical choice and preference tasks (where choices have no real impact on the participant) may result in inaccurate reflections of true choices and preferences for stimuli items. To date, little research has investigated the validity of these alternative measures as predictors of longer-term food consumption and/or weight loss, which is problematic when attempting to use these variables as indicators of behaviour change within CBM contexts.

1.7. Interim summary and thesis aims

While CBM paradigms are a theoretically driven, novel, non-invasive intervention strategy to reduce unhealthy food-related behaviours (and potentially weight), there are inconsistencies in relation to post training behavioural outcomes and subsequently, the true potential of CBM training within food contexts is unclear. The lack of standardisation between studies makes it extremely difficult to draw overall conclusions regarding training efficacy (and identify mechanisms of effect), and additional concerns across the literature in relation to appropriate control groups and individual differences between participants raise further questions in relation to the true impact of training on behaviour. Additionally, while measures of food behaviour (such as choice and preference) are used to evaluate training efficacy, the extent to which these measures are related to real-world food consumption is unknown.

The overall aim of this thesis was to investigate two popular CBM paradigms (cue-ICT and EC) to evaluate their potential in terms of behavioural change and provide further understanding in relation to key psychological mechanisms that underlie potential behaviour change. A sub aim of the thesis was to address limitations of previous CBM literature by ensuring that appropriate experimental designs and control groups (where participants are not trained and respond/inhibit responses to stimuli equally as opposed to reversed contingency groups). It is hypothesised that these factors may inflate between group differences (Jones et al., 2018), making it difficult to evaluate standalone training efficacy. Consistent stimuli and trial protocols were also implemented throughout the thesis, allowing for direct comparisons between studies and task paradigms. The thesis also investigated alternative factors that may influence training outcomes, including cue-inhibition contingencies and participant beliefs in training outcomes. Measures of value and choice were also evaluated in terms of their translation to real world food consumption: these measures are frequently used to establish training efficacy, and examinations of these variables individually provided a greater understanding of between study outcome variations and the overall potential for CBM as an intervention strategy for unhealthy food consumption.

Chapter 3 directly compared two CBM approaches (cue-ICT and EC) to evaluate their potential as interventions to reduce unhealthy food consumption. These paradigms were selected as their hypothesised mechanisms of action were similar, and the evidence base for both training paradigms had similar issues in terms of inadequate control groups, poorly standardised experimental procedures and inconsistent training outcomes. Completion of this study resulted in the development of a standardised experimental protocol for both cue-ICT and EC for use in subsequent studies (allowing for direct comparisons in terms of experimental outcomes).

Chapter 4 further investigated cue-ICT and EC paradigms to identify the role of cue-inhibition contingencies and critical pairings in training outcomes. There is substantial variability in the proportion of critical trials presented within training across the CBM literature, however, the influence of these specific variations on training outcomes had not been investigated. Across two online studies, the percentage of critical trials presented (for both cue-ICT and EC) was systematically varied (25%, 50%, 75% and 100%) to identify the potential influence of inconsistent training paradigm presentation on measures of food value and explicit preference (and therefore perceived training efficacy).

As the results from previous chapters had found limited evidence to support the use of CBM within food contexts, Chapter 5 investigated the role of individual level variables in relation to training outcomes to attempt to explain previous positive training outcomes. Given that previous work had implicated training expectancies and beliefs in training outcomes, in these two online studies, participant beliefs in relation to training efficacy deliberately influenced (through a manipulation message) for both cue-ICT and EC to examine the influence of this information on training outcomes (in comparison to a control group who did not receive a message related to training purpose/potential effectiveness).

Chapter 6 examined commonly used measures of food preference and value to investigate the extent to which these measures predicted real world food consumption. These measures are commonly used as outcome variables (and indicators of success) within CBM studies, yet little is known about how well they relate to other behavioural measures of consumption. Using an EMA design, the predictive validity of food value, implicit preference and explicit preference measures was evaluated in relation to real-world snack food consumption over a 7-day study period.

Chapter 2. General Methods

This chapter details the methods used throughout the thesis. Any deviations from these methods are discussed within the respective chapter. Individual study chapters provide brief descriptions of each method as chapters are based on publications.

2.1. Measures

2.1.1. Three Factor Eating Questionnaire

The Three Factor Eating Questionnaire (TFEQ: Stunkard & Messick, 1985) was used in study 1 to assess cognitive restraint and disinhibition within the sample. While the full scale consists of 51 items, only items relating to the cognitive restraint and disinhibition subscales were used to reduce overall assessment length. Statements were responded to as ‘true’ (the statement does apply to the participant) or ‘false’ (the statement does not apply to the participant), on an anchored likert scale ranging between 1 (e.g., never) and 4 (e.g., always), or on the final question, scored between 0 and 5, with anchors ranging between ‘eat whatever you want’ and ‘constantly limiting food intake, never giving in’. Higher scores indicate increased prevalence of the individual factor in relation to eating behaviours. The TFEQ has been shown to have good levels of internal consistency (alpha = 0.75 – 0.87) across various countries (e.g. Chearskul et al., 2010; Löffler et al., 2015), and previous work has linked both cognitive restraint and disinhibition to weight related outcomes (e.g., Bryant et al., 2008; French et al., 2014; Thomas et al., 2014; Urbanek et al., 2015).

In study 5 (Chapter 5), the shorter 18 factor version of the scale (Three Factor Eating Questionnaire – Revised 18 item (TFEQ-R18); Karlsson et al., 2000) was used to identify between sample differences in relation to eating patterns and behaviours (and further reduce assessment length). This version of the questionnaire consists of 18 items assessing cognitive restraint, uncontrolled eating and emotional eating, and participants were asked to indicate how much they felt each presented statement applied to them on a four point scale with anchors including 1 (definitely false) and 4 (definitely true). Identically to the full version of the questionnaire, higher scores for each factor indicate increased prevalence of this behaviour in relation to food consumption and choice. Similarly to the full version of the scale, previous work has demonstrated that the TFEQ-R18 has good levels of internal consistency (alpha = 0.75 – 0.89) (e.g., Anglé et al., 2009; Martins et al., 2021), and has been linked to various weight and dietary behaviours (e.g., Braden et al., 2016; de Lauzon et al., 2004; Mason et al., 2019).

2.1.2. Food Frequency Questionnaire

In study 1, participants were asked to complete a food frequency questionnaire (FFQ) to measure consumption of specific food types for the week prior to and one week post study completion. Participants were presented with a list of 14 common unhealthy food items (e.g., chips, crisps, cake) and asked to indicate how many times they had eaten each item during the previous week (i.e., if crisps were eaten each day, a score of 7 would be provided). FFQs are frequently utilised to capture food behaviours outside of the laboratory (Cade et al., 2007), and are less invasive and easier for participants to complete than alternative measures of longer-term food consumption (such as a weighed food record) (Steinemann et al., 2017).

2.1.3. Ad Libitum Taste Test

In study 1, ad libitum food intake was assessed through a bogus taste test. Previous work has demonstrated that the taste test is likely to be a valid measure of food intake as it is correlated with participant characteristics reliably associated with food intake (such as hunger and food liking) and is sensitive to manipulations hypothesised to increase or decrease food consumption (Robinson et al., 2017). Participants were presented with four bowls, each containing 100g of healthy (carrot sticks, grapes) and unhealthy (crisps/chips, cookies) snack foods, in addition to 500ml of water. These foods were selected to ensure that both sweet and savoury healthy and unhealthy options were available to account for some individual variability in preference(s).

Participants were instructed to taste each food, and rate each individually across a variety of taste dimensions (e.g., sweet/salty) before providing an overall liking score using a 100mm visual analogue scale. They were told they could consume as much of each food as they liked, and were given 10 minutes to complete the ratings/taste test. Consumption was calculated by adding the number of grams consumed for each food type within each category (i.e., unhealthy food consumption (g) = crisps consumption (g) + cookies consumption (g)).

2.1.4. Implicit Association Test

Implicit preference for unhealthy food items was assessed in study 1 using the implicit association test (IAT, Greenwald et al., 1998). Implicit preferences have been linked to weight gain (e.g., Nederkoorn et al., 2010) and are often used within food related CBM studies as proxy measures of training success (e.g., Houben et al., 2012; Lebens et al., 2011). The task consisted of two main sections, where participants were asked to sort words and images into either hypothesis consistent (i.e., healthy food image, positive word; unhealthy food image, negative word) or hypothesis inconsistent (i.e., healthy food image, negative word; unhealthy food image, positive word) categories over a series of 120 experimental trials (60 per section, presented in blocks of 20 and 40 trials), with an additional 3 blocks of 'familiarisation' trials (20 trials in each block). Participants were instructed to sort displayed words and images as quickly as possible, using the 'I' and 'E' keys, based on the category labels presented within the specific block (see figure 2.1). Response latencies were recorded, and the D600 algorithm (Greenwald et al., 2003) was used to calculate an implicit preference score, where the means and standard deviations for correct responses (to both hypothesis consistent and inconsistent blocks) were analysed. Positive scores were indicative of a preference for healthy foods, and a negative score indicated a preference for unhealthy foods.

Figure 2.1. A schematic of a typical implicit preference task trial. Participants would press the 'I' key to sort the image presented into the category label on the right hand side of the screen (i.e., chocolate = unhealthy).

While evidence related to the validity of the IAT in food contexts is relatively mixed (Richetin et al., 2007), meta-analytic work has demonstrated that the overall effect size was *r* = .27 across all studies assessing an implicit attitude-behaviour association (Greenwald et al., 2009) and there is also some evidence to suggest the IAT is associated with subsequent self-reported food choice and consumption behaviours (e.g., Friese et al., 2008; Hofmann et al., 2008b).

Due to the length of the full IAT and the repeated assessments required within study 6, the brief implicit association test (BIAT, Sriram & Greenwald, 2009) was used to measure implicit preferences for healthy and unhealthy foods within this study. While the task parameters are identical to the full IAT (i.e., sort words and images into hypothesis consistent and inconsistent categories as quickly as possible), the BIAT reduces the number of experimental trials to 80 (40 trials per section, 20 per block), reducing the time required to complete the assessment. Only one category label is presented at a time, with participants instructed to sort anything other than the presented hypothesis consistent/inconsistent category items into 'anything else'. The BIAT has previously been applied to food contexts (e.g., Khan & Petróczi, 2015) and work has demonstrated that the BIAT outperformed several other indirect measures of attitude in terms of internal and test-retest reliability (Bar-Anan & Nosek, 2014).

2.1.5. Baseline Inhibitory Ability

Baseline inhibitory ability was measured in studies 2 and 3 (chapter 4) using a food specific go/no-go task (e.g., Houben & Jansen, 2011). The go/no-go task measures action restraint (i.e., can a response be *withheld* when stimuli are presented (Verbruggen & Logan, 2008)) and is a widely used measure of inhibitory ability in CBM contexts (e.g., Blackburne et al., 2016; Brockmeyer et al., 2016; Kakoschke et al., 2015). Participants completed 160 trials (in addition to 10 unrecorded practice trials) where they were required to respond as quickly as possible to 'go' trials (where no border was present around the image, 75% of trials) and withhold responses to 'no-go' trials (where a blue border surrounded the image, 25% of trials) (see figure 2.2).

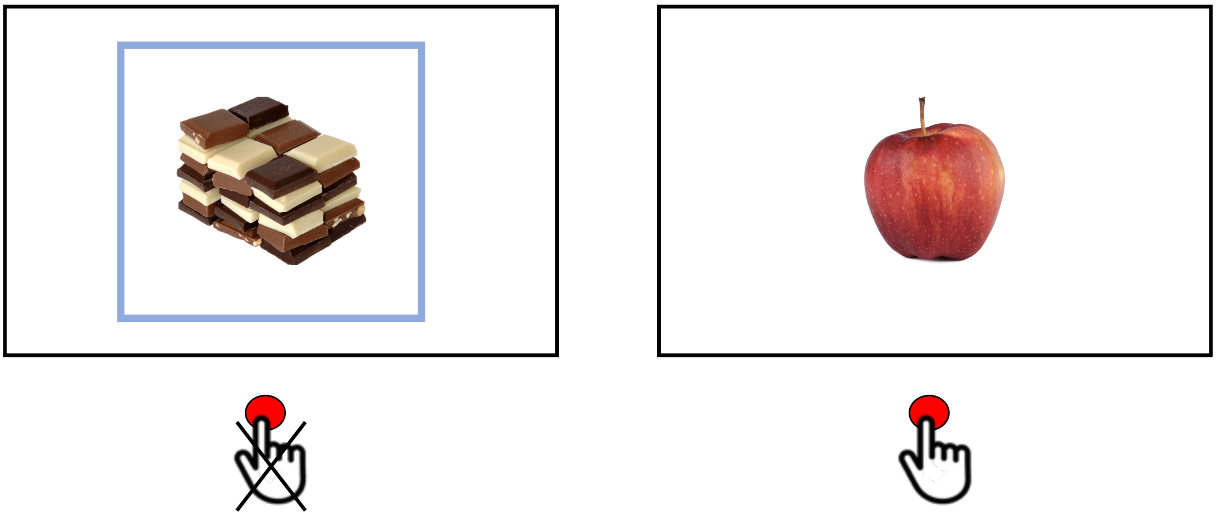


Figure 2.2. A schematic of a typical go/no-go trial. The image on the left is surrounded by a blue border, indicating a response should not be provided. The image on the right has no border, therefore a response is required.

The number of inhibition errors and median trial response times were used to determine baseline inhibitory ability, with higher error rates and median trial response times indicative of poorer inhibitory control. Previous work within CBM contexts has also used cue-ICT error rates and reaction times as measures of baseline inhibitory ability (e.g., Chen et al., 2018b; Houben, 2011).

2.1.6. Food Value

Food value was measured in studies 2 – 5 (chapters 4 and 5) to identify changes in healthy and unhealthy food appeal after completion of CBM. Participants were presented with images of 10 healthy (e.g., watermelon, carrot sticks) and 10 unhealthy (e.g., doughnut, chips/fries) food items, and asked *'How appealing do you find this image'*. Responses were provided on a visual analogue scale (VAS) ranging between -100 (not at all appealing) and +100 (extremely appealing) (see figure 2.3). These responses were used to calculate a mean appeal score for healthy and unhealthy foods. Previous work has suggested that VAS scales are most appropriate for use within repeated measures designs (Stubbs et al., 2000) and researchers have previously used these scales to identify changes to explicit food preferences within CBM contexts (e.g., Chen et al., 2018b, Lawrence et al., 2015a).

Figure 2.3. A schematic of a typical food value assessment. Participants click on the bottom line to provide their response.

Although food value was also measured in study 6, a shorter version of the measure was completed with fewer food images (5 healthy, 5 unhealthy) to reduce the length of the assessment (and participant burden) for the ecological momentary assessment (EMA) design of the study.

2.1.7. Explicit Preference

A forced choice task was used in all studies to assess explicit preference (food choice) post CBM training. Participants were presented with images of 8 food items (4 healthy, 4 unhealthy) and asked to select the two items that they would most like to consume at that moment in time. The images included equal numbers of sweet (e.g., chocolate, apple) and savoury options (e.g., chips/crisps, cucumber sticks). Healthy food choices were scored as +1 and unhealthy foods were scored as 0, resulting in a score ranging between 0 (two unhealthy choices) and 2 (two healthy choices) in line with previous work (Hollands & Marteau, 2016).

2.1.8. Social Desirability

The socially desirable response set five item survey (SDRS-5, Hays et al., 1989) was used in study 5 (chapter 5) to investigate the potential role of social desirability in observed training effects. Participants were asked 5 questions about their typical responses to various everyday scenarios (e.g., '*I sometimes feel resentful when I don't get my way*') and provided responses on a scale of 1 (definitely true) to 5 (definitely false). Only extreme scores (1 or 5 depending on question direction) were used to calculate the final score, with a final score ranging between 0 (low social desirability) and 5 (high social desirability). Previous validation work has demonstrated that the scale has acceptable internal consistency (alpha = 0.66 – 0.68) and good test-retest reliability (0.75) (Hays et al., 1989).

2.1.9. Belief in Science

The belief in science scale (BISS, Farias et al., 2013) was used in study 5 (chapter 5) to explore potential mechanisms of action related to the perceived value of science as an information source. Only the three items (item 5 (*'All the tasks human beings face are soluble by* science'), item 6 ('*The scientific method is the only reliable path to* knowledge'), item 7 ('*The only type of knowledge we can have is scientific knowledge'*), with the highest factor loadings (as identified by Dagnall et al., 2019) were completed to limit assessment length and reduce participant burden. Participants responded on a 6-point likert scale ranging from 1 (strongly disagree) to 6 (strongly agree). Scores were then added to create an overall score, with higher scores representing stronger beliefs in science. The overall scale has been shown to have convergent validity (Dagnall et al., 2019) and has previously been applied to health contexts (Stosic et al., 2021).

2.1.10. Snack Food Recall

To measure real-world food consumption in study 6 (chapter 6), participants completed a food log, where they were provided with several free recall boxes and asked to list any snack food item that they had consumed since the last assessment. Snack foods were defined as any food item consumed that was not part of a main meal (Hess et al., 2016), and participants were reminded of this definition at each assessment. Participants were asked to provide as much detail as possible in relation to the food item, including amount consumed and brand of item. Participants were also asked to take photographs (using a smartphone) of both the food packaging and their consumed portion (where possible) and upload these images to a folder only accessible to them and the research team. Previous work has demonstrated that the use of photographs in dietary assessments can increase reporting accuracy and supports participant recall during assessments (Zhao et al., 2021), and this additional information also supported the research team when extracting nutritional and portion size information for items consumed (where this information was not provided by participants in the text recall).

2.1.11. Body Mass Index

In all studies, body mass index (BMI) was calculated to characterise the sample, using the formula weight(kg)/height(m^2). For study 1, measurements were collected in the lab using a stadiometer and weighing scales. Due to the online nature of the subsequent studies, BMI was calculated by the researcher using self-reported height and weight measurements. This was the case for all remaining studies in the thesis, including study 6 where BMI was also used as a predictor variable. While there are concerns in relation to the accuracy of self-reported height and weight measurements (e.g., Flood et al., 2000), previous research has demonstrated that there is a strong positive association between self-reported and lab measured height, weight and BMI ($R_s = 0.87 – 0.92$) (Olfert et al., 2018) and longitudinal work has suggested the discrepancies between self-reported and lab height, weight and BMI measurements are reducing over time, resulting in improved accuracy for participant reported anthropometrics (Stommel & Osier, 2013).

Chapter 3. Comparing the effects of Inhibitory Control Training and Evaluative Conditioning for unhealthy food behaviours.

This chapter contributed to the overall aim of the thesis by directly comparing two CBM techniques (cue-ICT and EC) in terms of their influence on measures of unhealthy food preference and consumption (in a laboratory context). The study contained within this chapter is currently under review as: Masterton, S. & Jones, A. (under review). Comparing the effects of Inhibitory Control Training and Evaluative Conditioning for unhealthy food behaviours.

In relation to contributions for this manuscript, I designed the study (which was approved by Andrew Jones), collected and analysed the data and wrote the manuscript. Andrew Jones also provided feedback on the completed manuscript.

Abstract

Cognitive Bias Modification (CBM) is hypothesised to reduce unhealthy food behaviour through the completion of computerised cognitive training tasks. While there is evidence to suggest that two popular CBM paradigms (Inhibitory Control Training (ICT) and Evaluative Conditioning (EC)) can have a positive influence on food-related outcomes, issues (and inconsistencies) related to task standardisation and control group design make it difficult to evaluate their standalone efficacy. In a pre-registered laboratory study, our aim was to directly compare a single session of ICT and EC on implicit preference, explicit choice and ad-libitum food intake, while ensuring appropriate active control groups were utilised for each training type (in addition to a passive control group). The results revealed that while participants in the active EC group made an increased number of healthy choices in comparison to the active ICT group, there were no other significant differences in terms of implicit preferences or ad-libitum food consumption. These results provide limited evidence to support the use of CBM as a psychological intervention for unhealthy food choices. Further work is needed to isolate mechanisms of effect for successful training and identify the most effective CBM protocols for implementation in future studies.

3.1. Introduction

Individual variations in food choice and intake can have substantial influences on weight status: increased consumption of highly palatable unhealthy foods has been linked to weight gain, with poor diet quality associated with the development of overweight and obesity (Hruby et al., 2016). While the obesogenic environment makes significant contributions to food choices and consumption patterns (Swinburn et al., 2011; Townshend & Lake, 2017), differences in terms of unhealthy food consumption and weight status within the population suggest that individual factors also have a substantial role in dietary behaviours. Investigation of these factors may provide insight into the psychological mechanisms that contribute to weight status.

Dual process models of health behaviours (Strack & Deutsch, 2004) frame the consumption and choice of food as the interaction between 'reflective' and 'implicit' processes. Reflective processes are effortful and goal-oriented (e.g., not consuming unhealthy foods in line with longer-term health goals), whereas implicit processes are (relatively) automatic, based on previous experiences and reward-driven (e.g., consuming unhealthy foods due to feelings of pleasure elicited by previous consumption, or triggered by appetitive cues). Eating behaviours are thought to be regulated through these two processes, with stronger reflective systems able to successfully resist hedonic drives for unhealthy foods and environmental food cues (Finlayson et al., 2007; Friese et al., 2011; Hofmann et al., 2008, 2009; Jones et al., 2018). Previous research conducted within food contexts provides support for these models: motor impulsivity (acting without thinking (Stanford et al., 2009)) has been linked to weight gain in participants with attentional biases and implicit preferences for high calorie food items (Meule & Platte, 2016; Nederkoorn et al., 2010) and work by Kakoschke et al., (2015) revealed that participants with higher approach biases for unhealthy foods and poor inhibitory control consumed higher amounts of unhealthy snack foods in an ad-libitum taste test.

Cognitive Bias Modification (CBM) refers to a specific branch of cognitive training that attempts to reduce unhealthy food intake by targeting reflective and/or implicit processes to strengthen self-regulatory capacity or modify the associations that underlie automatic processes (Friese et al., 2011; Jones et al., 2018). One example is cue-specific Inhibitory Control Training (cue-ICT), where participants are taught to repeatedly inhibit motor responses to unhealthy food cues. Behavioural-Stimulus interaction theory (Veling et al., 2008) hypothesises that this inhibition to unhealthy food cues creates a response conflict for individuals with weaker implicit processes (as their usual response would be to approach unhealthy food cues (Kakoschke et al., 2015)). To resolve the conflict, negative valence is attached to stimuli items that were previously positively rated (i.e., unhealthy food items), reducing their value (devaluation). While various mechanisms of action have been proposed by researchers, the devaluation hypothesis has substantial emprical support (e.g., Chen et al., 2016; Quandt et al., 2019; Veling et al., 2013b) and is thought to be the most likely mechanism for observed training effects (Veling et al., 2017).

Previous research suggests that cue-ICT can have a positive impact on various food behaviours (such as choice, preference and consumption: Chen et al., 2018b; Houben & Jansen, 2011, 2015; Lawrence et al., 2015a, 2015b; Veling et al., 2013b), with meta-analytic work revealing that a single session of cue-ICT leads to small (yet robust) reductions in food intake in the lab (Allom et al., 2016; Jones et al., 2016). Despite this, there are variations in training outcomes both within and between studies and several researchers have found limited evidence to support cue-ICT in relation to food consumption and preference (Aulbach et al., 2020; Adams et al., 2017 (Study 1); Bongers et al., 2018; Carbine et al., 2021) and recent work by Adams et al., (2021) revealed that while cue-ICT significantly reduced liking for energy dense foods, there were no significant differences between groups in terms of food consumption frequency and weight loss. As a result, researchers have raised concerns about the true evidential value of ICT (Carbine & Larson, 2019).

Evaluative Conditioning (EC) is another popular CBM approach where images of target stimuli (e.g., food cues) are paired with either positively or negatively valenced images over a series of experimental trials. EC is also hypothesised to reduce unhealthy food consumption through a devaluation mechanism, where repeated exposure to unhealthy food cues paired with negative images reduces the value and appeal of these items (and subsequently their consumption: Hollands et al., 2011). Previous work supports the application of EC to eating behaviours, with a single EC session resulting in decreased unhealthy food preferences and healthier explicit food choices (Haynes et al., 2015; Hollands et al., 2011; Hensels & Baines, 2016; Walsh & Kiviniemi, 2014), however, these results are not consistently replicated across studies. Work by Wang et al., (2017) found that although EC resulted in less favourable implicit and explicit attitudes towards chocolate (in comparison to fruit), there were no significant differences in chocolate consumption between experimental and control groups. Additionally, recent applied work has discovered that pairing image-only health warning labels and energy-dense snack food images had no significant influence on food choice or implicit/explicit attitudes (Asbridge et al., 2021).

One potential explanation for variations in training outcomes across both cue-ICT and EC studies may be related to the considerable heterogeneity between studies in terms of the control groups used. While control groups are generally utilised within CBM studies, these groups often experience reverse contingencies to training groups (e.g., for cue-ICT, instead of withholding responses to all unhealthy food images, control group participants respond to all unhealthy food images) which may unintentionally inflate between-group differences (Jones et al., 2016). Employing active control groups (e.g., for cue-ICT, where participants respond to 50% and inhibit responses to 50% of unhealthy stimuli) helps to ensure that control group participants are not being trained to approach unhealthy stimuli (Jones et al., 2018), however, this approach is not reliably applied across studies. There are also additional inconsistencies in relation to control group stimuli choices, with images utilised in training varying between neutral objects (e.g., household items) and healthy food images (e.g., strawberries) which may have implications for perceived training effectiveness and behavioural outcomes.

Therefore, the aim of the current research was to directly compare two CBM approaches (cue-ICT and EC) to evaluate their potential as intervention strategies to reduce unhealthy food consumption and preference. These two approaches were selected due to their similarities in terms of hypothesised mechanism of effect (devaluation) and the lack of standardisation in relation to paradigm design across studies. To identify potential differences in outcome based on control group design, we included *active* (experiencing 50% of each trial type) control groups for each type of training, in addition to a *passive* control group who simply responded to food-related image locations. We also used both explicit (ad-libitum taste test (e.g., Robinson et al., 2017), forced choice task (e.g., Hollands & Marteau, 2016)) and implicit (implicit association task (IAT, e.g., Hollands et al., 2011)) measures of choice and consumption as dependent variables to ensure that we were able to adequately compare our results to previous work and were also able to examine potential differences (in terms of training outcomes) between explicit and implicit measures of preference. We hypothesised that i) Participants in the intervention groups (cue-ICT or EC) will show a reduction in implicit food preferences for unhealthy foods compared to those involved in either active or passive control conditions. ii) Participants in the intervention groups (cue- ICT or EC) will make healthier explicit choices compared to those in active or passive control conditions, iii) Participants involved in the intervention groups (cue-ICT or EC) will consume less unhealthy food in an ad-libitum tasting compared to active and passive control groups.

3.2. Method

3.2.1. Participants

One hundred and twenty-nine participants aged between 18 and 50, (M = 22.51, SD = 6.68) completed the laboratory session. The sample was predominantly female (N = 109, 90%), with the average participant BMI falling within the healthy weight range (M = 24.60 kg/m^2, ± 4.44)[1]. Participants were also required to be aged 18 +, self-report no history of eating disorders, not be taking medication that influences appetite, and report no food allergies. Participants were recruited from the local community using print and social media advertisements. Participants received a £10 high street shopping voucher or course credit for completing the session. An a-priori power calculation determined that 140 participants would be required (d = .30 (Allom et al., 2016) $\alpha = 0.05$, $1 - \beta = 0.80$) to detect a within*between interaction across experimental conditions. We did not quite meet this target as data collection ceased as a result of the COVID-19 pandemic restrictions. We chose not to resume data collection due to the comparability of pre/post pandemic data (particularly, due to the impact of COVID-19 on food related behaviours (Robinson et al., 2020)); lack of taste test product availability, and funding for the lead authors PhD ending. With the participants recruited, we would be able to reliably detect an effect size of d = .31, with the same error control. The study was approved by the University Research Ethics Committee (approval code: 2926), and the pre-registration can be accessed here [https://osf.io/esw6n].

[1] While initially participants were required to have a BMI of 25 (i.e., overweight and obesity) or above, recruitment issues (due to a lack of participant awareness in relation to BMI status (i.e., participants not knowing BMI status/incorrectly assuming BMI status/no access to weighing equipment pre-study)) and potential biases associated with weight stigma within this population (e.g., Romano et al., 2018) led to the removal of this criteria.

3.2.2. Measures

3.2.2.1. Implicit Preference

The implicit association test (IAT, Greenwald et al., 1998) was used to measure relative measure preference for healthy vs unhealthy food items. The task consisted of two main sections, where response latencies to ‘hypothesis consistent’ (i.e., healthy food image, positive word; unhealthy food image, negative word) and ‘hypothesis inconsistent’ (i.e., unhealthy food image, positive word; healthy food image, negative word) trials were recorded. Overall there were 120 experimental trials (60 per section, presented in blocks of 20 and 40 trials), in addition to three ‘familiarisation’ blocks of 20 trials each. During each experimental block, participants were asked to sort words and images (using the ‘I’ and ‘E’ keys) based on the category labels (either hypothesis consistent or hypothesis inconsistent categories) as quickly as possible, with block order counterbalanced based on participant number.

3.2.2.2. Explicit Preference

Participants completed a forced choice task where they were asked to select 2 food images (out of a possible 8) that represented the foods that they would most like to consume at that moment (see Hollands & Marteau, 2016). Food images consisted of 4 healthy (e.g., apple, cucumber sticks) and 4 unhealthy (e.g., cake, chips/crisps) sweet and savoury items. A healthy food choice was scored as +1, and an unhealthy food choice scored as 0, resulting in a possible score ranging between 0 (two unhealthy choices) and 2 (two healthy choices).

3.2.2.3. Food Consumption and Preference

Food consumption was assessed through a bogus *ad-libitum* taste test (see Robinson et al., 2017). Participants were presented with four bowls, each containing 100g of healthy (carrot sticks, grapes) and unhealthy (crisps/chips, cookies) foods (in addition to 500ml of water) and were informed that they were going to complete a taste test as a cover story. They were instructed to taste the foods, and rate each individually across several dimensions (e.g., how sweet/salty is this food) before finally scoring each food for overall liking (using 100mm visual analogue scales). Participants were given 10 minutes to complete this, and were told that they could consume as much of the test foods as they would like to. The bowls were weighed (out of sight of participants) before and after the taste test to measure how much of each food was consumed (in grams). Healthy and unhealthy food consumption scores were calculated by adding the number of grams consumed for each food within the category (e.g., healthy food consumption = carrot consumption + grapes consumption).

3.2.2.4. Inhibitory Control Training Task

Participants in the ICT groups completed a food-specific go/no-go task, which was either an active training task (100% inhibit to unhealthy foods: ICT active) or a control training task (50% inhibit to unhealthy foods, 50% respond to unhealthy foods: ICT control) dependent on condition allocation. Images of 6 healthy (e.g., watermelon, vegetable platter) and 6 unhealthy (e.g., chocolate, fries) foods were used within the tasks, and participants were asked to either respond (using the spacebar) or withhold their response, depending on trial type.

Food images used within this task were selected based on previously conducted pilot work (see Masterton et al., 2021). Participants completed 10 unrecorded practice trials, before completing 100 trials (50 go and 50 no-go), with an untimed comfort break provided after the first 50 trials. Participants in the control training group received a message after 50 trials (during the break) informing them that the required response had changed (to allow for trial contingency manipulation (e.g., if participants had initially been responding to healthy foods, for the final 50 trials, they would be withholding responses to healthy foods)). Each image remained on screen for 1500ms (or until a response was provided for go trials), and response feedback was provided after each trial (either ‘correct’ or ‘incorrect’ displayed for 250ms). A 50% critical trial ratio was selected in line with previous work that has successfully demonstrated ICT effects (e.g., Houben & Jansen, 2011; 2015). Split half reliability analyses using ‘go’ trial reaction times demonstrated an acceptable level of reliability for this task (r = .69, p < .001).

3.2.2.5. Evaluative Conditioning Task

Participants in the EC groups completed an evaluative conditioning task (see Hollands & Marteau, 2016), where they were presented with pairs of images consisting of healthy or unhealthy foods, followed by a positive or negative health outcome (see https://osf.io/esw6n for example images). Participants completed either active (100% unhealthy foods paired with negative health outcomes) or control (50% unhealthy foods paired with negative health outcomes, 50% healthy foods paired with negative health outcomes) training. Food images used within these tasks were identical to those used in the ICT conditions, and the health outcome images were selected based upon previously conducted pilot work (see Masterton et al., 2021). To ensure participants remained engaged with the task, they were asked to respond to the location of stimuli on the screen, using the ‘E’ key for image pairs displayed on the left, and the ‘I’ key for image pairs on the right. Each image within the pair was displayed for a minimum of 1000ms, and the final image (outcome image) remained on screen until a response was provided. After 10 unrecorded practice trials, participants completed 100 experimental trials (50 healthy foods, 50 unhealthy foods), with an untimed comfort break provided after 50 trials in line with previous work (e.g., Hollands et al., 2011; Hollands & Marteau, 2016). Similarly to the ICT conditions, participants were provided with feedback after each trial (‘correct’ or ‘incorrect’ displayed for 250ms). Split half reliability analyses using reaction time data revealed high levels of internal reliability for this task (r = .85, p <.001).

3.2.2.6. Passive Control Task

Participants assigned to the passive control group completed a forced response reaction time task, where a single image of either a healthy or unhealthy food appeared on screen, and participants responded to the location of the image using the ‘E’ (left hand side) and ‘I’ (right hand side) keys as quickly as possible. This ensured that passive control group participants remained engaged with the images, as the task would not continue until a keyboard response was provided. Similarly to the other experimental tasks, participants completed 10 practice trials, before completing 100 (50 healthy food, 50 unhealthy food) experimental trials, with an untimed break provided after 50 trials. Again, participants were provided with trial by trial feedback (either ‘correct’ or ‘incorrect’ presented on screen for 250ms).

3.2.2.7. Food Frequency Questionnaire

Participants were provided with a list of 14 common unhealthy food items (e.g., chips, crisps, cake), and asked to indicate how many times they had eaten each food during the previous week (i.e., if cake was eaten each day, a score of 7 would be provided). A full list of foods can be found at https://osf.io/esw6n.

3.2.2.8. Three Factor Eating Questionnaire

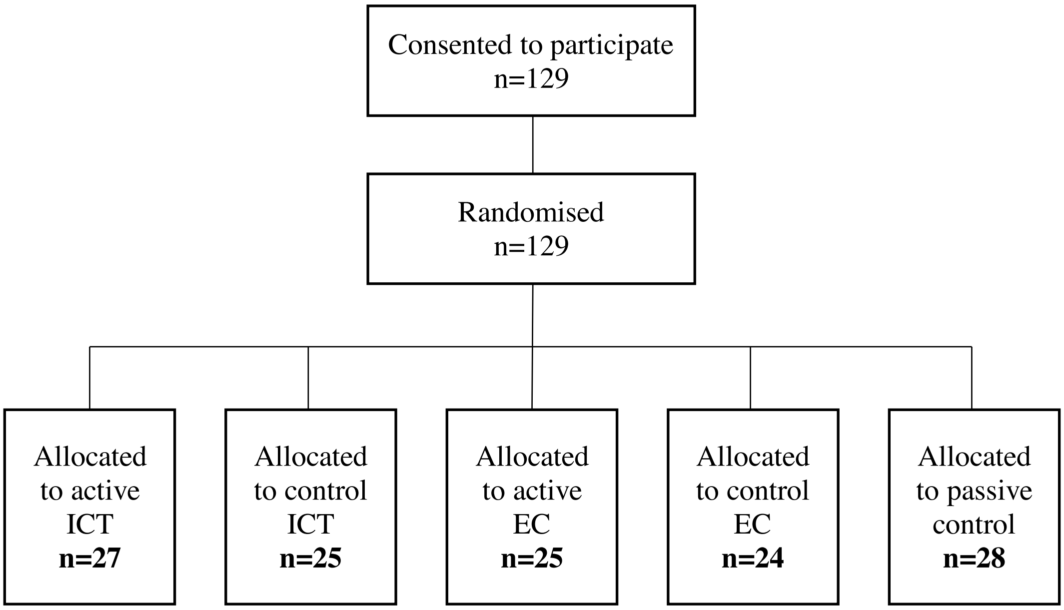
Cognitive restraint and disinhibition were measured using the relevant items (37 questions total (20 restraint, 17 disinhibition)) from the Three Factor Eating Questionnaire

(*TFEQ,* Stunkard & Messick, 1985). Higher scores indicate increased factor prevalence in relation to eating behaviours. Internal reliability was good for both factors (cognitive restraint, α = .84, disinhibition α = .77).

3.2.3. Procedure

Participants attended a weekday laboratory session lasting ~45 minutes at the University of Liverpool between the hours of 11am and 6pm, and were asked to refrain from eating for one hour prior to their study timeslot. After providing informed consent, height and weight measurements were collected, and participants were taken to an individual testing booth where they provided demographic information (including age and sex), responded to a question regarding hunger levels (a likert scale ranging between 1 (not at all hungry) and 10 (extremely hungry)), and completed the FFQ and TFEQ. Participants then completed the pre-intervention IAT, followed by a short distraction task (to prevent IAT task demands from influencing intervention engagement). Participants were randomly allocated (via simple randomisation without stratification) to complete one of five tasks (see figure 1), followed by a second distraction task. Participants then completed the post intervention IAT and the bogus taste test. Finally, participants completed the explicit preference measure, before being asked for a contact email address for the follow-up element of the study. One week after the initial lab session, participants were contacted and asked to complete the FFQ, the IAT and the explicit preference measure for a second time, before receiving a full debrief. All experimental tasks and questionnaires were presented using Inquisit 5 (Millisecond Software, SA).

Figure 3.1. A schematic flow diagram of participant recruitment and condition allocation.



3.2.4. Statistical Analysis

Analyses were pre-registered prior to data collection (https://osf.io/esw6n). To assess changes to implicit food preferences, a 5 (training condition: active ICT, control ICT, active EC, control EC, passive control) x 2 (time: pre training, post training) Mixed ANOVA was conducted. The *D600* algorithm (Greenwald et al., 2003) was used to calculate implicit preference scores, with positive scores representing a preference for healthy foods, and a negative score representing a preference for unhealthy foods. Explicit food preference data was analysed using a one-way ANOVA (with training condition as the independent variable), and healthy/unhealthy food consumption was analysed using individual one way ANOVAs, again, with training condition as the independent variable. While we had initially planned to conduct additional analyses in relation to food consumption (as measured by the FFQ) and preferences one-week post training (as outlined in the study pre-registration), these analyses were not performed due to high levels of participant attrition for the follow up measurements and insufficient statistical power. As per our pre-registered analysis plan, the analyses were repeated with outliers for the DVs removed (see supplementary materials, appendix A)). Additional exploratory analyses were performed including the generation of Bayes factors to examine if data was sensitive enough to provide support for the null vs alternative hypotheses (Dienes, 2014).

3.3. Results

See table 3.1 for descriptive statistics split by experimental group.

Table 3.1. Descriptive statistics for participant demographics split by condition. Values for age and BMI represent M (±SD).

Condition	Age (y)	Sex (M:F)	BMI
Active ICT	22.85 (6.37)	3:24	24.64 (4.04)
Control ICT	22.16 (8.31)	3:22	24.15 (5.24)
Active EC	22.32 (6.50)	5:20	24.67 (3.93)
Control EC	22.71 (7.17)	6:18	25.79 (5.14)
Passive Control	22.50 (5.45)	3:25	23.87 (4.07)

3.3.1. H1 - Participants in the intervention groups (cue-specific ICT or EC) will show a reduction in implicit food preferences for unhealthy foods compared to those involved in either active or passive control conditions.

A 5 (condition: active ICT, control ICT, active EC, control EC, passive control) x 2 (time: pre and post intervention) mixed ANOVA with IAT score as the dependent variable revealed that there was a significant main effect of time (F (1, 124) = 31.73, $p < .001$, $\eta p2$ =

.20), with lower IAT scores post intervention (*M* = 0.75, *SD* = 0.36) compared to pre intervention (*M* = 0.93, *SD* = 0.37) (indicating increased preference for unhealthy food items) (*d* = 0.50). There was no significant main effect of condition (*F* (4, 124) = 0.41, p = .802, ηp2 = .01), and no significant condition by time interaction (*F* (4, 124) = 0.42, p = .797, ηp2 = .01) (see table 3.2 for descriptive statistics).

To further evaluate our findings, we generated Bayes factors for this analysis which provided strong support for the Null for the condition*time interaction (BF_{01} = 142.86) (see supplementary materials (Appendix A) for full model reporting)

Table 3.2. Means and standard deviations for IAT pre and post intervention. Higher scores represent increased preference for healthy foods, scores range between -2 and +2.

Condition	Pre intervention	Post intervention
Active ICT	0.96 (0.30)	0.77 (0.37)
Control ICT	0.93 (0.43)	0.74 (0.29)
Active EC	0.88 (0.39)	0.67 (0.36)
Control EC	0.93 (0.37)	0.84 (0.36)
Passive Control	0.93 (0.40)	0.76 (0.40)

3.3.2. H2 - Participants in the intervention groups (cue-specific ICT or EC) will make healthier explicit choices compared to those in active or passive control conditions.

A one way ANOVA with condition (active ICT, control ICT, active EC, control EC, passive control) as the independent variable and explicit preference as the dependent variable showed that there was a weak significant main effect of condition (*F* (4, 124) = 2.54, p = .043, ηp2 = .08). Post hoc Tukey tests revealed that this was due to a significant difference between the active ICT and active EC groups, with participants in the active EC groups making an increased number of healthy choices in comparison to the active ICT group (see figure 3.2) ($p = .027$). No other groups differed significantly ($p > .05$ in all cases).

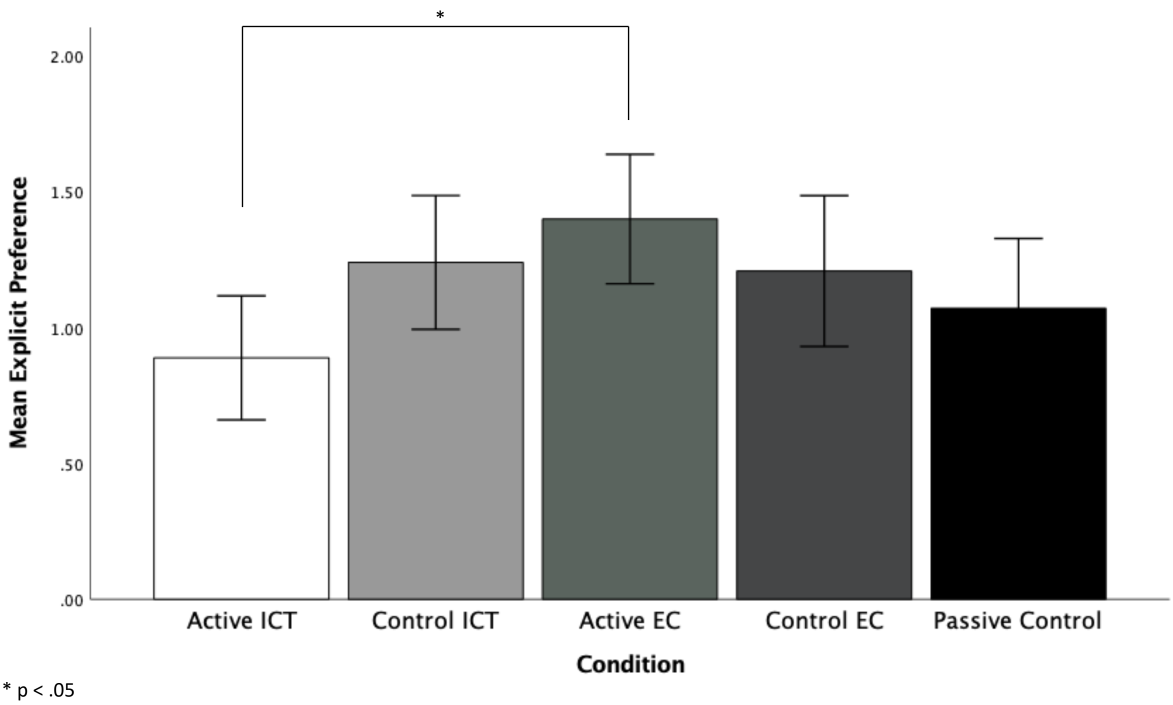


Figure 3.2. A bar chart displaying explicit preference scores split by condition. Higher scores represent healthier explicit choices (scores range between 0 and 2). Bars represent 95% CI.

3.3.3. H3 - Participants involved in the intervention groups (cue-ICT or EC) will consume less unhealthy food in an ad-libitum tasting compared to active and passive control groups

A one way ANOVA with condition (active ICT, control ICT, active EC, control EC, passive control) as the independent variable and healthy food consumption as the dependent variable revealed that there was no significant main effect of condition (F (4, 124) = 0.86, $p = .489$, $\eta p2 = .03$). This analysis was repeated using unhealthy food consumption as the dependent variable, and again, no significant main effect of condition was found (F (4, 124) = 0.79, p = .534, $\eta p2$ = .03) (see table 3.3 for descriptive statistics).

Bayes factors provided further support for these findings, with strong evidence in favour of the Null provided for both healthy (BF_{01} = 10.85) and unhealthy (BF_{01} = 12.04) food consumption.

Table 3.3. Means and standard deviations for healthy and unhealthy food consumption during the taste test (g consumed) per condition. Maximum possible intake is 200g.

Condition	Healthy food consumption	Unhealthy food consumption
Active ICT	76.12 (41.89)	42.78 (26.12)
Control ICT	69.44 (40.07)	32.27 (23.06)
Active EC	54.78 (39.86)	32.60 (27.72)
Control EC	63.85 (43.77)	39.40 (23.98)
Passive Control	65.10 (47.81)	36.47 (27.02)

3.4. Discussion

The aim of the current study was to directly compare two CBM approaches (cue-ICT and EC) in a laboratory environment to evaluate their effectiveness in terms of reducing unhealthy food preference and consumption. Although there was a difference in explicit choice between active cue-ICT and EC, the different types of training had no influence on implicit preference for unhealthy food items, and there were no significant differences between groups in terms of healthy and unhealthy food consumption in an ad-libitum taste test.

The results revealed that no training (or control) groups differed significantly in IAT scores. While previous research has reported decreases to implicit unhealthy food preferences post-CBM (supporting a devaluation hypothesis: e.g., Haynes et al., 2015; Hensels & Baines 2016; Hollands et al., 2011; Wang et al., 2017), the results of the current study (and inferential Bayesian analysis) provide evidence that questions the robustness of this effect. As stimulus devaluation is more consistently observed for explicit measures of preference (e.g., Adams et al., 2021; Chen et al., 2016; 2018; Lawrence et al., 2015a), it may be that implicit preferences (while implicated in the engagement of inhibitory control (Nederkoorn et al., 2010)) are not as susceptible to CBM training effects. Given that both cue-ICT and EC are hypothesised to target the associations that underlie automatic processes (Jones et al., 2018), the lack of evidence to support training-induced implicit preference change raises questions in relation to the precise mechanism of action for CBM training paradigms. While preference measures are frequently utilised to evaluate intervention success, the extent to which these changes relate to real-world behavioural change (and subsequently, weight loss) is unclear. Future work should investigate how both explicit and implicit preference changes relate to health behaviours to understand the impact of CBM on real world behaviour.

It was also hypothesised that participants in active training groups would consume less unhealthy food in an ad-libitum taste test, however, there were no significant differences in consumption between groups for either healthy or unhealthy snack foods. As a relatively objective measure of eating behaviour (Robinson et al., 2017), unhealthy food consumption is a frequently used outcome for intervention assessments in the laboratory, with previous research finding significant reductions in unhealthy snack food consumption following ICT (e.g., Houben & Jansen, 2011, 2015; Lawrence et al., 2015b). One potential explanation for these differences in results may be related to methodological variations. While the current study used 50% contingency control groups (i.e., withhold responses to 50% healthy food/50% unhealthy food images) in addition to a passive control group, previous work has often utilised reverse contingencies for control groups (i.e., respond to 100% of unhealthy foods), potentially training control participants *towards* unhealthy foods, inflating differences between training and control groups (Jones et al., 2016). Design variations such as this make it difficult to draw robust conclusions in relation to CBM efficacy: future research should attempt to investigate these inconsistencies in isolation to ascertain the impact of paradigm variation on behavioural outcomes. This would not only help to identify the true potential of training (in relation to behavioural change), but would also support the development of a standardised protocol for CBM interventions across the literature.

For explicit food preferences, while there was no significant difference between the active and control conditions for each technique, participants in the active EC condition made healthier explicit choices than those in the active ICT condition. As cue-ICT and EC are hypothesised to have similar mechanisms of action, a difference in explicit preferences between the active versions of both types of training was unexpected (as differences were hypothesised between *control* and active training groups). This finding may be due to the way in which stimuli are presented within each type of training: while cue-ICT paradigms encourage rapid responses to stimuli, EC paradigms typically have longer minimum trial durations, as both stimuli images have to be displayed before participants can make a response. This increased trial duration may have consequences for both participant performance and contingency awareness. Previous work has highlighted that the proportion of successful inhibitions is predictive of ICT effect size (Jones et al., 2016), and the encouragement of 'rapid responses' within ICT tasks may have influenced performance within these tasks (in comparison to EC tasks where participants make a response within each trial irrespective of content), resulting in differences between the two training groups.

Alternatively, previous work investigating contingency awareness has discovered that some CBM training effects (including healthy food liking) can be moderated by awareness of experimental aims (Adams et al., 2021). It may be that the increased duration of EC trials allowed participants to study image content more comprehensively, resulting in healthier explicit choices being made due to increased manipulation awareness (and potential demand characteristics): this idea is supported by work from Quandt et al., (2019) who discovered stronger ICT effects where participant attention was drawn to cues within training. Expectations in relation to training also appear to be linked to successful training outcomes, with recent work revealing that both cue-ICT and EC effects appeared to be dependent on the presentation of a message describing training positively as opposed to the actual content (i.e., active or control) of training (Masterton et al., 2022).

Despite these potential explanations, we would advise caution when interpreting these results: while the forced-choice task is a well-utilised measure within CBM research (e.g., Hensels & Baines, 2016; Hollands et al., 2011; Veling et al., 2013b), the predictive validity of this measure is relatively understudied in terms of translation to real world eating behaviours. Decisions made within this task have no real-world implications for participants which may influence participant choices (i.e., participants may select a healthy food item knowing they will not have to consume it (irrespective of true preference)). Furthermore, our sample was predominantly female, and our analyses were underpowered. However, our Bayesian analyses suggest that we had enough data to provide moderate support for the null hypotheses (Dienes, 2012).

As the current study used a combined student and community sample, the average participant BMI fell just within the healthy range. It is possible that participants with overweight and obesity (a target for interventions designed to reduce unhealthy food intake) display specific preferences and consumption behaviours, and may respond differently to CBM training paradigms. While recent work has discovered that cue-ICT did not appear to influence weight or dietary intake over a 12 week study period for individuals with overweight and obesity (Carbine et al., 2021), unhealthy food preferences were not measured and dietary recall data was obtained through 24 hour recalls, which may introduce issues related to underestimations of unhealthy food intake (Macdiarmid & Blundell, 1998). It may be useful to further examine CBM paradigms within this specific population using alternative, real-time methods of dietary assessment (such as Ecological Momentary Analysis) to fully identify the impact of training within this group.

In conclusion, the aim of the current study was to directly compare the efficacy of two CBM techniques (cue-ICT and EC) to reduce unhealthy food consumption and preference. The results revealed that neither type of CBM training influenced implicit preferences for unhealthy foods or resulted in differences in healthy and unhealthy food consumption (in an ad-libitum taste test). Inconsistencies in terms of training outcomes across the literature suggest that further work is needed to isolate mechanisms of effect and develop standardised training protocols for successful CBM. This would support attempts to review the use of cognitive training in the reduction of unhealthy food consumption and preference to evaluate the potential for CBM as an intervention for overweight and obesity.

Chapter 4. Examining Cognitive Bias Modification interventions for reducing food value and choice: Two pre-registered, online studies.

This chapter contributed to the overall aim of the thesis by investigating the role of cue-inhibition contingencies and critical pairings in perceived training effectiveness. Due to inconsistencies across the literature, the extent to which these specific task variations influenced training outcomes was unclear. The study contained within this chapter has been published as: Masterton, S., Hardman, C., Halford, J. C. G., & Jones, A. (2021). Examining cognitive bias modification interventions for reducing food value and choice: Two pre-registered, online studies. *Appetite, 159*, 105063. https://doi.org/10.1016/j.appet.2020.105063

In relation to contributions for this chapter, I designed the study (which was approved by Andrew Jones and Charlotte Hardman), collected and analysed the data and wrote the manuscript. All authors provided feedback on the original manuscript and subsequent revisions (in response to reviewer feedback).

Abstract

There is considerable interest in Cognitive Bias Modification (CBM) as a potential treatment for overweight / obesity. Inhibitory Control Training (ICT: also known as motor response training) and Evaluative Conditioning (EC) are two popular paradigms which rely on associatively learned responses (unhealthy food -> inhibition, or unhealthy food-> negative stimulus, respectively) through repeated cue-response contingencies. Both ICT and EC have demonstrated some effectiveness for reducing food intake, value and / or choice, when administered in the laboratory and online. However, studies have been criticised for inconsistencies in design (e.g. use of inadequate control groups) which makes it difficult to draw robust conclusions. In two pre-registered, online studies our aim was to examine active ICT (study 1: N = 170) and EiC (study 2: N = 300) in multiple groups where the cue-> response contingencies were systematically varied (100%, 75%, 50%, 25%), before examining food-cue valuations and hypothetical food choice. In both studies varying the cue-> response contingencies did not lead to significant changes in food-cue devaluation following training. ICT did not substantially influence hypothetical food choice, whereas there was weak evidence that EC reduced choice for unhealthy foods, compared to a control group with 50% cue-response contingencies. Taken together both studies provide limited evidence for online CBM as a viable psychological treatment – at least through the mechanism of food-cue devaluation or changes in healthy and unhealthy food choice. Future research is needed to investigate the factors that contribute towards successful CBM training to critically evaluate the potential for these strategies within health interventions.

4.1. Introduction

The prevalence of overweight and obesity has increased to pandemic levels over the past 50 years (Blüher, 2019), and is at least partly attributed to an obesogenic environment saturated with unhealthy food-cues which signal high availability of these foods (Sample et al., 2015). Not everybody exposed to the obesogenic environment demonstrates excessive weight gain, therefore a focus on individual differences could lead to the development of effective interventions (Houben et al., 2015). Interventions that aim to reduce the value of unhealthy food- cues and to increase behavioural control, particularly if administered online, may be a fruitful area of research.

Dual process models (Hofmann et al., 2008; Strack & Deutsch, 2004) have informed a variety of psychological interventions, known collectively as Cognitive Bias Modification. These models suggest that individual responses to food-related cues are regulated through the interactive influences of implicit and reflective processes, which subsequently determine food selection and consumption. Implicit processes are fast acting, require minimal conscious effort and are based on previously formed memory associations (unhealthy food -> feelings of pleasure). Reflective processes are slower, cognitively demanding and serve to direct behaviour towards longer term goals (e.g. *'I will resist unhealthy food now, as I am attempting to lose weight'*). Although alternative explanations for unhealthy food selection exist (e.g., value-based choice model of self-control (Berkman et al., 2017)), research related to dual process models suggests that individuals who make poorer (unhealthy) food choices may possess strong implicit biases for unhealthy food items, in addition to a weaker reflective system which is unable to resist the desire to consume unhealthy foods (Forman et al., 2019; Jones et al., 2018; Nederkoorn et al., 2010). In support of dual process models, Price et al., (2016) discovered that poorer inhibitory control (the ability to inhibit or delay behavioural responses in line with longer-term goals (Houben et al., 2014)) was associated with overeating in response to palatable stimuli. Lower levels of inhibitory control have also been linked to unsuccessful diet attempts (Brockmeyer et al., 2016; Nederkoorn et al., 2007), with research by Spitoni et al., (2017) discovering that individuals with obesity had poorer inhibitory control abilities compared to healthy weight participants.

Cognitive Bias Modification (CBM) paradigms attempt to target these implicit and / or reflective processes to attenuate or strengthen their influence on subsequent behaviour (Friese et al., 2011). A typical example is Inhibitory Control Training (ICT). In this paradigm, participants learn to repeatedly inhibit a motor behaviour in the presence of unhealthy-food cues (cue->inhibition response contingency), which is thought to reduce preference and approach related behaviours for these foods (potentially through an object evaluation mechanism rather than training individual inhibitory ability (Johannes et al., 2021). As such ICT is also referred to as motor response training, due to the lack of inhibitory control change as a potential mechanism). Cue-specific inhibition training was developed from Behavioural-Stimulus interaction theory (Veling et al., 2008), which hypothesises that inhibiting to positively valenced cues (e.g. palatable foods) creates a response conflict as the typical response would be to approach these cues (assuming strong implicit processes (Kemps & Tiggemann, 2015)). To reduce the conflict, negative valence is attached to the previously positively valanced cues, reducing their perceived value (known as *devaluation*). Devaluation of food-related cues following ICT has been observed reliably in a number of studies (e.g., Chen, et al., 2016; van Koningsbruggen et al., 2014), and is hypothesised as the most likely mechanism of ICT (Veling et al., 2017).

Meta-analyses suggest that ICT has a small but robust effect on food choice and intake for healthy weight participants in the lab (Allom et al., 2016; Jones et al., 2016). However, there is considerable variation in effect sizes between individual studies, and not all studies report positive post training outcomes (Adams et al., 2017 (Study 1); Allom &

Mullan, 2015 (Study 2); Bongers et al., 2018; Forman et al., 2016; Oomen et al., 2018), and there is wider debate on the existence of a true underlying effect (known as evidential value (Carbine & Larson, 2017)). This may indicate that differences in the designs of existing research could influence training outcomes, raising uncertainty in relation to cue-ICT effectiveness.

While there is evidence to suggest that a single session of ICT can positively influence health behaviours (Allom et al., 2016), the protocols used within cue-ICT itself are relatively inconsistent. There is some variation between studies in terms of the number of times that participants are required to inhibit responses towards target stimuli (cue->inhibition contingency) in experimental conditions, ranging between 87.5% (Adams et al., 2017; Lawrence et al., 2015b) and 100% (Houben & Jansen, 2011, 2015). Meta analytic work (Jones et al., 2016) revealed that ICT effect size is significantly influenced by participant performance during training, with increased inhibition failures linked to smaller ICT effects. Task performance was also positively correlated with cue->inhibition contingency (i.e., participants are more successful at training where cue->inhibition contingencies are higher), which may partially explain the larger effect sizes observed where studies use Go/No-go training (as the cue->inhibition contingencies within these studies are typically closer to 100%) compared to Stop Signal tasks. This raises questions in relation to the role of the training paradigm within ICT research: variations in cue->inhibition contingencies prevent the direct comparison of studies, which makes it difficult to draw overall conclusions related to ICT effectiveness.

A second CBM approach, evaluative conditioning (EC), attempts to modify the valence of stimuli by pairing images of a target stimuli with either positive or negative images. Pairing food-related cues to negative images (cue->response contingency) is thought to influence preference for the original target stimuli, and reduce appeal and preference for these items (Hollands et al., 2011), suggesting a similar underlying mechanism (*devaluation*) to ICT. EC approaches are used as part of various behaviour change campaigns (for example, anti-smoking (Măgurean, Constantin & Sava, 2016)) and have been successfully applied to the context of eating behaviours, with research demonstrating reductions in unhealthy food intake and preference post EC (Bui & Fazio, 2016; Haynes et al., 2015b; Hensels & Baines, 2016; Hollands et al., 2011; Shaw et al., 2016). Despite the apparent success of EC strategies, there are some inconsistencies related to the effectiveness of training: recent work has discovered that while there was some evidence to suggest that EC appeared to be effective at reducing explicit preference for alcoholic drinks, there was no significant effect of active EC on explicit attitudes towards healthy or unhealthy foods (Zerhouni et al., 2019). Similarly, Hollands et al (2016) failed to replicate EC effects from an earlier study (Hollands et al, 2011) and research by Wang et al., (2017) discovered that while an EC intervention influenced attitudes towards chocolate (the target stimuli), there was no significant difference between EC and a control group in subsequent chocolate consumption.

Parallel to the literature on Inhibitory Control Training, there is considerable heterogeneity in the design of studies within the literature. The image type paired with the target stimuli varies across studies, with some work using negative health outcome images (Hollands et al., 2011; Hollands & Marteau, 2016) alongside unhealthy foods, while others use images of negative facial expressions (Shaw et al., 2016) or present information in word form (Bui & Fazio; 2016; Haynes et al., 2015b). While most EC training studies pair the target stimuli with the negative outcome for all trials where the target is presented, there is variation in the number of critical trials, ranging from 30 trials per target stimuli (Zerhouni et al., 2019) to 100 (Hollands & Marteau, 2016), and it is not clear how many pairings of the target stimuli and negative outcome are optimal for influencing consumption and preference measures. Meta analytic work (Hofmann et al., 2010) suggests that the number of pairings may influence the strength of the training effect, however, to our knowledge, no study to date has investigated the number of critical pairings at which EC training becomes ineffective. The between study variations make it difficult to identify the most effective training paradigm for EC interventions, and raise questions in relation to the overall impact (and potential application) of training.

A further inconsistency that applies to both cue-ICT and EC research relates to the use of (in)appropriate control/comparison groups. To ensure causal inferences can be made, the inclusion of a control/comparison group is required, however the content of these control groups is not consistent and often *suboptimal* (Jones et al, 2018). While some studies use designs where control participants complete a reversed contingency of the experimental task (e.g., instead of inhibiting responses to 100% of target stimuli, participants inhibit to 0% of target stimuli) there is a risk that this strategy results in an inflation of between group differences (as participants are being trained away from target stimuli rather than not being trained as in a traditional control group (Jones et al., 2016; Jones et al., 2018). Where control groups are designed in this way (sometimes unintentionally) participants are being trained towards healthy food items (known as cue-approach training (Schonberg et al., 2014)), therefore changes in choice and preference for healthy foods should also be measured in CBM studies to thoroughly evaluate effectiveness. Studies should also implement a true control group who complete 50% of each trial type (dependent upon the specific CBM technique) to ensure that an appropriate comparison is made (for example, cue-ICT control participants should respond to 50% healthy and 50% unhealthy items during training (Jones et al., 2018)). While some researchers have expressed concerns in relation to this approach (stating that placebo training can behave as an active training group for participants with pre-existing biases (Kakoschke, Kemps, & Tiggemann, 2018)), Kruijt and Carlbring (2018) argue that 50%/50% control groups are not more or less beneficial for individuals who possess pre-existing biases, and therefore function as an appropriate control comparison group.

Therefore, the aim of the current research was to investigate two specific CBM strategies (cue-specific inhibitory control training (cue-ICT) and evaluative conditioning (EC)) to identify the role of cue-inhibition contingencies and critical pairings in training effectiveness. We chose these two paradigms as both have a large evidence base, and are hypothesised to exert effects on choice / intake through devaluation of unhealthy food-related cues. As the current study is the first (to our knowledge) to directly manipulate cue-inhibition contingencies and critical pairings, we aimed to recruit participants with a range of BMIs to allow for direct comparison with previous work examining the mechanisms of these training paradigms (where the mean BMI typically falls within the 'healthy' range (e.g., Adams et al., 2017)). In study 1 we examined Inhibitory Control Training and in study 2 we examined Evaluative Conditioning. In both studies participants were randomly allocated to one of four conditions (25% vs. 50% vs. 75% vs. 100%, unhealthy-food inhibition/unhealthy-food negative health outcome pairings). Pre/post training we examined subjective value of food (Chen et al., 2018; Lawrence et al., 2015a), and post intervention explicit food choice (Hollands & Marteau, 2016) as our dependent measures. We also included baseline inhibitory control to food-cues as a covariate in both studies: previous work suggests that state inhibitory control has been linked to variations in CBM training outcomes (Haynes et al., 2015b) and theoretical models suggest cognitive bias modification approaches should be more effective in those with pre-existing biases (e.g. poor inhibitory control to food cues (Franken & van de Wetering, 2014)).

Both studies were pre-registered and data is freely accessible (Study 1: https://osf.io/kjpq3; Study 2: https://osf.io/zy27u).

4.2. Study 1: Inhibitory control training

We hypothesised that: i) Participants in the highest cue-inhibition contingency group (100%) will show more pronounced food value changes post training compared to those in lower contingency groups (75%, 50% and 25%)), ii) Participants in the highest cue-inhibition contingency group (100%) will show healthier explicit choices compared to those in lower contingency groups (75%, 50% and 25%), iii) Participants with poorer levels of inhibitory control pre training will show greater benefits from food specific cue-ICT.

4.2.1. Method

4.2.1.1. Participants

One hundred and seventy participants aged between 18 and 75 years (M = 27.78 ± 12.20) completed an online study. While 188 participants were recruited, only 170 were eligible for inclusion (due to drop out prior to completion of the second food value measure). The sample consisted of 88 females (M_{age} = 29.36 ± 13.36) and 82 males (M_{age} = 26.07 ± 10.63), with an average BMI of 24.95 kg/m^2 (5.33). Participants were required to be aged 18+ and self-report no history of eating disorders. We had two recruitment strategies; first, we recruited via online advertisements which mainly targeted the local and wider student community (N = 70), second, we recruited using prolific academic (N=100). Individuals recruited via online advertisements were entered into a prize draw (£50), whereas those participating via Prolific Academic received £3 for completing the study. Importantly, participants from the two recruited samples did not significantly differ on measured demographic variables (age and BMI, see supplementary materials (see appendix B)). Our a-priori power analysis revealed that a minimum of 128 participants were required (d = .30 (Allom et al., 2016), $\alpha = .05$, $1 - \beta = 0.80$) to detect a within * between interaction across the experimental conditions, however we were able to over-sample to increase the accuracy of our effect size estimates.

4.2.1.2. Measures

4.2.1.2.1. Baseline Inhibitory Control

To identify the pre-existing inhibitory control ability of participants, a food specific go/no-go task was completed (Houben & Jansen, 2011). After 10 unrecorded practice trials, participants completed 160 trials. Participants were required to respond as quickly and accurately as possible by pressing the space bar if no border was present around the image ('go trial') , and refrain from responding if a blue border was present ('no-go') trial. There were 120 (75%) go trials and 40 (25%) no-go trials. Infrequent no-go trials were used to increase inhibition pressure on the task, in line with recommendations (Meule, 2017). If there was no response, images remained on screen for 1500 ms, and trial-by-trial feedback ('correct', 'incorrect') was provided for 500 ms. Internal reliability for the measure was high as assessed through split-half measures using 'go' trial reaction times (r = .80, p < .001).

The number of inhibition errors and the median reaction time (RT) for 'go' trials were used to determine baseline levels of inhibitory control, with higher scores (for both measures) indicating poorer initial inhibitory ability. Signal detection (*d*) was also calculated, which is a combined score that represents the ability to respond to, and withhold responses to stimuli. This involved subtracting the z-score for the number of incorrect 'no-go' trials from the z-score for the number of correct 'go' trials, resulting in data from both 'go' and 'no-go' trials being included (Littman & Takács, 2017).

4.2.1.2.2. Food Value

Food value was measured by presenting participants with images of 10 healthy and 10 unhealthy food items, and asking '*How appealing do you find this image?*' (Chen et al., 2018). For each food type (healthy/unhealthy), images consisted of trained (N = 6; used in the intervention task) and novel (N = 4; not included within intervention task) images, to determine whether training can result in generalisation to novel stimuli (Veling et al., 2017). The number of images rated (per category) is similar to previous work (Lawrence et al., 2015a; Veling et al., 2013b). Participant responses were measured on a visual analogue scale (VAS) ranging from -100 (not at all) to +100 (extremely). A mean score was then calculated for healthy and unhealthy food item appeal (Lawrence et al., 2015a).

4.2.1.2.3. Explicit Preference (based on Hollands & Marteau, 2016)

Explicit preference was assessed through a forced choice task, where participants were presented with images of 8 food items (four sweet (e.g., chocolate) and savoury (e.g., cucumber sticks); four healthy (e.g., apple) and unhealthy options (e.g., crisps/chips)), and prompted to select the two items that they would most like to consume at that moment in time. Participants could select unhealthy food items (scored as 0), or healthy food items (scored as +1), which resulted in a combined score ranging from 0 (two unhealthy choices) to 2 (2 healthy choices).

4.2.1.2.4. Inhibitory Control Training task

Previous work has used stimulus relevant responding (responding to the content of the images) to determine required participant responses in go/no-go training tasks (Teslovich et al., 2014), but due to the unique manipulation of cue-inhibition contingencies within this study, participants were asked to respond to stimulus irrelevant features (e.g. borders surrounding the images), with an image border prompting participants to withhold their response (no-go trial), and no image border indicating a response was required (go trial)). Images of 6 healthy (e.g. fruits, vegetables) and 6 unhealthy (e.g. chocolate, pizza) foods were presented individually in random locations on screen, and participants either responded to their presentation (by pressing the spacebar), or did not respond. Images remained on screen for 1500 ms if no response was made. Participants received feedback on a trial-by-trial basis ('correct' or 'incorrect') for 250 ms. The task consisted of 200 trials (100 go, 100 no-go), with the number of each type of trial (unhealthy go/unhealthy no-go/healthy go/healthy no-go) determined by condition allocation, and an untimed comfort break provided after 100 trials. Cue-inhibition contingencies varied per experimental condition, with four possible condition allocations (100% (N = 47), 75% (N = 44), 50% (N = 35) or 25% (N = 44)). The percentage for each group represents the proportion of unhealthy images the group were required to inhibit their responses to (for example, the 100% group inhibited responses to 100% of unhealthy food images, and responded to 100% of healthy food images, participants in the 50% group inhibited to 50% unhealthy food images and 50% healthy food images). Split-half reliability analyses demonstrated high levels of internal reliability for this task (r = .86, p < .001), and participant engagement was good, with a mean error rate of 2.40% (*SD* = 6.00) for go trials and 2.87% (*SD* = 3.83) for no-go trials (average error of 2.60% (*SD* = 4.26) across go and no-go trials). There were 10 unrecorded practice trials, which consisted of 50% go and 50% no-go trials.

Healthy and unhealthy food images were selected based upon previously conducted pilot work where 30 food images were scored for appeal. Participants were instructed '*For the below images, please indicate how unpleasant or pleasant the image is'* and asked to provide their responses using individual Likert scales ranging from 1 (unpleasant) to 10 (pleasant). The most highly rated images (for healthy and unhealthy foods) were used within the intervention (see supplementary materials (appendix B) for example images).

4.2.1.3. Procedure

Participants completed all tasks using Inquisit web 5 (Millisecond Software, SA). After providing informed consent, participants completed basic demographic measures (age, sex, height, weight), and then completed the baseline measure of inhibitory control. This was followed by the pre training food value measure, then one of four versions of the go/no-go training task. The food value measure was then completed for a second time, before participants completed the final explicit preference task. Finally, participants completed a funnelled debrief, where they were shown an image of a healthy food item with no border and asked to select what they predicted to be the required response were the image included in a task (either press the spacebar, do not press the spacebar, or unsure). They were then asked to explain in their own words what they believed the true aim of the study to be using a free text box. Finally, participants were thanked and debriefed. Ethical approval for both studies was granted by the University of Liverpool Health and Life Sciences Ethics Committee.

4.2.1.4. Statistical Analysis

Analyses were pre-registered prior to data collection (https://osf.io/kjpq3). To compare food value preferences dependent on condition, 4 (condition: 25% vs 50% vs 75% vs 100% unhealthy food inhibition) x 2 (time: pre training vs post training) Mixed ANCOVAs were conducted for both healthy and unhealthy food value scores, with number of inhibition errors in the baseline task used as the covariate (to adjust for baseline inhibitory ability). The analyses were repeated with median 'go' RT as the covariate (as an alternative measure of inhibitory ability). Explicit food preference was analysed using a one way ANCOVA, again, with inhibition errors as the covariate, with a second analysis conducted using median ‘go’ RT as a covariate, in line with previous work (Littman & Takács., 2017; Verbruggen & Logan, 2008). However, we also clarified these effects using Chi-square due to limit variation in the dependent variable (scores of 0 – 2, see supplementary materials (appendix B)). Additional exploratory analyses were also conducted including Bayes factors, signal detection, generalisation and aim awareness (see supplementary materials).

4.2.2. Results

4.2.2.1. Hypothesis one (Participants in the highest cue-inhibition contingency group (100%) will show more pronounced food value changes post training compared to those in lower contingency groups (75%, 50% and 25%)) and Hypothesis three (Participants with poorer levels of inhibitory control pre training will show greater benefits from food specific cue-ICT).

Differences in healthy food value based upon condition were analysed using a 4 (cue-inhibition contingency: 25%, 50%, 75% and 100%) x 2 (time: pre training, post training) ANCOVA, with healthy food VAS scores as the dependent variable, and number of inhibition errors in the standard go/no-go task as the covariate. There was no significant main effect of condition (F (3,165) = 0.67, p = .573, ηp^2= .01), or time (F (1,165) = 0.13, p = .720, ηp^2= .001), and there was no significant time by condition interaction (F (3,165) = 0.73, p=.536, ηp^2= .01). This analysis was repeated using median ‘go’ trial RT as the covariate, and no significant main effects of condition (F (3,165) = 0.69, p = .560, ηp^2= .01), time (F (1,165) = 0.27, p = .602, ηp^2= .002) or interaction (F (3,165) = 0.74, p = .531, ηp^2= .01) were observed.

To assess unhealthy food value changes, the above analysis was repeated, however, unhealthy food VAS scores were used as the dependent variable. The first ANCOVA (with inhibition errors as the covariate) revealed that there were no significant differences in unhealthy VAS scores based on condition (F (3,165) = 0.79, p = .502, ηp^2 = .01) or time (F (1,165) = 0.49, p = .486, ηp^2 = .003), and there was no significant interaction between the variables (F (3,165) = 1.15, p = .331, ηp^2 = .02). When controlling for median 'go' trial RT, there was no main effect of condition (F (3,165) = 0.97, p = .407, ηp^2 = .02), time (F (1,165) = 0.22, p = .642, ηp^2 = .001), or time by condition interaction (F (3,165) = 1.14, p = .336, ηp^2 = .02) (see table 4.1).

Table 4.1. Descriptive statistics for mean VAS scores for healthy and unhealthy foods, both pre and post training. Scores range from -100 to +100, with higher scores representing higher food value. Values are mean ± SD.

	Healthy food VAS		Unhealthy food VAS	
Condition	Pre training	Post training	Pre training	Post training
25% Inhibition Unhealthy	22.09 (27.48)	22.22 (30.42)	25.48 (29.11)	25.69 (30.63)
50% Inhibition Unhealthy	25.27 (20.47)	26.26 (21.68)	15.77 (25.17)	17.09 (27.60)
75% Inhibition Unhealthy	29.84 (28.21)	28.74 (28.47)	19.79 (31.27)	17.89 (32.40)
100% Inhibition Unhealthy	26.71 (27.61)	29.22 (32.67)	16.30 (31.72)	13.06 (36.24)

4.2.2.2. Hypothesis two: Participants in the highest cue-inhibition contingency group (100%) will show healthier explicit choices compared to those in lower contingency groups (75%, 50% and 25%).

A one way ANCOVA was conducted, with condition as the independent variable (cue-inhibition contingency: 25%, 50%, 75% and 100%), explicit preference score as the dependent variable and number of inhibition errors as the covariate. There were no significant differences in explicit preference choices based upon condition allocation (F (3,164) = 0.46, p =. 709, ηp^2=. 01). This was also the case when median 'go' trial RT was used as the covariate (F (3,164) = 0.49, p =.738, ηp^2= .008) (see table 4.2).

Table 4.2. Mean and standard deviation for explicit preference score. Higher scores represent increased healthy choices.

Condition	Mean explicit preference (± SD)
25% Inhibition Unhealthy	0.91 (0.60)
50% Inhibition Unhealthy	0.82 (0.63)
75% Inhibition Unhealthy	1.00 (0.68)
100% Inhibition Unhealthy	0.94 (0.73)

4.2.2.3. Supplementary analyses (appendix B)

We conducted a number of supplementary analyses, which we briefly summarise here. First, we generated Bayes factors for our hypothesis tests which were broadly supportive of the Null Hypothesis (BF_{01}s > 5.27). Second, we demonstrated that the effects of ICT did not differ based upon image novelty (trained vs. non-trained images). Third, we categorised 33 participants as being aware of the experimental aims. Removal of these participants did not meaningfully change our results.

4.2.3. Interim summary

Varying the healthy food cue-inhibition contingencies during an online Inhibitory Control Training task did not significantly influence commonly used outcome measures of stimulus value and food choice. These findings raise questions in relation to the effectiveness of ICT delivered online (see also Wiers et al., 2018), when targeting food value or choice.

4.3. Study 2: Evaluative Conditioning

While evidence suggests that EC training can influence food preferences and consumption, there are issues within the research area in relation to research design and the use of suitable control groups, with some inconsistent findings between studies. Many EC studies pair all images of unhealthy foods with negative outcome images, there is no research to identify the point at which training effects begin to appear (or disappear). Similarly to ICT, the majority of EC research is conducted in laboratory settings, therefore the application of EC interventions to real world contexts is relatively understudied. While EC training focuses on the development of associations between target stimuli, previous research has demonstrated that EC training outcomes were moderated by state inhibitory control (Haynes et al., 2015b). The aim of the second study is to investigate how the number of critical pairings in EC influences training effectiveness, which will inform future study and intervention design. We hypothesised that: i) Participants who experience unhealthy food images paired with 100% negative images will show greater changes in food value post training compared to those where unhealthy stimuli are paired with fewer negative images (75%, 50% and 25%)), ii) Participants who experience unhealthy food images paired with 100% negative images will make healthier explicit food choices post training compared to those where unhealthy stimuli are paired with fewer negative images (75%, 50% and 25%),

iii) Participants with lower levels of inhibitory control pre-study will benefit more from food based evaluative conditioning online training

4.3.1. Method

4.3.1.1. Participants

Three hundred participants aged between 18 and 70 completed an online study (*M* = 32.09. ±10.58). Although 338 participants were initially recruited, only 300 were eligible for inclusion (due to drop out prior to completion of the second food value measure). From the included sample, one-hundred and thirty-eight participants were female (M_{age} = 33.78 ±11.32) and 162 were male (M_{age} = 30.66 ± 9.70). The average BMI across the sample was 24.98 kg/m^2 (SD = 5.34). Identically to study one, participants were required to be 18+, and have no history of eating disorders. All participants were recruited via prolific academic, and received £3 for full completion of the study. A-priori power analysis revealed that a minimum of 128 participants were required (d = .30, α = .05, $1-\beta = 0.80$) to detect a within * between interaction across the experimental conditions, however, similarly to the first study, we over-sampled to increase the accuracy of our inferences. Participants were not permitted to participate in both studies via Prolific Academic

4.3.1.2. Measures

The measures used within study two were identical to those of study one, with the exception of the training task (detailed below).

4.3.1.2.1. Evaluative Conditioning Task

Participants were presented with pairs of images consisting of a healthy or unhealthy food item, followed by a positive or negative health outcome. Image pairs were either congruent (healthy foods paired with positive health outcomes, unhealthy foods paired with negative health outcomes) or incongruent (healthy foods paired with negative health outcomes, unhealthy foods paired with positive health outcomes), with the number of each trial type varying based upon condition. To ensure participants were engaged with the task, they were asked to respond to the spatial location of stimuli on screen using the 'E' (for images presented to the left) and 'I' (for images presented to the left) keys (both images were presented on the same side of the screen). The task consisted of 200 trials (100 healthy food images, 100 unhealthy food images). Each image within the pair was presented for a minimum of 1000ms, with the second image remaining on screen until a response was provided. Participants were provided with feedback after each trial ('correct' or 'incorrect' displayed on screen for 250ms) and also completed 10 unrecorded practice trials prior to training (50% congruent, 50% incongruent).

The number of congruent and incongruent trials presented varied dependent upon experimental condition, with four possible allocations (100%, N = 157[2], 75% N = 45, 50% N = 49, 25% N = 49). The percentage for each group represents the percentage of congruent trials presented to participants (for example, the 100% group were presented with only congruent trials). Split-half reliability analyses (using reaction times) demonstrated high levels of internal reliability for the task (r = .75, $p < .001$).

Food images used in the task were identical to those in study one, and positive (e.g., healthy weight individual) and negative (e.g., individual with obesity) health outcomes were selected from pilot work where 30 positive and negative health images were scored for appeal. Participants were instructed '*For the below images, please indicate how unpleasant or pleasant the image is'* and asked to provide their responses using individual Likert scales

[2] Due to an error in our online randomisation we considerably over-sampled for the 100% contingency condition.

ranging from 1 (unpleasant) to 10 (pleasant). For positive health outcomes, the most highly rated images were used within the intervention, whereas for negative health outcomes, the lowest rated images were used (i.e., the least appealing).

4.3.1.2.2. Baseline Inhibitory Control

Split-half reliability analyses (as calculated using task reaction time) demonstrated high levels of internal reliability (r = .81, p < .001) for this task within the second study.

4.3.1.3. Procedure

The procedure mirrored that of study one; however, instead of the go/no-go training task, participants completed the evaluative conditioning task (at the same point in the study). There was also a slight change to the debrief task, as participants were shown an image of a healthy food item and asked which type of image would follow were this a trial in the task (positive health outcome, negative health outcome, or unsure). They were then asked to explain in their own words what they believed the true aim of the study to be using a free text box.

4.3.1.4. Statistical Analysis

Analyses were identical to those of study one, and were pre-registered prior to data collection (https://osf.io/zy27u). Two participants were removed from the final analysis due to non-engagement with the baseline inhibitory control measure (100% error rate for 'go' trials).

4.3.2. Results

4.3.2.1. Hypothesis one (Participants who experience unhealthy food images paired with 100% negative images will show greater changes in food value post training compared to those where unhealthy stimuli are paired with fewer negative images (75%, 50% and 25%)) and Hypothesis three (Participants with lower levels of inhibitory control pre-study will benefit more from food based evaluative conditioning online training).

Differences in healthy food value based on condition were analysed using a 4 (congruent trials: 100%, 75%, 50% and 25%) x 2 (time: pre training, post training) ANCOVA, with healthy food VAS as the dependent variable, and number of baseline inhibition errors as the covariate. There was a weak significant main effect of condition (F (3, 292) = 2.72, p =.045, ηp^2 = .03), with post hoc tests revealing participants in the 100% condition rated healthy foods higher overall (M = 42.68, SE = 1.72) compared to participants in the 25% group (M = 32.56, SE = 3.19) (p = .033). Despite this, there were no significant main effects of time (F (1, 292) = 0.77, p =.380, ηp^2 = .003), and importantly, no significant interaction between condition and time (F (3,292) = 0.74, p = .530, ηp^2=.01). The above analysis was repeated using median 'go' RT as the covariate, and while the main effect of condition was again significant (F (3, 292) = 2.90, p = .035, ηp^2=.03), the main effect of time (F (1,292) <.001, p = .998, ηp^2<.001) and the condition by time interaction (F (3,292) = 0.75, p = .524, ηp^2 = .01) were not.

The above analyses were repeated using unhealthy food VAS as the DV. With number of inhibition errors as the covariate, there was a main effect of condition (F (3,292) = 2.80, p = .040, ηp^2 = .03), however, post hoc analyses revealed no significant differences between groups (p>.05 in all cases). There was no significant main effect of time (F (1,292) = 3.60, p = .059, ηp^2 = .01) and no significant condition by time interaction (F (3,292) = 0.61, p = .608, ηp^2 = .01). When the analysis was repeated using median 'go' RT as the covariate, the results were identical, with a main effect of condition (F (3,292) = 2.74, p = .044, ηp^2= .03), no main effect of time (F (1,292) = 0.86, p = .356, ηp^2=.003) and no condition by time interaction (F (3,292) = 0.53, p = .662, ηp^2= .01) (see table 4.3).

Table 4.3. Descriptive statistics for mean VAS scores for healthy and unhealthy foods, both pre and post training. Scores range from -100 to +100, with higher scores representing higher food value. Values are mean ± SD.

	Healthy food VAS		Unhealthy food VAS	
Condition	Pre training	Post training	Pre training	Post training
25% Congruent Trials	31.20 (31.13)	33.95 (26.10)	23.52 (31.29)	21.21 (34.41)
50% Congruent Trials	39.31 (23.21)	38.69 (27.65)	28.48 (32.84)	22.87 (40.66)
75% Congruent Trials	37.43 (27.52)	40.15 (28.13)	24.60 (38.34)	20.37 (33.48)
100% Congruent Trials	38.72 (30.74)	46.60 (29.31)	20.22 (32.85)	9.29 (37.10)

4.3.2.2. Hypothesis two (Participants who experience unhealthy food images paired with 100% negative images will make healthier explicit food choices post training compared to those where unhealthy stimuli are paired with fewer negative images (75%, 50% and 25%))

A one way ANCOVA was conducted, with condition (congruent trials: 100%, 75%, 50% and 25%) as the independent variable, explicit preference score as the dependent variable and number of inhibition errors as the covariate. The analysis showed a significant effect of condition (F (3,289) = 4.16, p = .007, ηp^2= .04), with post-hoc tests revealing a significant difference between the 100% and 50% groups, with the 100% group making healthier choices than the 50% group (p = .026). This was also the case where median 'go'

RT was used as the covariate (F (3,289) = 4.49, p = .004, ηp^2=.05) with the 100% group making healthier choices than the 50% group (p = .020) (see table 4.4).

Table 4.4. Mean and standard deviation for explicit preference score. Higher scores represent increased healthy choices

Condition	Mean explicit preference (± SD)
25% Congruent Trials	1.07 (0.70)
50% Congruent Trials	0.98 (0.73)
75% Congruent Trials	1.02 (0.67)
100% Congruent Trials	1.29 (0.64)

4.3.2.3. Supplementary analyses (appendix B)

Similarly, to the first analysis, several supplementary analyses were conducted, which we briefly summarise here. Bayes factors were calculated for our hypothesis tests, and provided strong support for the Null Hypotheses on devaluation (BF_{01}s > 51.93), and weak evidence for the effect on food choice (BF_{01}s ~ 1.16) Secondly, the analyses revealed that there were no effects of generalisation, with no differences in preference between novel and trained images. Finally, 70 participants were able to successfully identify the experimental aims, yet removal of these participants did not meaningfully change the outcome of the analyses.

4.4. Discussion

Across two pre-registered studies, we investigated online CBM training techniques (Inhibitory Control training and Evaluative Conditioning) to identify the most effective training protocols for interventions designed to reduce unhealthy eating behaviours. We attempted to overcome limitations of previous research by; comparing interventions to adequate control groups, examining changes in both healthy/unhealthy food-related outcomes, and adjusting for pre-existing biases (inhibitory control to food-cues) in our models. In Study 1, it was revealed that cue-ICT training did not significantly influence healthy or unhealthy food preferences, and did not influence explicit food choices in a forced choice task. The results from Study 2 showed that while EC training did not appear to significantly influence healthy or unhealthy food preferences, participants who were in the 100% training group (all unhealthy food images paired with negative health outcome images, all healthy food images paired with positive health outcome images) made healthier explicit food choices compared to those in the 50% training group (control group), with no other between groups differences found.

It was hypothesised that when participating in cue-ICT or EC training with cue-inhibition contingencies or critical pairings of 100% (i.e., inhibit to 100% unhealthy food images or experience 100% of unhealthy foods paired with negative health outcome images), participants would show greater changes in food value ratings for healthy and unhealthy foods compared to lower percentage groups. It was also hypothesised that individuals with poorer levels of pre-existing inhibitory control would show greater benefits from training participation (Franken & van de Wetering, 2015; Haynes et al., 2015b; Price et al., 2015). The results demonstrated that there were no significant differences in food value ratings as a result of training participation, irrespective of training type (cue-ICT or EC), percentage of cue-inhibitions / critical pairings used, or baseline inhibitory control to food-cues. While cue-ICT and EC task design has not been independently investigated prior to this study, research has demonstrated that both lab based and online cue-ICT and EC can significantly influence food preferences, with CBM training linked to decreased evaluations for targeted food items

(Hensels & Baines, 2016; Hollands et al., 2016; Veling et al., 2013b). Previous work has highlighted the positive association between task performance and training effectiveness, with increased performance more likely at higher cue-inhibition percentages (Jones et al., 2016) which suggests that participants in the 100% percentage groups ought to have exhibited pronounced changes to food value (at least in comparison to the 50% control groups) in addition to a linear decrease in effectiveness across the additional percentage conditions (75%, 25%) as expected responses became less predictable (making the development of cue-inhibition associations more difficult) (Verbruggen & Logan, 2008). This raises questions in relation to the impact of the training component within CBM interventions: inferential Bayesian analyses performed within this study provided evidence in support of the null hypothesis, and while work by Oomen et al., (2018) revealed reductions in snack consumption post cue-ICT, there were no changes to food cue sensitivity (as may be expected in line with the devaluation hypothesis (Veling et al., 2017)).

It was also hypothesised that training participation would influence explicit food choices, with higher cue-inhibition / critical pairing percentages (100%) resulting in healthier food choices. While cue-ICT did not significantly influence explicit food selection, participants who completed the 100% version of EC training made healthier explicit choices when compared to participants in the 50% condition. This supports work conducted by Hollands et al., (2011) who also found that a single session of EC led to increased healthy choices in a forced choice task, however, the lack of significant findings for cue-ICT contrasts with previous work, where active training has been associated with increased healthy food selection (Veling, Aarts & Stroebe., 2013b) (particularly where participants are required to make decisions under time pressures (Chen et al., 2019; Chen et al., 2020)).

Utilising an online platform to deliver training allowed for the large-scale recruitment of a diverse participant group, which overcomes previous limitations of convenience samples (mainly psychology students: Jones et al, 2018). Furthermore, the design of the studies ensured that appropriate comparisons were made between active and control groups to determine the true impact of training while also allowing within participant changes to be assessed. Despite this, the online nature of the studies (and the associated variety of contexts in which participants may have completed the tasks) may have influenced completion of, and engagement with the measures. The use of online preference measures also raises issues in relation to validity, as there are no real-world consequences for participants based upon their food choices during the study (Hollands & Marteau, 2016), which may influence participant responses (i.e., making a healthy choice as they will not have to actually consume the food selected). Field et al., (2021) suggests that although many studies measure various proxies of appetitive behaviour, these measures do not always result in robust behavioural changes that would be desirable in an intervention context. The extent to which forced choice tasks are associated with real world food consumption (and subsequently, weight status) is relatively understudied (despite the prevalence of related measures throughout the literature), therefore, these results should be interpreted with caution. Similarly, Wiers et al., (2018) suggests that the lack of control observed within online CBM studies results in less effective bias changes (and subsequently reduced behavioural change), however, work by Kakoschke et al., (2018) found healthy food choices improved after the use of a smartphone app to deliver multiple sessions of ICT training. This mixed evidence may be related to the specific training paradigms, as research suggests that CBM training delivered over multiple sessions is highly effective (Lawrence et al., 2015a).

There are further issues which may complicate the interpretation of our 'null findings'. Whilst all participants completed the baseline inhibitory control measure prior to training (regardless of condition allocation), engagement with a similar task (with inconsistent food -> inhibition pairings) prior to training may have influenced training outcomes, despite the inclusion of the food value measurement between tasks. Additionally, while the participant group was more representative of the typical population in comparison to previous work, the average participant BMI fell just within the healthy range. Individuals with overweight and obesity may respond differently to CBM training (due to differences in inhibitory ability towards food stimuli (Spitoni et al., 2017)), and future research should examine the impact of CBM training within this specific population. Finally, it is also suggested that personalising task stimuli (i.e., allowing participants to select liked and disliked food items prior to task completion) can lead to more pronounced responses to training (Veling et al., 2013a). Given these issues (a lack of control over personalised stimuli and time pressured responding, and the inclusion of baseline measures of inhibitory control), it is possible that the training effects in this study were weak, and we were not able to reliably detect them based on our sample size (given consistent findings elsewhere (Chen et al, 2019; 2020)). Furthermore, although EC demonstrated weak effects on food choice, caution should be taken when directly comparing ICT and EC here given we were powered to detect much smaller EC effects due to over sampling.

A final methodological issue relates to participant awareness: recent work (Zerhouni et al., 2019) revealed that contingency aware participants (able to recall the type of image (positive, negative or neutral) following a food stimuli item) rated unhealthy food items more positively after completing a training task. Both cue-ICT and EC are relatively simple tasks in terms of their presentation, and it may be that participants are able to identify stimuli presentation patterns to determine the experimental aims, particularly where inhibition cues and critical pairings are consistent (such as the 100% groups). While in the current study excluding participants aware of the aims did not appear to influence the results, it would be interesting to investigate how participant beliefs in relation to training effectiveness may influence training outcomes.

As such, future research should investigate the effectiveness of repeated online (longitudinal) CBM training and personalisation of task images. Research into potential moderators of the effects of CBM interventions, such as participant awareness, and emotional or restrained eating (e.g. Lawrence et al, 2015) should also be undertaken, to determine if some individuals might benefit more than others. Taken together, this would determine whether multiple (tailored) CBM online training sessions targeted to specific individuals' are required to effectively elicit behavioural changes, and would also allow for longer term behavioural measures (e.g., weight change) to be monitored to further assess training effectiveness.

In conclusion, two pre-registered studies investigated CBM training strategies (cue-ICT and EC) to identify the role of cue inhibition contingencies and critical pairings in training outcomes. The results revealed that online cue-ICT and EC training did not influence food value (for healthy or unhealthy foods) at any percentage cue inhibition or critical pairing, and only EC training influenced explicit choices, with healthier choices observed when participants completed the 100% version of training (i.e., all unhealthy foods followed by negative health outcome images) compared to control training. These findings raise further questions in relation to the effectiveness of CBM based training strategies in line with recent pre-registered studies (Jones et al., 2020) and meta-analyses (Cristea et al., 2016) in similar fields. Future research should investigate variations that exist between studies to attempt to explain inconsistencies observed throughout the literature and to determine whether CBM approaches have potential as theoretically driven psychological interventions for overweight and obesity.

Chapter 5. 'Don't stop believing': the role of training beliefs in cognitive bias modification paradigms

As the results from chapters 3 and 4 provided limited evidence to support CBM as a standalone training paradigm for unhealthy food behaviours, this chapter focused on examining the influence of individual variability within CBM (specifically belief in training). The study contained within this chapter has been published as: Masterton, S., Hardman, C., & Jones, A. (2022). 'Don't stop believing': The role of training beliefs in cognitive bias modification paradigms. *Appetite, 174*, 106041. https://doi.org/10.1016/j.appet.2022.106041.

In relation to contributions for this chapter, I designed the study (which was approved by Andrew Jones and Charlotte Hardman), collected and analysed the data and wrote the manuscript. All authors provided feedback on the original manuscript and subsequent revisions (in response to reviewer feedback).

Abstract

Cognitive Bias Modification (CBM) paradigms have previously been applied to target appetite (craving, hunger) and food intake and are hypothesised to reduce unhealthy food consumption. However, inconsistencies in relation to training outcomes raise questions regarding the efficacy of CBM as a standalone intervention. Individual level factors (such as belief in the intervention efficacy) may influence expectations of behaviour change following training. Across two pre-registered studies, our aim was to investigate how directly manipulating beliefs in relation to training purpose and effectiveness influenced food value and choice across two popular CBM paradigms (Inhibitory Control Training (ICT: Study 1) and Evaluative Conditioning (EC: Study 2)). In online studies, participants were presented with a paragraph describing the CBM technique positively (or an unrelated control message) prior to completing either active or control CBM training. Across both studies, the results revealed that active CBM training resulted in a reduction to unhealthy food value (relative to pre-training), but only when paired with a positive manipulation message. Participants who received a control message displayed no significant changes to food value, even where active CBM training was provided. These results suggest that participant beliefs and expectancies have important consequences for CBM effectiveness. Future research should further investigate these factors within CBM contexts to identify their role within successful behaviour change interventions.

5.1. Introduction

An unhealthy diet is one of the most important modifiable risk factors for numerous diseases (Danaei et al., 2009; Fransen et al., 2017), with the excess consumption of highly palatable, unhealthy foods linked to the development of overweight and obesity (Barlow et al., 2016). While the obesogenic environment promotes unhealthy food consumption (Chaput et al., 2011) through exposure to high fat, salt and sugar food-cues, there are differences between individuals in relation to their responses to these cues: not all individuals demonstrate excessive weight gain, despite the temptations created by repeated exposure to unhealthy food-cues and easily accessible, energy dense foods (Jansen et al., 2015). Examination of the psychological processes that underlie these individual differences in environmental responses may support the development of interventions designed to reduce unhealthy food intake.

Dual process models (Hofmann et al., 2009; Strack & Deutsch, 2004) suggest that responses to food cues are regulated through conflict between implicit and reflective processes, with behavioural outcomes driven by the relative strength of each system. Implicit processes are based on previously formed associations between food cues and outcomes (e.g., feelings of satisfaction after eating an unhealthy food item). These processes are thought to be relatively automatic, and fast acting. Reflective processes are effortful, require conscious thought, and focus on longer-term goals (e.g., consuming healthy food items to maintain weight despite increased reward from unhealthy foods). Dual process models hypothesise that unhealthy food choices are the result of strong implicit preferences for unhealthy foods combined with a weak reflective system unable to resist the intrinsic rewards associated with unhealthy food consumption (Hofmann et al., 2008; Jones et al., 2018), which may help to explain variations in responses to food cues between individuals.

Previous research has supported the application of these models to eating behaviours: work by Kakoschke et al., (2015) demonstrated that while approach biases (the tendency to attend to and approach specific stimuli) and inhibitory control did not independently predict unhealthy food consumption, participants who had a high approach bias for unhealthy food combined with poor inhibitory control abilities consumed higher amounts of unhealthy snack food. Research by Carbine et al., (2017) revealed that not responding to high calorie foods required increased recruitment of inhibitory control processes (as measured through N2 amplitudes), and lower levels of inhibitory control have previously been linked with overweight and obesity (Sellaro & Colzato, 2017; Spitoni et al., 2017; Yang et al., 2018).

The investigation of dual process models within food contexts has facilitated the development of cognitive training to reduce unhealthy food consumption, referred to as Cognitive Bias Modification (CBM). CBM attempts to address potential imbalances between implicit and/or reflective processes through the completion of tasks designed to improve self-regulatory capacity or weaken the associations that drive automatic processes (Friese et al., 2011; Jones et al., 2018). Cue-specific Inhibitory Control Training (cue-ICT (also referred to as motor response training)) is a novel CBM paradigm that has been applied to food-related responses: during training, participants are prompted to consistently inhibit responses to unhealthy food cues, which is thought to decrease approach behaviours for unhealthy foods and reduce unhealthy food preference and consumption (e.g., Chen et al., 2018a; Lawrence et al., 2015a; Veling et al., 2021). The mechanisms through which cue-ICT exerts its effects are debated, however, an object evaluation mechanism (potentially devaluation, where training results in a reduction to hedonic stimuli value) is hypothesised to be the most likely mechanism of action (Johannes et al., 2021; Veling et al., 2017). Previous research suggests that cue-ICT can positively influence food choice, preference and consumption behaviours (Chen et al., 2018a; Oomen et al., 2018; Houben & Jansen, 2011; Jones et al., 2016; Veling et al., 2021; Yang et al., 2019), however, these findings are not consistent across all studies utilising cue-ICT paradigms (Adams et al., 2017; Becker et al., 2015; Bongers et al., 2018; Carbine et al., 2021; Masterton et al., 2021), and there are broader concerns in relation to the evidential value of existing studies (see Carbine & Larson, 2019).

Evaluative conditioning (EC) is an alternative CBM approach, where participants are exposed to image pairs consisting of a target stimulus (i.e., unhealthy food cues) and positively or negatively valenced images. Similarly to cue-ICT, it is hypothesised that pairing unhealthy food cues with negative images reduces the appeal and subjective value of these items (devaluation), which decreases subsequent unhealthy food consumption (Hollands et al., 2011). EC paradigms have been applied to various health behaviour contexts (including alcohol (Zerhouni et al., 2018), exercise (Antoniewics & Brand, 2016) and smoking (Scholten et al., 2019)), and previous work has demonstrated that EC training is linked to reduced unhealthy food choice and decreased preference for unhealthy foods (Bui & Fazio, 2016; Hollands et al., 2011; Haynes et al., 2015b). While successful EC holds potential in relation to population level behaviour change interventions (Marteau et al., 2012; Hollands et al., 2013)), not all research has found training to be effective. Work by Lebens et al., (2011), demonstrated that while EC had a positive influence on implicit attitudes towards unhealthy foods, there were no differences in calories purchased from fruit/snacks between groups on a virtual shopping task, and Wang et al., (2017) discovered that while EC appeared to have some influence on both implicit and explicit attitudes towards chocolate, there were no differences in chocolate consumption between an experimental and control group. Additionally, recent work (focusing on the application of EC paradigms) found no significant differences in food choice after exposure to pairings of text or image-based health warning labels and unhealthy snack foods (Asbridge et al., 2021).

Although previous research has investigated the design of CBM tasks to attempt to explain inconsistencies in training effectiveness across the literature (e.g., Masterton et al., 2021; Veling et al., 2021), there has been less focus on the participant level factors that may influence the success of CBM interventions. Evidence suggests that contingency awareness (participants' ability to recognise responses and pairings observed within the CBM manipulation) is associated with increased intervention effectiveness within EC paradigms (Hofmann et al., 2010). Work by Zerhouni et al., (2019) demonstrated that a significant main effect of EC on alcohol was partly dependent on contingency awareness, and contingency awareness was predictive of healthier explicit evaluations for high fat foods (within control group participants). Additionally, work by Kattner (2012) revealed that EC training was most effective where participants were instructed to memorise the specific pairs of images used within training tasks. While contingency awareness is not typically measured within cue-ICT contexts, research has shown that *some* participants (albeit a minority) were correctly able to identify true experimental aims within an ICT training study (Di Lemma & Field, 2017).

Contingency awareness within CBM studies raises important questions in relation to participant expectations and beliefs: if some participants are able to correctly identify experimental aims and target stimuli within a study, this may influence their engagement with (and belief in) training, and consequentially, food preference and choice outcomes. Previous work (Boot et al., 2013) has highlighted the role of participant expectations within the evaluation of psychological interventions: while active training groups can help to match experimental and control groups in terms of experimental demands, participant beliefs in relation to the purpose and benefits of training appear to also influence outcome measures, which, if not accounted for, could undermine conclusions regarding intervention effectiveness. Specifically, previous work investigating the acceptability of CBM as a treatment for anxiety disorders (Beard et al., 2012) highlighted that many participants were sceptical about the potential of training to influence behaviour, and felt that CBM was only useful to them when they understood the purpose of the tasks and the potential benefits of training. Additionally, Rabipour et al., (2015) investigated how beliefs about cognitive 'training' tasks related to perceived effectiveness, and found that a positive manipulation message increased participant expectations for training (although the subsequent impact on behaviour was not measured). These findings suggest that participant beliefs and understanding of training have implications for engagement with (and expectations for) training: to our knowledge, no study to date has investigated how participant beliefs in relation to CBM (within a food context) can directly influence intervention success.

Therefore, the aim of the current research was to investigate how directly manipulating participant beliefs regarding the efficacy of two CBM approaches (cue-specific inhibitory control training and evaluative conditioning) influenced training outcomes. As previous research has demonstrated that design differences (in relation to cue-inhibition contingencies/critical pairings) for these two specific CBM strategies do not significantly influence training outcomes (Masterton et al., 2021), we focused on 100% contingencies (unhealthy food – inhibition/negative outcome image) for active training, and 50% contingencies for control training to avoid inflating between group differences (Jones et al., 2018). Subjective food value (Chen et al., 2018a; Lawrence et al., 2015a) was assessed both pre and post manipulation within study 1 (with an additional timepoint of one-week post study added for study 2) in addition to post manipulation explicit food preference (Hollands & Marteau, 2016) (again, with an added one-week post study timepoint for study 2).

Both studies were pre-registered, and data is freely available (Study 1: https://osf.io/n4cb3/; Study 2: https://osf.io/4ryg7/).

5.2. Study 1: Inhibitory control training

We hypothesised that: i) Participants who receive a positive message related to ICT effectiveness and active ICT will show greater changes in food value (increase in healthy / decrease in unhealthy) in comparison to other training groups, ii) Participants who receive active training and a positive message related to training effectiveness will make healthier explicit choices in comparison to other training groups, iii) Participants who receive a positive message (and active training) or a positive message (and control training) will show greater changes in food value and make healthier explicit choices, compared to a group with no positive message and control training (primary hypothesis).

5.2.1. Method

5.2.1.1. Participants

One hundred and twenty-nine participants aged between 18 and 82 years (Mean age = 28.79 ± 12.86) completed the online study. The sample included 77 females (Mean age = 28.17 ± 12.63) and 52 males (Mean age = 29.71 ± 12.63) with a mean BMI of 25.02 kg/m^2 (± 5.34). To be eligible for participation, participants were required to be aged over 18 and have no (self-reported) history of eating disorders. Participants were recruited through posters and online advertisements targeting the student and wider community (N = 79), or through Prolific Academic (N = 50). Individuals recruited through advertisements were entered into a prize draw (for one of two £50 Amazon vouchers), whereas Prolific Academic participants were paid £1.88 for completing the study. Participants did not differ significantly on measured demographic variables dependent on recruitment method (age and sex, see supplementary table 5.1). An a-priori power analysis indicated that 128 participants (d = .30, $\alpha = .05$, $1 - \beta = 0.80$) were required to identify a within*between interaction (group*time).

Ethical approval for both studies was granted by the University of Liverpool Health and Life Sciences Ethics Committee (approval code: 4007).

5.2.1.2. Measures

5.2.1.2.1. Inhibitory Control Training task

To identify potential differences in outcomes based upon training content, participants completed a food-specific go/no-go task with either active training (100% inhibit to unhealthy food items) or control training (50% inhibit to unhealthy foods, 50% respond to unhealthy foods) contingencies. Images of 6 healthy (e.g., fruits, vegetables) and 6 unhealthy (e.g., chocolate, crisps/chips) foods were used within the trials, with images presented individually in random locations on screen. Participants were asked to withhold responses in trials where a yellow coloured border surrounded the food image (no-go trial), and provide a response (by pressing the spacebar) where no border was present (go trial). After 10 unrecorded practice trials, both active and control training tasks consisted of 200 trials (100 go, 100 no-go) with an untimed comfort break provided after 100 trials. Each image remained on screen for 1500 ms (or until a response was provided), and participants were provided with feedback after each trial ('correct' or 'incorrect' presented for 250ms after response (or no response) provided).

5.2.1.2.2. Belief Manipulation

To influence participant beliefs prior to participation in the ICT task, participants in the ICT message conditions were asked to read a short message describing ICT in a positive way (in terms of purpose, effectiveness and application) in relation to unhealthy food choice and preference (see supplementary materials (appendix C)). Prior to the current study, three potential versions of the ICT message were piloted to 41 participants (including those familiar and unfamiliar with ICT research) who were asked to rate the messages from best (i.e., accessible, believable) to worst. To ensure that cognitive demand was consistent between conditions, participants in the control message conditions were provided with a message matched for length and complexity on an unrelated topic (MMR vaccination).

Participants were asked to read the information carefully, and forewarned that they would be asked questions about the information contained within the message to ensure they fully engaged with the material presented. In all conditions, after completing ICT (or control training), participants were asked three multiple choice questions related to the information (either ICT or MMR) that they were presented with. Participants in the ICT message conditions also responded to one critical question to assess the extent to which the ICT message was believed *'How effective do you believe ICT is as an intervention'* which was scored on a visual analogue scale (VAS) from -100 (not at all) to +100 (extremely) (control message participants responded to an identical question in relation to the MMR vaccination). *We assumed scores ~0 would be indicative of no strong belief in the message, which would be likely under no awareness of ICT or information regarding the effectiveness.*

75% of participants correctly responded to at least two of the three questions presented ($M = 2.10 \pm 0.95$). A one-sample t-test was performed to assess the extent to which the ICT manipulation message was believed by participants. The results showed that the sample mean for the critical question differed significantly from 0 ($M = 17.08 \pm 38.83$), indicating that the manipulation message was effective ($t(67) = 3.63$, p = .001, $d = .44$).

5.2.1.2.3. Food Value

Participants were presented with images of 10 healthy and 10 unhealthy food items and asked to rate the appeal of each image. For each image category, items were included from the training task (N = 6) in addition to untrained, novel stimuli (N = 4), with responses measured on a VAS ranging from -100 (not at all appealing) to +100 (extremely appealing). Task responses were used to calculate mean appeal scores for healthy and unhealthy food items.

5.2.1.2.4. Explicit Preference

To assess explicit preference for healthy and unhealthy food items, participants completed a forced choice task, where they were presented with 8 food images (4 healthy, 4 unhealthy) and asked to select the two items that they would most like to consume given the opportunity. Food images included equal numbers of both sweet (e.g., chocolate, apples) and savoury (e.g., chips/crisps, cucumber sticks) options. A combined score was calculated based on participant selections, with unhealthy food items scored as 0, and healthy food items scored as +1 (in line with previous research (see Hollands & Marteau, 2016)). This resulted in a combined score ranging between 0 (two unhealthy options) and 2 (two healthy options).

5.2.1.3. Procedure

All tasks were presented online using Inquisit web 5 (Millisecond Software, SA). Participants provided informed consent, then completed basic demographic measures (age, sex, height, weight). This was followed by the food value measure (pre manipulation/task), after which participants were randomly allocated to one of four belief manipulation message and ICT task combinations (ICT message and ICT (N = 33); ICT message and control training (N = 35); control message and ICT (N = 38); control message and control training (N = 23)), where the manipulation (or control) message was presented prior to the task, with message memory assessed after the task. Participants then completed the second food value measure (post manipulation/task), followed by the explicit preference task. Participants also completed a funnelled debrief, where a task image was displayed (a healthy food item with a border surrounding it) and participants were asked to select what they would expect the correct response to be for that image (press the spacebar, do not press the spacebar, unsure)[3]. Finally, participants were asked to describe what they thought the true aims of the study were (using a free text box), before being debriefed. The study took approximately 20 minutes to complete.

5.2.1.4. Statistical Analysis

To analyse food value changes dependent on condition, 4 (condition: ICT message and ICT; ICT message and control training; control message and ICT; control message and control training) x 2 (time: pre manipulation, post manipulation) ANOVAs were conducted for healthy and unhealthy food value scores, with significant interactions analysed using post hoc pairwise comparisons (with a Bonferroni correction). Explicit food preference was analysed using a one way ANOVA and a post hoc Tukey test (with condition as the independent variable), however, we also examined these effects using Chi-square due to the nature of the data (scores between 0 – 2, see supplementary materials (appendix C)). Analysing the data using a 2 (message: control, ICT message) x 2 (training: control, ICT) x 2 (time: pre manipulation, post manipulation) model is also reported in supplementary materials.

5.2.2. Results

5.2.2.1. Participant Demographics

Participant demographic information is presented in supplementary table 2 (appendix C).

[3] Due to a data storage error, data related to the debrief portion of the study is not available.

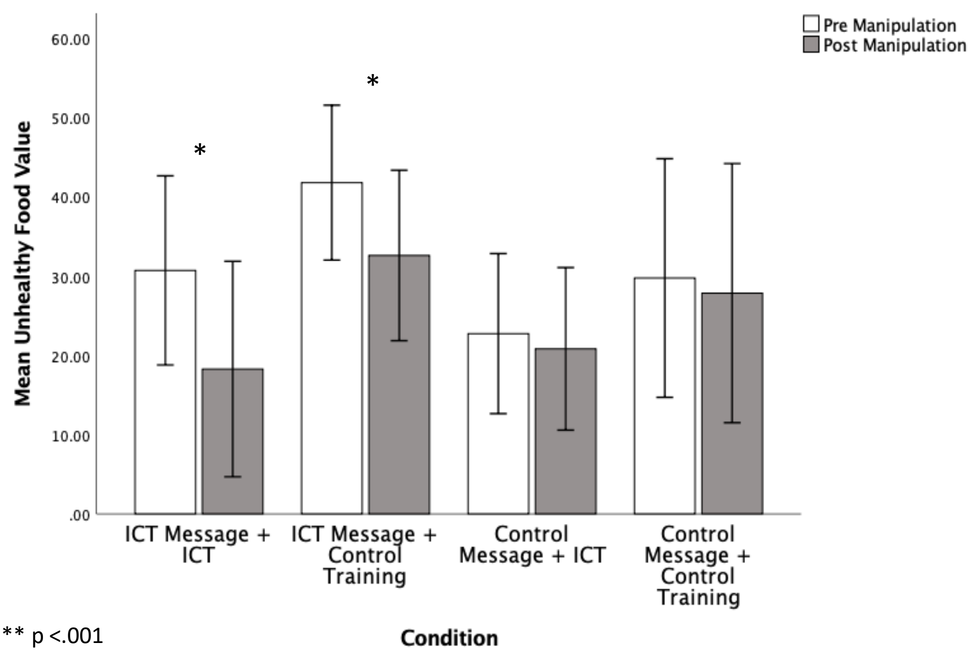
5.2.2.2. Healthy Food Value

The healthy food value analysis revealed that there was no significant main effect of time (F (1, 125) = 3.12, p = .080, ηp^2 = .02), condition (F (3, 125) = 2.12, p = .103, ηp^2 = .05) or a time by condition interaction (F (3, 125) = 1.86, p = .139, ηp^2 = .04).

5.2.2.3. Unhealthy Food Value

The above analysis was repeated using unhealthy food value as the dependent variable. While there was no main effect of condition (F (3, 125) = 1.37, p = .255, ηp^2 = .03), there was a significant main effect of time (F (1, 125) = 26.44, p < .001, ηp^2 = .18), in addition to a significant time by condition interaction (F (3, 125) = 4.72, p = .004, ηp^2 = .10). This was due to significantly lower food value scores post manipulation (relative to pre-manipulation) in both the ICT message/ICT group (p < .001) and ICT message/control training group (p <.001). The two groups who received the control message (with either ICT or control training) did not differ significantly in terms of food value scores pre and post manipulation (p = .393 and p = .509 respectively) (see supplementary table 3 for descriptive statistics).

Figure 5.1. A bar chart displaying mean unhealthy food value scores pre and post manipulation. Bars represent 95% CI.

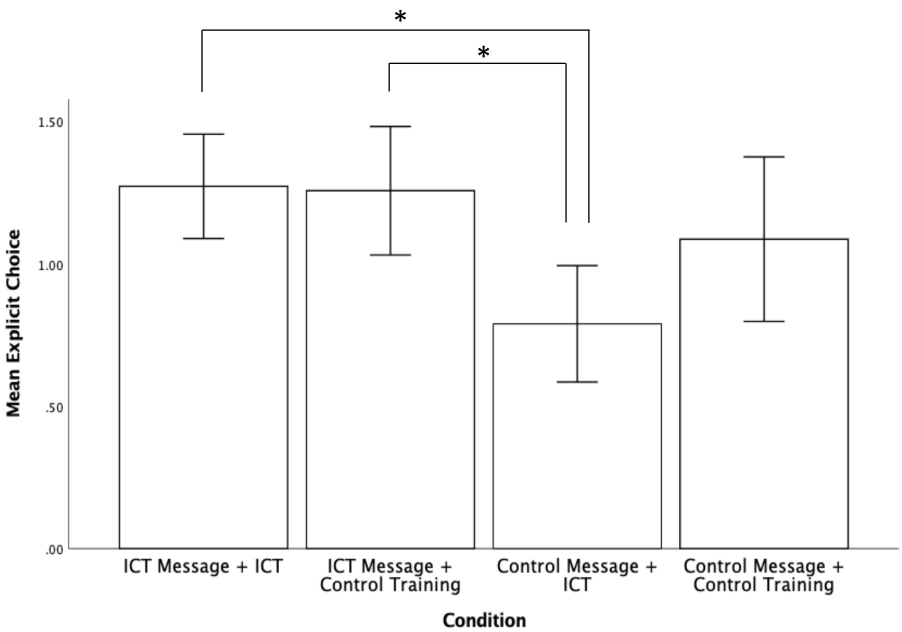


** p <.001

5.2.2.3. Explicit Preference

The analysis revealed a significant main effect (F (3, 125) = 4.85, p = .003, ηp^2 = .10), with post hoc tests revealing this was due to participants making an increased number of healthy choices in the ICT message/ICT group in comparison to the control message/ICT group (p = .007). A significant difference was also found between the ICT message/control training group and the control message/ICT group, with the ICT message/control training group making an increased number of healthy choices (p = .008). No other groups differed significantly (p > .05 in all cases).

Figure 5.2. A bar chart displaying mean explicit preference scores for each condition. Bars represent 95% CI.



* p < .01

5.2.3 Interim summary

Providing participants with a positive manipulation message related to cue-ICT prior to training significantly reduced unhealthy food value, irrespective of the type of training provided (active or control). Interestingly, cue-ICT had no significant effect on food value where the control message was presented, which raises questions in relation to the role of participant beliefs within CBM contexts.

5.3. Study 2: Evaluative conditioning

While contingency awareness is more routinely assessed within evaluative conditioning studies (e.g., Kattner, 2012, Zerhouni et al., 2019), the extent to which beliefs in relation to training can influence outcome measures of food choice and preference has not yet been independently investigated. Work by Benedict et al., (2019) discovered that EC effects are vulnerable to misinformation, and providing participants with false information after an event can influence both explicit memory and attitudes. Additionally, the longevity of the effects from a single EC session is unknown in eating behaviours: work by Houben et al., (2010) demonstrated that participants consumed significantly less alcohol one week after an EC intervention, and work by Shaw et al., (2016) demonstrated that an EC training session reduced soda consumption for the week following training. Therefore, the aim of the second study was to investigate how belief manipulation and training type influenced EC training outcomes, and whether training effects were still evident one week after training. We hypothesised that: i) Participants who are provided with a positive EC message in addition to active EC training will show greater changes in food value in comparison to other training groups (primary hypothesis), ii) Participants who are provided with a positive EC message in addition to active EC training will make an increased number of healthy explicit choices in comparison to other training groups, iii) Manipulation related effects will still be evident one week after training has been completed. We also investigated potential explanatory mechanisms for manipulation effects, including belief in science, social desirability and cognitive restraint.

5.3.1. Method

5.3.1.1. Participants

One hundred and thirty-nine participants fully completed part one of the study. Participants were aged between 18 and 61 years (*Mean age* = 29.01 ± 9.58), with 86 males (*Mean age* = 28.17 ± 9.56) and 53 females (*Mean age* = 30.38 ± 9.54) with a mean BMI of 24.93 (± 5.39). All participants were recruited through Prolific Academic, and received £3 for completing both parts of the study (£2 for part 1, £1 for part 2). Participants were aged over 18 at the time of the study, and self-reported no history of eating disorders. An a-priori power analysis demonstrated that 128 participants (d = .30, α = .05, $1 - \beta = 0.80$) were required to identify a within*between interaction (group*time), however, we recruited additional participants (~10%) to account for potential attrition between the two parts of the study.

5.3.1.2. Measures

Measures used within the second study were identical to those used in study one with the below exceptions.

5.3.1.2.1. Evaluative Conditioning task

Similarly to study one, participants completed either active (100% unhealthy food and negative health outcome image pairings) or control (50% unhealthy food images paired with negative health outcome images, 50% paired with positive health outcome images) Evaluative Conditioning (EC) training. Healthy and unhealthy food images used within the task were identical to those used in the ICT task, and positive and negative health outcome images were selected based upon previously conducted pilot work (see Masterton et al., 2021). Participants were asked to respond to the location of pairs of images (food image followed by health outcome image) on the screen using the 'E' (for images presented on the left) and 'I' (for images presented on the right) keys. Participants completed 200 trials in total (100 healthy food images, 100 unhealthy food images) and were provided with an untimed comfort break after 100 trials. Each image was presented on screen for a minimum of 1000ms, and the second image remained on screen until the participant provided a response. Feedback was provided on a trial by trial basis, with 'correct' or 'incorrect' presented on the screen for 250ms.

5.3.1.2.2. Belief Manipulation

In line with the ICT belief manipulation, participants in the EC message conditions were presented with a paragraph describing EC positively in relation to decreasing unhealthy food preference. The EC message was matched to the original ICT message in terms of structure and complexity, with only the critical information modified to ensure the messages were consistent across studies (see supplementary materials (appendix C)). The MMR based control message from study one was used for participants in the control groups, and identically to study one, participants in all groups were asked three multiple choice questions in relation to the content of the messages they had read (after completion of training). Participants in the EC message groups were also asked a critical question to identify the effectiveness of the belief manipulation '*How effective do you believe EC is as an intervention*' (control group participants completed an identical question related to the MMR vaccination).

Participant performance in relation to EC multiple choice questions was strong, with 90.70% of participants correctly responding to at least two of the three presented MCQs (M = 2.44 ± 0.73). Similarly to study one, a one sample t-test was conducted to assess the effectiveness of the message manipulation. The results showed that the mean response for the critical question significantly differed from 0 (M = 27.52 ± 37.45), again, indicating that the manipulation message was effective ($t(60) = 5.76$, $p < .001$, $d = .73$). There was also no significant difference in critical question response between the ICT (study 1) and EC (study 2) message ($t(127) = 1.55$, $p = .123$, $d = .27$), indicating strength in the belief following message manipulation did not differ significantly across studies.

5.3.1.2.3. Socially Desirable Response Set Five Item Survey (SDRS-5, Hays et al., 1989)

Participants completed the SDRS-5, a five-item scale that measures social desirability by asking participants questions about their typical responses to various everyday situations. Participants were asked to respond on a scale of 1 (definitely true) to 5 (definitely false), with only extreme responses (i.e., either 1 or 5 depending on the direction of the question) contributing towards the final score. Extreme responses were scored as '1', resulting in a possible score ranging from 0 (low social desirability) to 5 (high social desirability).

5.3.1.2.4. Belief in Science Scale (BISS, Farias et al., 2013)

The extent to which participants valued science as an information source was measured using three questions from the BISS (items with the highest factor loadings (Dagnall et al., 2019)). BISS responses were measured on a 6 point likert scale, ranging from 1 (strongly disagree) to 6 (strongly agree). Scores for each question were totalled to create an overall score (with higher scores indicating stronger belief in science), and internal reliability measures indicated that consistency was good between items ($\alpha = .81$)

5.3.1.2.5. Three Factor Eating Questionnaire – Revised 18 item (TFEQ-R18, Karlsson et al., 2000)

Participants completed the TFEQ-R18 to identify potential differences in eating patterns and behaviours. This questionnaire consists of 18 items which load onto three factors; cognitive restraint, uncontrolled eating and emotional eating. Participants are presented with various statements in relation to their eating behaviours and asked to indicate how much they feel that each statement applies to them (on a four-point scale). Higher scores for each factor indicate greater instances of that behaviour in relation to participants food behaviours. Internal reliability ranged between acceptable (cognitive restraint, $\alpha = .69$) and good (uncontrolled eating, $\alpha = .83$; emotional eating, $\alpha = .81$) for individual factors.

5.3.1.3. Procedure

Participants completed all tasks online using Inquisit web 6 (Millisecond Software, SA). Participants provided informed consent and completed demographic measures (including age, sex, height and weight) in addition to the TFEQ-R18. Identically to the first study, participants then completed the first food value measure (pre manipulation/task) and were allocated to one of four message and task combinations (EC message and EC training (N = 29); EC message and control training (N = 32); control message and EC training (N = 37); control training and control message (N = 41)) where the manipulation (or control) message was displayed, followed by the task, then the message memory measure. They then completed the second food value measure (post manipulation/task) before completing the explicit preference task (post manipulation/task). Participants finally completed the SDRS-5 and BISS before being thanked and informed they would be contacted in a week to complete the second part of the study.

One week later, participants were contacted to complete the follow up measures. They completed the food value measure for a third time (one week post manipulation/task) in addition to the explicit preference task (one week post manipulation/task). After this, participants completed a funnelled debrief (identically to study one), where they were asked to identify the image that would be follow a healthy food item image (either positive or negative health outcome) were it presented in the task they had completed the week before. They were also asked to describe what they believed the true aims of the study to be before receiving a debrief.

Participant attrition was higher than anticipated, with 103 participants (74%) completing both parts of the study (EC message and EC training (N = 23/ 79%); EC message and control training (N = 21 / 66%); control message and EC training (N = 29 / 78%); control training and control message (N =30 / 73%)).

5.3.1.4. Statistical Analysis

Identically to study one, food value changes dependent on condition were analysed using 4 (condition: EC message and EC; EC message and control training; control message and EC; control message and control training) x 2 (time: pre manipulation; post manipulation) ANOVAs for healthy and unhealthy food value scores (with significant interactions analysed using post hoc pairwise comparisons with a Bonferroni correction), and explicit preference scores were analysed using a one way ANOVA (with a post-hoc Tukey test and exploratory Chi-square). Due to the additional time-point within this study, 4 (condition: EC message and EC; EC message and control training; control message and EC; control message and control training) x 3 (time: pre manipulation; post manipulation; one week post manipulation) ANOVAs were performed for healthy and unhealthy food value scores, in addition to a 4 (condition: EC message and EC; EC message and control training; control message and EC; control message and control training) x 2 (time: post manipulation, one week post manipulation) ANOVA for explicit food preference. Analyses were run separately for follow-ups, to ensure any attrition did not reduce the power of post-manipulation analysis). Exploratory analyses were also conducted related to belief in science, social desirability and cognitive restraint (see supplementary materials (appendix C)).

Analysing the data using a 2 (message: control, EC message) x 2 (training: control, EC) x 2 (time: pre manipulation, post manipulation) model is also reported in supplementary materials.

5.3.2. Results

5.3.2.1. Participant Demographics

Participant demographic information is presented in supplementary table 5 (appendix C).

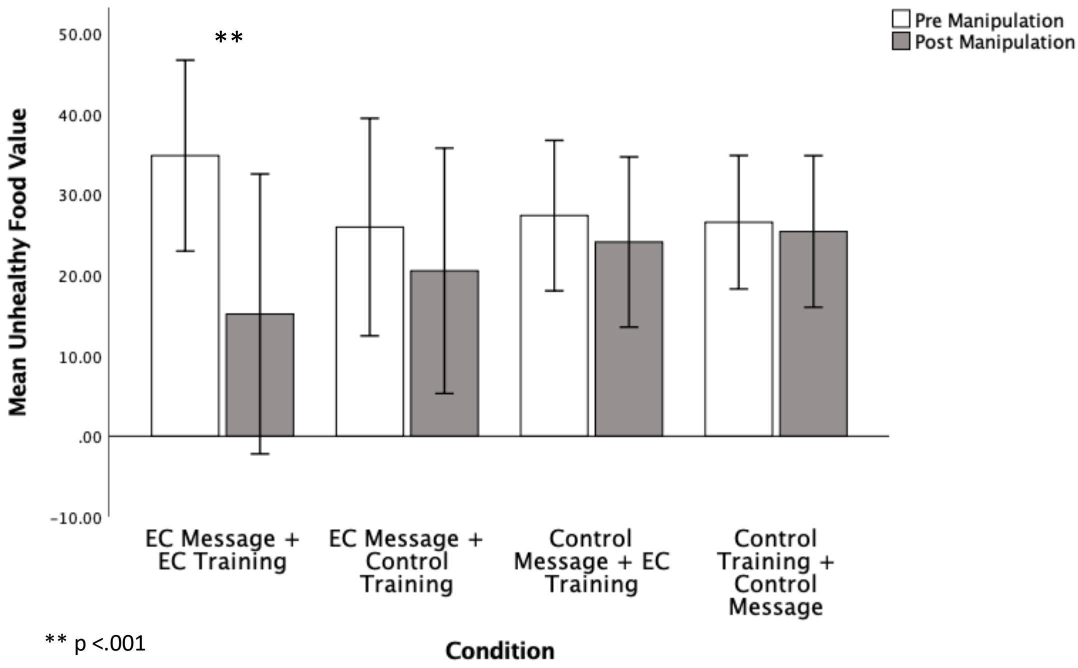
5.3.2.2. Healthy Food Value

The analysis revealed that while there was a significant main effect of time (F (1, 135) = 34.21, $p < .001$, $\eta p^2 = .20$) (with higher healthy food value scores post manipulation (M = 37.47, SD = 29.53 compared to M = 30.41, SD = 29.59)), there was no significant main effect of condition (F (3, 135) = 0.08, $p = .969$, $\eta p^2 = .002$) and no time by condition interaction (F (3, 135) = 0.33, $p = .807$, $\eta p^2 = .01$).

5.3.2.3. Unhealthy Food Value

The analysis was repeated with unhealthy food value scores as the dependent variable. While no main effect of condition was found (F (3, 135) = 0.05, $p = .985$, $\eta p^2 = .001$), there was a significant main effect of time (F (1,135) = 21.96, $p < .001$, $\eta p^2 = .14$) in addition to a significant condition by time interaction (F (3,135) = 6.52, $p < .001$, $\eta p^2 = .13$). Subsequent analyses revealed that this was the result of significantly lower scores for unhealthy food value post manipulation for the EC message and EC training group ($p < .001$). No other significant differences were found ($p > .05$ in all cases).

Figure 5.3. A bar chart displaying mean unhealthy food value scores pre and post manipulation. Bars represent 95% CI.



5.3.2.4. Explicit Preference

The explicit preference analysis revealed that there was no significant main effect of condition (F (3,135) = 0.63, p = .596, ηp^2 = .01).

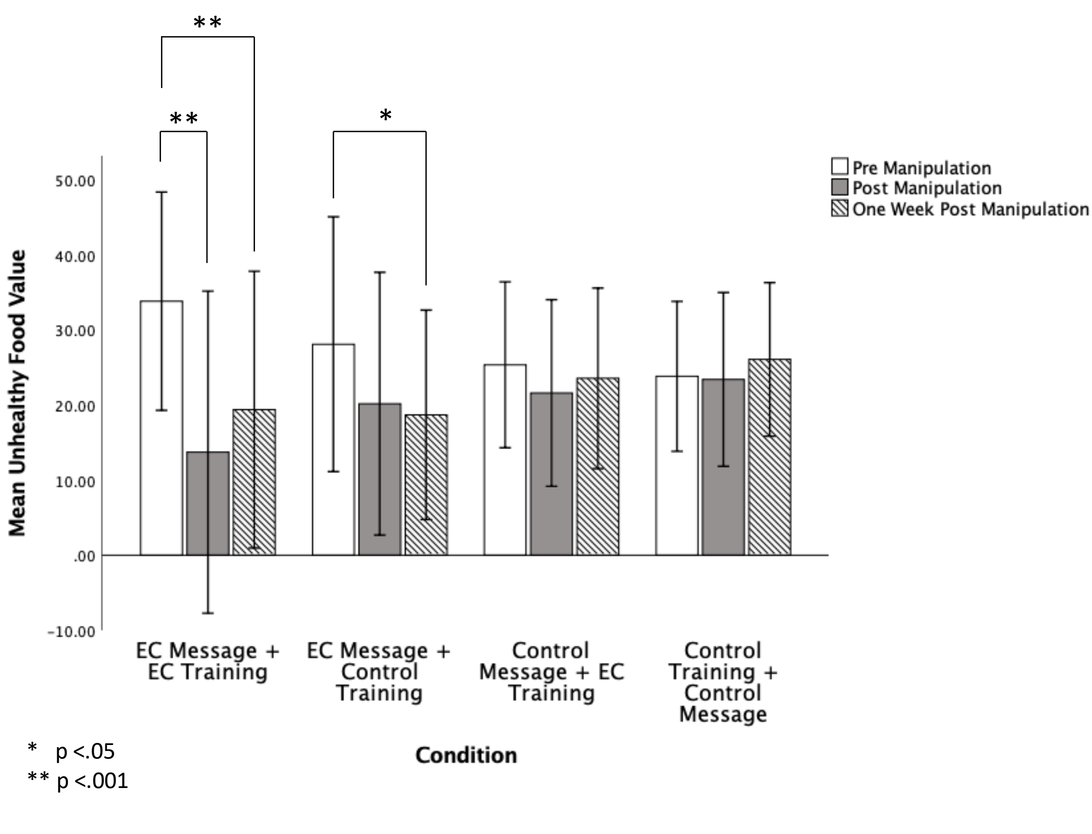
5.3.2.5. Healthy Food Value (Follow Up)

To investigate the duration of potential training related effects, the above analyses were repeated with the inclusion of an additional time point (one week post training). The analysis revealed that while there was a significant main effect of time for healthy food value scores (F (2, 198) = 10.07, p <.001, ηp^2 = .10), there was no significant main effect of condition (F (3, 99) = 0.03, p = .992, ηp^2 = .001) and no time by condition interaction (F (6, 198) = 0.49, p = .816, ηp^2 = .02).

5.3.2.6. Unhealthy Food Value (Follow Up)

When the analysis was repeated using unhealthy food value scores as the dependent variable, while there was no main effect of condition (F (3, 99) = 0.03, p = .994, ηp^2 = .001), there was a significant main effect of time (F (2, 198) = 10.54, p <.001, ηp^2 = .10) and a significant condition by time interaction (F (6, 198) = 3.52, p = .002, ηp^2 = .10). The interaction was due to significantly lower unhealthy food value scores for the EC message and EC training group both immediately post manipulation (p <.001) and one-week post manipulation (p <.001) in comparison to baseline. There was also a significant difference within the EC message and control training group, with participants scoring lower for unhealthy food value one week post intervention compared to pre manipulation (p = .036). No other significant differences were found (p >.05 in all cases) (see supplementary table 7 (appendix C) for descriptive statistics).

Figure 5.4. A bar chart displaying mean unhealthy food value scores pre, post and one week post manipulation. Bars represent 95% CI.



5.3.2.7. Explicit Preference (Follow Up)

The explicit preference analysis was also repeated with the additional one-week post manipulation timepoint, and while there was a significant main effect of time (F (1, 99) = 7.86, p = .006, ηp^2 = .07), there was no main effect of condition (F (3, 99) = 0.29, p = .831, ηp^2 = .01) and no significant time by condition interaction (F (3, 99) = 1.18, p = .320, ηp^2 = .04).

5.3.2.8. Supplementary analyses

To investigate potential mechanisms for manipulation effects, we conducted exploratory analyses, repeating the main analyses, and including belief in science, social desirability and cognitive restraint as covariates. Inclusion of these variables did not meaningfully influence the results (see supplementary materials (appendix C)).

5.4. Discussion

The aim of the current research was to investigate the impact of manipulating beliefs related to training effectiveness across two CBM paradigms (Inhibitory Control Training and Evaluative Conditioning). In study 1, the analyses revealed that while message and training manipulations had no influence on healthy food value, unhealthy food value only decreased when a positive ICT message was presented to participants, irrespective of training content (active or control). There was also evidence to suggest that participants who received positive ICT messages (paired with either active or control training) made an increased number of healthier explicit choices than participants in the control message and active training group. In study 2, manipulations had no influence on healthy food value, however, participants who received a positive EC message and active EC training had lower unhealthy food value ratings both immediately post manipulation and one week post manipulation. Although participants presented with a positive EC message and control training showed no significant decreases in unhealthy food value immediately post training, there was a significant decrease in unhealthy food value one week post manipulation. Similarly to study 1, control message manipulations (irrespective of training content) resulted in no significant changes to unhealthy food value across all three time points.

It was hypothesised that participants who received a positive training message and active training (either ICT or EC) would show greater changes in food value in comparison to other training groups. In both studies, while the manipulations did not have any significant impact on healthy food value, participants who experienced the training message and active training manipulations had significant decreases in unhealthy food value both post manipulation (study 1 and 2) and one week post manipulation (study 2). The difference between healthy vs unhealthy food value may be partially explained by the framing of our message, as participants were informed ICT and EC directly influenced *unhealthy* food behaviours ('… *this type of training reduces how pleasurable you find unhealthy foods and improves your ability to resist eating unhealthily*') but made no mention of healthy food behaviour.

Previous work investigating CBM feasibility discovered that positive manipulation messages increased participant expectations for training (Rabipour et al., 2015), and work by Kattner (2012) discovered that asking participants to memorise training image pairings increased training effectiveness. As the positive message promoted the potential benefits of CBM (in relation to reductions in unhealthy food consumption), it may be that this increased expectations in relation to training efficacy while also highlighting responses and pairings utilised within training tasks, resulting in significant decreases to unhealthy food value within these groups.

Notably, across both studies, control message participants displayed no changes to unhealthy food value, irrespective of training content (active or control). This may suggest that CBM as an isolated intervention is not robust enough to elicit changes to explicit measures of unhealthy food value and preference, with the observed effects here appearing to be at least partially dependent on the presentation of the manipulation message, irrespective of the actual training content itself. While previous research has suggested that CBM can positively influence food choice and value ((e.g., Chen et al., 2018a; Hollands et al., 2011; Oomen et al., 2018), in the current study, there was only limited evidence to suggest that the CBM training independently influenced unhealthy food value and choice, supporting the findings of previous work that did not find evidence to support the use of CBM training within food contexts (e.g., Becker et al., 2015; Carbine et al., 2021; Masterton et al., 2021). The inconsistent outcomes reported throughout the literature in relation to training effectiveness could indicate that factors external to training (and not consistently measured (such as beliefs or expectations in relation to training impact)) may play an important role in successful intervention outcomes.

Where it has been measured, most studies identify at least *some* participants who can correctly guess the aim of the training provided despite this not being addressed by the researchers (e.g., Di Lemma & Field, 2017; Lawrence et al., 2015a), which could suggest that individual-level variations between participants (e.g., beliefs in relation to CBM or the expectation that training will have a positive impact on behaviour) may have a substantial influence on both training engagement and outcomes (Beard et al., 2012; Boot et al., 2013). This is an important consideration for future studies, and researchers should further investigate individual variations within CBM contexts to fully identify the impact of CBM training as standalone paradigms.

While the content of training did not appear to influence ICT positive message outcomes, for EC, the interaction between manipulation message and training type appears to be more complex. Although a positive EC message and active EC led to reductions in unhealthy food value both immediately and one week post manipulation, a positive EC message and control training only led to a significant reduction in unhealthy food value when comparing pre manipulation and one week post manipulation. In comparison to ICT, EC is arguably a simpler (and more predictable) task, with participants required to respond to the location of each stimuli pair after both images are displayed (rather than withholding/rapidly providing responses to a single stimuli item), potentially resulting in decreased task demand (Wessel., 2018) and increased trial duration, which may have implications for participant awareness and training effectiveness. Work by Benedict et al., (2019) highlighted that EC effects are highly vulnerable to misinformation, which can influence both explicit memory and attitudes towards training stimuli. The presentation of inconsistent information (through positively describing active training and providing control training) may have increased uncertainty in relation to training purpose within this group, which could have reduced the immediate impact of the manipulation message. While this explains the lack of significant results immediately post training for EC, this does not explain why the decrease in unhealthy food value was significant one week post training. Interestingly, in the follow up contingency awareness assessment, 67% of participants who received the control training and positive message manipulation identified that a healthy food image would be followed by a positive health outcome, despite this not always being the case for the training they completed. This may indicate that the content contained within the positive message (i.e., informing participants of active training pairings) may have had a greater influence on food value in the week following the intervention (despite active training not being provided), however, future research would need to investigate factors such as message memory to further isolate these effects.

Although it was hypothesised that both ICT and EC manipulations would result in healthier explicit choices, results varied across studies. While there was some evidence within study 1 to suggest participants in the positive message groups (both active and control) made healthier explicit choices than those in the control message and active ICT group, it is not clear why the true control group (control message and control training) did not significantly differ from the positive message groups, or why there was no significant effect of manipulation on explicit preference in study 2. While previous work investigating CBM has utilised online forced choice measures of preference (e.g., Hollands et al., 2011; Veling et al., 2013a), as choices have no real-world consequences for participants, there are concerns in relation to the validity of the measure (Hollands & Marteau, 2016). It is also possible that the manipulation message (combined with the short nature of the explicit preference task) led to increased bias within this measure, with participants deliberately controlling their responses (i.e., specifically selecting healthy or unhealthy items) to support or refute the message received during the manipulation (although we found no evidence to support social desirability mechanisms within study 2). Notably, the follow-up analysis of this study was slightly underpowered due to attrition. Future work should attempt to systematically explore potential bias within forced choice tasks to investigate their validity in relation to real world food choice contexts (Klein et al., 2012).

While the manipulation messages did significantly influence unhealthy food training outcomes, the extent to which participants were motivated to change their behaviour was unclear. The message manipulations did appear to be effective overall, however not all individuals within the study necessarily believed the message presented (some participants scored < 0 on the manipulation check). Additionally, we did not measure belief in CBM training in participants who did not receive the manipulation message, therefore we were unable to compare belief in training between manipulation and control message groups. It is also worth noting that the manipulation check is limited given we did not measure pre-message beliefs, and therefore could not infer a *change* in beliefs as a result of exposure to the manipulation message (but measuring beliefs prior to the message may have increased demand characteristics). Previous work has highlighted that participants can question the credibility of CBM approaches (Beard et al., 2012), and it may be that individual level variations in training belief (in addition to motivation to change (Field et al., 2020)) could also influence engagement with training and training outcomes. Additionally, while proxy measures of food intake (such as value and choice) are used throughout the literature (e.g., Chen et al., 2018a; Hollands & Marteau, 2016; Lawrence et al., 2015a), the extent to which these measures are related to real world consumption behaviours is relatively understudied. Work by Wang et al., (2017) discovered that while participants evaluated chocolate more negatively after training, there were no significant differences in relation to actual chocolate consumption, and work by Kakoschke et al., (2017) found that although combined CBM training resulted in reduced unhealthy snack food choice, there was no significant influence on food intake. Future research should investigate the impact of belief manipulations on more objective measures of consumption (such as bogus taste tests (Robinson et al., 2017)) within participants motivated to change their behaviour (i.e., individuals wishing to reduce unhealthy food consumption). This would help to identify the true potential of belief manipulations (in CBM contexts) within populations most likely to benefit from intervention participation.

While we focused on explicit measures of preference (i.e., value and choice) within the current study, it would be interesting to examine the influence of message manipulations on implicit measures of preference (given the associations between implicit food preference and long-term weight gain (Nederkoorn et al., 2010)). Similarly to explicit preferences, the influence of CBM on implicit preferences for unhealthy foods is unclear: While Lebens et al., (2011) found that post-training, participants had more negative associations with unhealthy foods (compared to control group participants), meta-analytic work by Jones et al., (2016) revealed that the influence of ICT on implicit preferences was not robust across various appetitive stimuli. Previous work has discovered that implicit preferences can be influenced by propositional knowledge (De Houwer, 2006), therefore it is likely that these preferences are also susceptible to the influences of experimental belief manipulations, which could be an interesting avenue for future research.

In conclusion, the aim of the current research was to investigate the influence of directly manipulating beliefs in relation to CBM effectiveness (cue-ICT and EC) on training outcomes. The results indicated that unhealthy food value and choice were only reduced where a positive manipulation message was presented to participants, and that there was no significant change to unhealthy food value where no positive message was presented beforehand (irrespective of training content). These findings raise questions in relation to the role of awareness and expectancies within cognitive training tasks: future research should further explore these variables within CBM contexts to improve behavioural and intervention outcomes.

Chapter 6. Are commonly used lab-based measures of food value and choice predictive of self-reported real-world snacking? An ecological momentary assessment study

While measures of preference and choice are commonly used within CBM research as an indication of training efficacy, the associations between these measures and real-world food behaviours are unclear. This chapter investigated the associations between three commonly used measures of preference and choice and real-world snack food consumption to investigate the extent to which these measures predicted food behaviours. The study within this chapter has been published as: Masterton, S. Hardman, C.A., Boyland, E., Robinson, E., Makin, H.E. & Jones, A. (2022). Are commonly used lab-based measures of food value and choice predictive of self-reported real-world snacking? An ecological momentary assessment study. *British Journal of Health Psychology*. Advance online publication. https://doi.org/10.1111/bjhp.12622

In relation to contributions for this chapter, I designed the study (which was approved by Andrew Jones and Charlotte Hardman) and collected the data. Andrew Jones, Harriet Makin and I cleaned and analysed the data, and I wrote the final manuscript. All authors provided feedback on the original manuscript and subsequent revisions (in response to reviewer feedback).

Abstract

While the assessment of actual food intake is essential in the evaluation of behaviour change interventions for weight-loss, it may not always be feasible to collect this information within traditional experimental paradigms. For this reason, measures of food preference (such as measures of food value and choice) are often used as more accessible alternatives. However, the predictive validity of these measures (in relation to subsequent food consumption) has not yet been studied. Our aim was to investigate the extent to which three commonly used measures of preference for snack foods (explicit food value, unhealthy food choice and implicit preference) predicted self-reported real-world snacking occasions. Using an ecological Momentary Assessment (EMA) design over a seven-day study period, participants ($N = 49$) completed three daily assessments where they reported their healthy and unhealthy snack food consumption and completed the three measures of preference (explicit food value, unhealthy food choice and implicit preference). Our findings demonstrated some weak evidence that unhealthy VAS scores predicted between-subject increases in unhealthy snacking frequency ($OR = 1.018$ [1.006, 1.030], $p = .002$). No other preference measures significantly predicted self-reported healthy or unhealthy snacking occasions ($ps > .05$). These findings raise questions in relation to the association between measures of preference and self-reported real-world snack food consumption. Future research should further evaluate the predictive and construct validity of these measures in relation to food behaviours and explore the development of alternative assessment methods within eating behaviour research.

6.1. Introduction

The development of interventions that reduce motivation to consume unhealthy food are essential to reducing the prevalence of overweight and obesity in society, and the associated burden of disease (GBD 2019 Risk Factors Collaborators, 2020; Scarborough et al., 2011). Theory and intervention development often requires *proof-of-concept* testing in the laboratory, under Experimental Medicine Framework approaches (Field et al., 2020, Sheeran et al., 2019), by which candidate variables of interest are assessed and/or modified before participants are given fixed or *ad-libitum* meals. Such lab-based measures of eating behaviour allow for precise measurement under controlled and manipulable conditions (Blundell et al., 2010). However, this increased control comes at a cost. Strategies utilised in the laboratory (such as the presence of an observer during test meals) can heighten participants' awareness that their consumption is being monitored (Robinson et al., 2015), which may lead to smaller effects in the laboratory than the real world (Gough et al, 2021). Unfortunately, long term, direct measurement of eating behaviour is difficult outside of controlled, laboratory settings.

Given the difficulty in unobtrusively measuring energy intake, researchers often turn to alternative measures of eating-behaviours, including the measurement of self-reported *current* food value and motivation to eat. Within experimental medicine approaches, these measures have become critical in the evaluation and development of theoretical models and interventions to identify paradigms with the greatest potential for real life behavioural change, and to isolate possible mechanisms of action (Field et al., 2020). While various measures of value and preference are utilised throughout the literature, some of the most commonly used measures include hedonic food value ratings (where participants are presented with food images and asked to rate images on a scale for valence (e.g., Burger et al., 2011; Chen et al., 2018a; Lawrence et al., 2015a)), explicit (or forced) choice tasks (where participants are presented with food images and asked to select the item(s) that they would like to consume (e.g., Charbonnier et al., 2015; Hollands & Marteau, 2016; Kakoschke et al., 2018)), and implicit association tests (IAT: where response latencies to categorisation tasks are used to infer preferences for healthy or unhealthy items (e.g., Greenwald et al., 1998; Houben et al., 2012; Nederkoorn et al., 2010)). As such, intervention successes are often evaluated in terms of reductions in unhealthy food value or increases in healthier explicit choices (e.g., Chen et al., 2018a, 2019; Miguet et al., 2020; Hensels & Baines, 2016; Hollands et al., 2011; Hollands & Marteau, 2016; Kakoschke et al., 2018; Veling et al., 2013b).

Despite their widespread use, these measures have been criticised for a lack of construct validity. Klein and Hilbig (2019) suggest that the hypothetical nature of preference and choice tasks (in which there are no real-life consequences for the participant) may bias behavioural outcomes. While many measures rely on single assessments of preference or choice, weight change (and related food intake) is the result of sustained behavioural change, and evaluating intervention efficacy (and predicting longer term behavioural change) from a single measurement has implications for the translation of results to real world contexts (given the variability in food selection and consumption over time within individuals) (Loyka et al., 2020). To date, the predictive validity of preference and choice measures (in relation to self-reported snack food consumption) has yet to be formally investigated.

Ecological momentary assessment (EMA) techniques are well-placed for examining the predictive validity of these measures. EMA designs allow for repeated measurement of behaviour *within* individuals, in their everyday life. They overcome many of the limitations of lab-based research. For example, traditional retrospective recall methods (such as 24-hour recall or food frequency questionnaires) can lead to biased estimates of food consumption (Hebert et al., 1997, 2008; Schoch & Raynor, 2012; Shim et al., 2014). Additionally, allowing participants to go about their daily lives without direct observation means that eating behaviour is less likely to be supressed (Gough et al., 2021). As such EMA designs allow researchers to measure food behaviours '*in the moment*' which is thought to increase reporting accuracy, reduce participant burden, and increase the ecological validity of outcome data (Maugeri & Barchitta, 2019). Traditional laboratory measures (such as the IAT) have successfully been applied to EMA contexts, with previous work investigating smoking behaviours discovering that lab-assessed IAT preferences for smoking stimuli were also observed during EMA IAT assessments for participants who smoked (compared to non-smoking participants) (Waters et al., 2010).

Although EMA studies have been used to measure food related behaviours in real-world contexts (see, Elliston et al., 2017; Powell et al., 2017; Zenk et al., 2014), no study to date has investigated the associations between measures of food value / choice and self-reported real world snack food consumption (i.e., are experimental measures of food preference and choice associated with real world eating behaviour?). Here we chose to examine snack food consumption rather than typical meals, as many laboratory eating assessment paradigms (e.g. *ad-libitum*: Robinson et al., 2017) focus on snack-foods, and snacking is thought to contribute to increased overall daily energy intake (Mattes, 2018). While reducing energy intake is a key aim of many studies within the research area, highly controlled laboratory experiments monitoring longitudinal food consumption in response to an intervention may not be practical (or applicable to real world contexts) (de Castro, 2000; Gibbons et al., 2014; Gough et al., 2021). It is therefore important to evaluate the extent to which easily administered measures of value and choice are related to reports of real-world snack food consumption (Field et al., 2020).

Therefore, the aim of the current study was to investigate whether three commonly used measures of food value and choice (implicit preferences, unhealthy food choices, explicit food value) predicted self-reported snacking behaviour across a 7 day period. We hypothesised that the measures of preference, choice and value would significantly predict healthy and unhealthy snacking occasions within the same assessment window over a 7 day study period. The study was pre-registered on OSF (https://osf.io/tswb2/). We also investigated the associations between implicit and explicit proxy measures in exploratory analyses.

6.2. Method

6.2.1. Participants

In line with our pre-registered sampling strategy, we recruited 50 participants (based on recommendations for multi-level modelling approaches (Maas & Hox, 2005)) and required a minimum of 50% assessment compliance for inclusion within the sample. Forty-nine participants completed at least 11 (50%) study period assessments in addition to baseline measurements and were retained. Participants were aged between 18 and 51 years (*M* = 26.82, SD ± 9.58), with 24 males (*M* = 32.92 ± 8.62) and 25 females (*M* = 20.96, ± 6.27), with an average Body Mass Index (BMI) of 23.38 kg/m^2 (± 3.30). To be eligible for participation, participants were required to be aged over 18, self-report no history of eating disorders, follow an omnivorous or vegetarian diet, have access to a smartphone with a camera and not be attempting to lose weight (or have recently dieted). Participants were recruited through online advertisements and the wider student and staff community at the University of Liverpool. Participants recruited through online advertisements received a shopping voucher, with the value dependent upon the number of EMA assessments completed (>70% completed = £20 voucher, 50-69% completed = £10 voucher). University of Liverpool students could participate for course credit, where a similar compensation structure was used (>70% completed = 10 points, 50-69% completed = 5 points). The study was approved by the Local Research Ethics Committee (approval code: 7617). Testing took place during the covid-19 pandemic (November – December 2020).

6.2.2. EMA Measures

6.2.2.1. Implicit Preference

The Brief Implicit Association Test (BIAT, Sriram & Greenwald, 2009) was used to measure implicit preference for healthy (e.g., banana, carrots) and unhealthy (e.g., biscuits, cheese) food items. Participants completed 4 blocks consisting of 20 trials (total 80 trials) in addition to two short unrecorded practice blocks (14 trials each). During each block, participants were asked to sort words (positive and negative) and images (healthy and unhealthy food items) into either a combined category (e.g., healthy foods and positive words) or an 'anything else' category. Participants were asked to respond using the on-screen keyboard, using the 'I' (if the item belonged to the combined category) and 'E' (if the item belonged to the anything else category) buttons. The combined category labels were either healthy-positive (i.e., healthy foods and positive words) or unhealthy-positive (i.e., unhealthy foods and positive words) combinations, with response latencies recorded for each trial. Participants completed two blocks of each type, the order of which was counterbalanced dependent upon session number. In line with recommendations (Nosek et al., 2014), the *D* algorithm for BIAT was used to calculate implicit preference scores, which included the removal of trials >10000ms in length in addition to the removal of assessments where more than 10% of trials were completed in less than 300ms (N = 55 assessments total, 6% of completed assessments). Positive scores indicated a preference towards healthy food items, and negative scores indicated a preference towards unhealthy food items.

6.2.2.2. Explicit Choice

Explicit preference for healthy and unhealthy food items was assessed through the use of a forced choice task, where participants were required to select 2 out of 8 snack food images (4 healthy options, 4 unhealthy options) that represented the foods that they would most like to consume at that moment (e.g., Hollands & Marteau, 2016). The images presented consisted of equal numbers of sweet (e.g., ice cream, pineapple) and savoury (e.g., pretzels, celery sticks) items. To prevent fatigue from repeated assessments, set blocks of images were randomly presented to participants at each assessment (ensuring that identical images were not presented in subsequent assessments and images reflected equal numbers of healthy/unhealthy sweet/savoury options). Healthy food choices were scored as +1 and unhealthy food choices were scored as 0, which when combined resulted in an explicit preference score ranging from 0 (two unhealthy selections) to 2 (two healthy selections).

6.2.2.3. Food Value

Participants were presented with 10 images of snack food items (5 unhealthy, 5 healthy) and asked to rate each item on a visual analogue scale (VAS) ranging from -100 (not at all appealing) to +100 (extremely appealing) to assess image appeal (‘*How appealing do you find this image’*) (e.g., Burger et al., 2011; Masterton et al., 2021). To avoid habituation, the 5 images presented for each category during the task were randomly selected from a possible 12 snack food items (see https://osf.io/tswb2/ for example images). Mean appeal scores were calculated at each assessment for healthy and unhealthy snack food items. Ten images were used within each assessment to reduce assessment duration and participant burden.

6.2.2.4. Snack Food Recall

At each assessment, participants were provided with several free recall boxes and asked to report any healthy and unhealthy snack food items (defined as any food item not consumed as part of a main meal (Hess et al., 2016)) that they had consumed since the last assessment *('Please list all healthy and unhealthy snack food items consumed since the last assessment. Please be as specific as possible (i.e., 30g cashew nuts). Snack foods are classified as items consumed outside of a main meal*'). Participants were asked to provide as much detail as possible (in relation to serving size/amount consumed and brand) for consumed foods, and were also asked to take photographs of snack food packaging (and servings) prior to consumption and send them to the research team. Participants were prompted to upload images at least once per day, but could upload images at any point throughout the study period. Although only the free text recall was compulsory, previous work has demonstrated that the use of images in dietary assessments supports participant recall and increases reporting accuracy (Zhao et al., 2021). The combination of food images and free text recall supported the research team in the extraction of accurate nutritional information for specific products, and identification of portion sizes (where this information was not provided by participants) (see König et al., 2021).). A combined time (free text recall) and event (image upload) based approach increases the accuracy and ecological validity of EMA assessments, as limitations associated with solely event-based approaches (i.e., inability to identify occasions where snacking *did not* take place) are eliminated (Maugeri & Barchitta, 2019). Therefore, while time-based assessments were used to measure snack food consumption, this data was validated by additional information provided through event-based assessments, improving data quality and accuracy.

The UK Nutrient Profiling Model 2004/5 (UKNPM) was used to individually profile each food item consumed by participants as 'healthy' or 'less healthy' (Department of

Health, 2011). The UKNPM categorises food items based on the healthy (fibre; protein; fruit, nuts and vegetables) and unhealthy (saturated fat; sugar; salt) components of the product (per 100g) in addition to the amount of energy provided by the product (kJ). A score of 4 or above indicated that the product was a 'less healthy' snack food item (referred to as unhealthy onwards), with foods scoring 3 and below categorised as healthy. A randomly selected sample (20%) of food scores were also independently profiled by a second researcher, with an excellent agreement rate of 95% (note: scoring discrepancies would not have resulted in any changes to food categorisation (healthy/unhealthy) and were resolved within the research team).

Where brand information was available (through participant descriptions and/or uploaded images), nutritional (and portion size) information was obtained through either the manufacturers website or from the Tesco UK website (largest UK supermarket chain). Where specific brand or product information was not available, information was extracted from an equivalent Tesco 'own brand' product for categorisation and portion size information. Across all participants, 282 unique food items were profiled, with 50 categorised as 'healthy' and 232 as 'unhealthy'.

6.2.3. Procedure

Participants who responded to study advertisements were provided with an information sheet (via email) providing key study details including exclusion criteria, type of tasks and measures, study duration and minimum participation thresholds. Eligible participants were then sent a URL link to the baseline assessment and prompted to install the Inquisit 6 (Millisecond Software, SA) application on their smartphone, where all assessments related to the study were completed. The baseline assessment included demographic measurements (age, sex, height and weight), the creation of a unique ID number (for future correspondence) in addition to a familiarisation session (including implicit food preference, food value, explicit choice). Self-reported height and weight information was used to calculate BMI (weight (kg)/height (m^2)). After completion of the baseline assessment, participants were sent further documentation in relation to accurately recording and reporting food consumption and were asked to contact the researcher should any issues arise with the application or completion of measures. We chose to recruit and conduct all testing online as completely online EMA studies have similar levels of compliance and data-quality to in-person recruitment (Carr et al., 2020).

Starting the day after the initial baseline assessment, participants were emailed a URL link to the Inquisit application three times per day at fixed intervals (12pm, 4pm and 8pm) for 7 consecutive days. Each assessment began with the snack food recall, followed by the measures of preference, choice and value (counterbalanced). A full list of food items (and example images) used within preference and value measures can be found at https://osf.io/tswb2/, and all images used within the study were of unbranded snack food items presented on a plain white background to avoid the potential influence of specific brand/flavour preferences. Participants were instructed to not backdate missed assessments, and where multiple assessments were completed within the same time period, data from the first valid assessment completed within that period were retained for analysis. After the 7 day study period, participants were contacted by email, thanked for their participation and fully debriefed and reimbursed (where appropriate).

6.2.4. Data reduction and analyses

We conducted multilevel logistic regressions using the 'glmer' function from the 'lme4' package in R (v1.1-27.1; Bates et al., 2015). Our predictor variables included IAT D' score, explicit food choices and explicit value ratings of healthy and unhealthy food items.

Our primary outcome variables were healthy and unhealthy snacking occasions within each assessment period (as reported by participants since their last assessment). These variables were lagged to ensure the predictor and consumption variables reflected the same assessment period(s). We also conducted exploratory analyses using the reported number of portions of unhealthy food consumed since the last assessment. In each model we also examined age, sex and BMI as predictors. Assessment level predictor variables were centred against the participant average (Paccagnella, 2006), to examine within-participant variance. To disaggregate between-participant variance the participant average was centred against the sample average (Curran & Bauer, 2011; Wang & Maxwell, 2015). Given studies often observe a reduction in compliance over time in EMA designs (see Jones et al. 2018; 2020), we also included session number as a predictor (1 – 21) to reduce any confounding.

To examine whether a multilevel model (with a random intercept of participant, and no predictors) was a better fit than a single level model (with no random intercept of participant, and no predictors) we examined whether there was a reduction in the AIC values for each (smaller AIC values are indicative of better fitting models, using the same data set). Here, we used the AIC change of > 10 as indicative of substantial support for a multilevel model (Burnham & Anderson, 2004). Multicollinearity was assessed via Variance Inflation Factors, using the 'performance' package. To assess between participant associations, we computed total healthy and unhealthy snacking occasions per participant, and used assessment-level averages of IAT D' score, explicit food choices and explicit value ratings of healthy and unhealthy food items as predictors in standard regression models. Aggregating assessment level EMA data can lead to more reliable person-level indices (Shiffman et al., 2008).

For compliance analyses, participants were deemed to have complied with the session if they had provided information on snacking behaviour on the assessment. Compliance was binary coded (0 = non-compliance, 1 = compliance) for each assessment. We conducted a generalised linear mixed model to examine if compliance was predicted by demographic variables (age, sex, BMI), or assessment number / day of assessment (data and analysis scripts are online https://osf.io/tswb2/).

6.3. Results

6.3.1.1. Descriptive statistics for assessment-level and outcome variables

Breakdown of assessment-level variables are shown in Table 6.1. Intraclass correlation coefficients demonstrate significant within-person variability across all assessment-level predictors. Breakdown of assessment level-variables by assessment day (1 – 7) is shown in supplementary online table 1 (appendix D).

Table 6.1. Mean values (±SD) of assessment level variables (overall and split by session number over 7 day assessment period)

	Mean Overall	Time 1 (12pm)	Time 2 (4pm)	Time 3 (8pm)	ICC
Food Preference					
IAT D'	0.37 (0.40)	.42 (.40)	.38 (.39)	.33 (.40)	.335
Explicit Choice	0.90 (0.70)	.97 (.70)	.87 (.72)	.85 (.68)	.268
Food Value					
Unhealthy food VAS	1.23 (40.29)	-0.79 (41.47)	3.79 (38.86)	0.76 (40.45)	.685
Healthy food VAS	9.71 (33.45)	12.81 (32.34)	10.81 (32.59)	5.50 (35.05)	.595

Legend: ICC = intraclass correlation coefficient (the association between observations within individuals). IAT D' scores range between -2 (strong preference for unhealthy foods) and +2 (strong preference for healthy foods). Explicit choice scores range between 0 (2 unhealthy choices) and +2 (2 healthy choices). Food value scores range from -100 (not at all appealing) to +100 (extremely appealing).

On average participants reported consuming 5.06 (± 6.12: Range 0 - 26.00) healthy snack portions and 12.28 (± 7.95: Range 0 - 35.33) unhealthy snack portions over the 7 day period. There was a significant difference between the two ($t(48) = -5.98$, $p < .001$, $d = 1.01$ [95% CI: 0.59 to 1.42]), but also a positive correlation ($r = .300$ [95% CI .020 to .534], $p = .037$), see supplementary figure 1 (appendix D).

6.3.1.2. Compliance

Out of 1029 possible assessments (49 participants x 21 assessments), participants completed 834 (81.0%), which is comparable to previous studies (e.g., Powell et al., 2017). On average, participants completed 17.02 assessments (st.dev = 3.55, range: 11 – 21).

Age (OR = 1.017 (95% CI: 0.972 to 1.065), $z = 0.748$, $p = .454$), sex (OR = 0.742 (95% CI: 0.299 to 1.751), $z = 0.715$, $p = .474$), and BMI (OR = 1.001 (95% CI: 0.874 to 1.145), $z = 0.011$, $p = .991$) were not significant predictors of compliance. However, assessment number (1 – 21) was (OR = 0.920 (95% CI: 0.893 to 0.947), $z = 5.605$, $p < .001$), whereby compliance decreased over the duration of the study. Additional confirmation of this was that assessment day (1 – 7) was also a significant negative predictor (OR = 0.777 (95% CI: 0.711 to 0.848), $z = 5.586$, $p < .001$).

6.3.2. Confirmatory hypotheses

6.3.2.1. Predictors of 'unhealthy' snacking occasions within and between individuals.

There were 328 unhealthy snacking occasions. The AIC for the null model was 1073.3 and the AIC for the multi-level model was 976.3, indicating the multi-level model was a substantially better fit of the data. The only significant predictor in the model was session number (OR 0.962 [95% CI: 0.929, 0.995]), which was associated with a reduction in snacking over time (see table 2). The model had a substantial reduction in AIC value (AIC =

760.0). There was some evidence of moderate multicollinearity (explicit choice between-participants VIF = 5.79). Removal of this variable from the model led to unhealthy food VAS becoming a significant between-participants predictor (OR = 1.018 [95% CI: 1.006, 1.030), Z = 3.091, p = .002) alongside session number. There was no significant improvement in AIC (761.8).

Table 6.2. A multilevel model predicting unhealthy snacking occasions.

	Odds Ratio	95% CI	Z stat.
Intercept	0.706	0.171, 2.911	
Demographics & Time			
Age	0.996	0.948, 1.046	-0.150
BMI	1.016	0.912, 1.133	0.300
Sex	1.173	0.482, 2.853	0.352
Session number	0.962	0.929, 0.995	-2.232
Within-subject			
D' Score	1.355	0.738, 2.488	0.981
Explicit Choice	0.731	0.530, 1.007	-1.913
Unhealthy VAS	0.994	0.986, 1.003	-1.207
Healthy VAS	1.002	0.993, 1.011	0.506
Between-subject			
D' Score	1.008	0.176, 5.770	0.009
Explicit Choice	8.759	0.981, 78.14	1.943
Unhealthy VAS	1.003	0.985, 1.022	0.877
Healthy VAS	1.021	0.999, 1.044	1.889

Legend: Sex (male ref. category)

6.3.2.2. Predictors of 'healthy' snacking occasions within and between individuals

There were 160 healthy snacking occasions. The AIC for the null model was 797.7 and the AIC for the multi-level model was 665.0 indicating the multilevel model was a better fit of the data. The only significant predictor in the model was session number (OR = 0.927 [95% CI: 0.930, 0.996), which was associated with a reduction in snacking over time (see table 3). There was some evidence of multicollinearity (explicit choice between-participants VIF = 5.05). Removal of this variable from the model did not influence the pattern of results.

Table 6.3. A multilevel model predicting healthy snacking occasions

	Odds Ratio	95% CI	Z stat.
Intercept	8.457	0.050, 142.17	
Demographics & Time			
Age	0.949	0.872, 1.034	-1.179
BMI	0.972	0.811, 1.164	-0.306
Sex	0.341	0.076, 1.518	-1.411
Session Number	0.927	0.885, 0.972	-3.149
Within-subject			
D' Score	0.619	0.287, 1.333	0.417
Explicit Choice	1.309	0.860, 1.991	1.257
Unhealthy VAS	0.989	0.978, 1.001	-1.765
Healthy VAS	1.004	0.993 1.015	0.765
Between-subject			
D'Score	0.362	0.020, 6.568	-0.686
Explicit Choice	3.300	0.107, 101.20	0.684

Unhealthy VAS	0.996	0.966, 1.097	-0.232
Healthy VAS	1.002	0.968, 1.037	0.165

Legend: Sex (male ref. category)

6.3.3. Exploratory hypotheses

6.3.3.1. Do measures of food value predict unhealthy snack portions?

Of the 328 unhealthy snacking occasions we examined the number of portions of unhealthy snacks as an outcome. The average number of portions was 1.63 (± 1.33). There were no significant predictors (see online supplementary materials for full model reporting). We did not replicate this analysis with healthy snacks, due to the smaller number of snacking occasions.

6.3.3.2. Do within-subject explicit measures of food value and choice predict implicit measures?

We examined assessment-level associations between explicit measures of value/choice (healthy VAS scores, unhealthy VAS scores and explicit choice) on implicit value (IAT D' score). There was a significant association between healthy VAS scores and IAT D' ($b = .001$(95% CI: > .001 to .002), $z = 2.028$, $p = .042$), but not with unhealthy VAS scores ($b < .000$, $p = .935$) or explicit choice ($b = .028$, $p = .153$). Variance inflation factors were < 1.05.

6.4. Discussion

The aim of the current study was to investigate the predictive validity of commonly used measures of food value and choice (food value, explicit choice, implicit preference) in relation to self-reported real-world healthy and unhealthy snack food consumption. The results demonstrated that, aside from unhealthy food VAS ratings, the preference measures were not robust predictors of healthy or unhealthy snacking occasions, and they also failed to predict the number of unhealthy snack portions consumed by participants. There were also no robust significant associations between individual measures of preference and choice, with the exception of healthy food value and IAT D' score, which may suggest that each of these measures are unlikely to relate to the same underlying construct.

Due to the extensive use of these measures throughout the literature, we predicted that the measures would be significant predictors of both healthy and unhealthy snack food consumption. However, this does not appear to be the case, as only unhealthy food VAS scores significantly predicted self-reported consumption behaviour within the study, and only within a model in which removal of parameters influencing multi-collinearity was undertaken (and this model was not an improved fit of the data). These findings are important as they may help to explain poor or inconsistent translations (in relation to theoretic predictions and behavioural change) between laboratory studies and clinical interventions where measures of food preference and choice have been used to evaluate outcomes: Field et al., (2020) suggest that while experiments can demonstrate causality within a controlled environment, interventions based upon these manipulations may not be feasible should outcomes not equate to desirable (and sustained) behavioural change. Significant changes to food preference and choice using measures similar to those tested in the present study have been documented within several intervention studies (e.g., Chen et al., 2018a, 2019; Hensels & Baines, 2016; Kakoschke et al., 2018), however, based on the present research it remains unclear whether these would translate to changes in snacking behaviour in the real-world.

One potential reason for a lack of consilience between preference measures and actual eating behaviour may be related to the nature of choice and preference measures within appetite research: responses have no real consequences for participants (Klein & Hilbig, 2019); therefore they may not be motivated to respond in a way that reflects their true food preferences or current underlying motivation. The findings from the current study raise questions in relation to the ability of food value and choice measures to predict future consumption behaviours, which has implications for the development and evaluation of current and future weight-loss interventions.

Interestingly, the results also revealed that different preference measures did not necessarily relate to each other within individuals (the association between IAT D’ and healthy VAS scores aside). Given that these measures are hypothesised to measure the similar constructs, some level of association would be anticipated between these variables (i.e., an implicit preference for healthy foods would be associated with increased healthy food value and healthier explicit choices). This finding may help to explain some of the inconsistencies observed within previous research: while Hollands and Marteau (2016) found that exposure to negative health related images led to increased explicit preference for fruit (within a forced choice task), there was no significant parallel effect on implicit preferences. The lack of association between preference measures could be related to the manner in which tasks are presented: explicit choice tasks are often relatively short, and participants are able to easily control and manipulate their responses, unlike implicit preference measures, which are indirect and more complex (with the ‘desirable’ response less obvious) (Goodall, 2011).

We demonstrated that compliance with EMA assessments decreased over time, which is common within EMA studies (Jones et al., 2020; Maugeri & Barchitta, 2019). The results also revealed that both healthy and unhealthy snacking significantly decreased during the study period (despite participants not reporting attempting to lose or reduce weight before participating). While it is possible that continued self-monitoring of behaviour reduced snack food consumption over time (e.g., Humphreys et al., 2021; Michie et al., 2009), reductions may be indicative of reduced engagement with assessments, or participants may have deliberately chosen to miss assessments/not report snacking occasions towards the end of the study (due to pressures associated with continual monitoring of food intake/study duration (Doherty et al., 2020)). As such, a potential limitation of this research is that we were not modelling *naturalistic* snacking behaviour or capturing all potential snacking outcomes. The EMA procedure we adopted is widely used, but its validity as a measure of snacking behaviour has not been tested. In addition, because snacking behaviour was self-reported (and will therefore be prone to bias), it may be the case participants chose not to report snacking occasions in an attempt at impression management/self-presentation (Vartanian, 2015). Therefore, future research should examine if preference measures would be more strongly associated with objectively measured snacking behaviour (such as data collected through wearable technology devices (Skinner et al., 2020)).

Whilst BMI was included within both models, it was not a significant predictor of healthy or unhealthy snack food occasions. The average participant BMI fell within the 'healthy' range, and while previous work has found no significant association between BMI and laboratory assessments of food consumption (Robinson et al., 2017), it is possible that individuals with overweight or obesity may exhibit specific consumption (and preference) behaviours not observed within healthy weight groups (Mattes, 2014; Rodrigues et al., 2012). As individuals with overweight and obesity are often a key target for weight reduction interventions, future research should investigate associations between preference and consumption within this specific group to identify any potential differences in predictive validity of choice and preference measures (based upon weight status). Future work could also measure additional participant level factors (such as dietary restraint and hunger) to investigate potential associations between these variables and measures of food preference/consumption.

The use of an EMA design allowed for the examination of real-world snack food consumption and preference over a seven-day period, however, there were limitations associated with this approach. Participants completed assessments within fixed time periods, which may have introduced issues in relation to recall accuracy (as participants would have to wait for the next assessment to report snack foods consumed irrespective of snack timing). While participants were asked to photograph consumed snack foods and upload images (to support recall between assessments), future research could explore the incorporation of event-contingent assessments within studies, where participants initiate assessments at each consumption occasion (although this reduces reporting and can make reviewing compliance more difficult (Maugeri & Barchitta, 2019)). Additionally, while EMA allows participants to complete assessments in environments of their choice (increasing ecological validity), research demonstrates that environmental cues (such as advertisements, social cues, and snack availability (Elliston et al., 2017)) are important predictors of consumption behaviours. Environmental variations between (and within) participants may have influenced (or prompted) snack choice and preference responses, and future research should attempt to further examine these factors by collecting information related to the context in which each assessment was completed. It is also possible that our between-participant effects are underpowered, indeed N=49 would only allow detection of relatively moderate associations in cross-sectional analysis (rs ~ .22). However, we note that lab-based studies have demonstrated effects greater than this for food-liking and consumption (r = .27: Robinson et al, 2017) and VAS motivation measures and consumption (rs ~.48: Hammond et al, 2022). Finally, it is worth noting that this study took place during the covid19 pandemic, and research has demonstrated changes in snacking and unhealthy behaviours during this time (Bakaloudi et al., 2021; Robinson et al., 2021). Replication of these findings post-pandemic is warranted.

In conclusion, using an EMA design, the current study investigated the predictive validity of three commonly used measures of value and choice (food value, explicit preference, implicit preference) in relation to real-world snack food consumption. The results demonstrated unconvincing evidence for their prediction of self-reported healthy or unhealthy snacking occasions, or the number of unhealthy snack food portions consumed by participants. These findings raise uncertainties about the use of food value and preference measures as predictors of snack food consumption across the wider literature. However, it is possible that limitations with the EMA design (i.e., influencing naturalistic snacking, non-reporting) may have obscured any relationships between these variables.

Chapter 7. General Discussion

The overall aim of this thesis was to compare and investigate two popular CBM paradigms (cue-ICT and EC) to evaluate their potential as behavioural interventions for unhealthy food behaviours and to investigate hypothesised mechanisms of action for training effects that underlie post-training behavioural change. A sub aim was to address limitations of previous research, including poorly designed control groups and inadequate sample sizes. Alternative factors implicated with training outcomes were also investigated (including cue-inhibition contingencies and participant beliefs) and commonly used measures of food preference and choice were also examined in relation to their association with real world food behaviour(s). This chapter summarises the findings from each study, followed by a discussion of how these findings relate to previous literature and the implications of this work for the wider research area.

7.1. Summary and discussion of findings

The aim of study one (chapter 3) was to directly compare two CBM strategies (cue-ICT and EC) in a laboratory environment to investigate the influence of each type of training on food preference and consumption behaviours and identify the most effective paradigm in terms of behavioural change. Participants were assigned to one of five experimental groups, where they completed active or control cue-ICT/EC training (or passive control training). The results revealed that neither cue-ICT or EC appeared to have a significant influence on implicit food preference or healthy/unhealthy food consumption in comparison to active control group(s). Exploratory Bayesian analyses provided additional evidence to support these findings, with BFs providing strong support for the null hypotheses (BF_{01}s > 10.85). Surprisingly, there was a significant difference between active EC and cue-ICT groups in terms of explicit choice, with participants in the active EC condition making an increased number of healthy choices in comparison to the active ICT condition. The completion of this study allowed for the development of a standardised experimental paradigm for both cue-ICT and EC for use in subsequent studies, as results could be directly compared in terms of outcomes (reducing the risk of inconsistent study design as a confound).

The aim of the second set of studies (chapter 4) was to investigate the role of experimental contingencies within CBM paradigms, as the lack of standardisation of training paradigms across the literature raised questions in relation to the role of the specific protocol in training outcomes. Across two online studies, participants completed either cue-ICT or EC training where the cue-inhibition contingencies and critical pairing percentages were systematically varied between 100% (inhibit to 100% of unhealthy food images for cue-ICT, experience 100% of unhealthy foods paired with negative outcome images for EC) and 25% (inhibit to 25% and respond to 75% of unhealthy food images for cue-ICT, experience 25% unhealthy food images paired with negative outcome images and 75% of unhealthy food images paired with positive outcome images for EC). The results demonstrated that while cue-ICT had no significant influence on healthy or unhealthy food preference or choice (at any cue-inhibition percentage) there was some evidence to suggest that EC had a significant influence on food choice, with participants in the 100% unhealthy food/negative image pairing group making healthier explicit choices than those in the 50% (control) group (although no other significant differences were found between other experimental groups).

Given that the previous set of studies provided limited evidence to support the use of CBM as a standalone intervention, the next two online studies (chapter 5) investigated the influence of individual level variations (in this case, belief in training) on CBM outcome measures. Participants completed active or control cue-ICT/EC combined with either a positive manipulation message (describing cue-ICT/EC in a positive way) or a control message (describing the MMR vaccination). The results revealed that active CBM training only had a significant influence on unhealthy food value when completed in combination with the message describing the CBM technique in a positive way. Participants who received the control message did not have any significant changes to food value, irrespective of actual training content (i.e., active or control). Specifically for EC, these effects appeared to still be evident one week after training, with participants in the two message conditions (paired with either active or control EC) having significantly lower unhealthy food value scores one week post manipulation (compared to their pre-training scores).

The final study (chapter 6) focused on the extent to which measures of preference and choice related to real world food consumption, as while these measures are widely used, little is known about their predictive validity and the extent to which they relate to each other (which may further explain inconsistencies between CBM studies using multiple measures of value, preference and consumption). Over a seven-day study period (using an EMA design), participants completed three daily assessments where they reported their snack food consumption and completed three measures of food preference (explicit food value, explicit food choice and implicit food preference). The results revealed that only unhealthy food value (and only in a model accounting for multi-collinearity that was not an improved fit for the data) predicted self-reported food consumption over the study period, with the other measures of preference and choice not predicting healthy or unhealthy snacking occasions (or number of unhealthy portions consumed). Additionally, implicit and explicit measures of preference did not significantly relate to each other within individuals (with the exception of a marginally significant association between IAT D' score and healthy food value), with no significant associations discovered between implicit preference and unhealthy food value or explicit food choice.

7.2. Theoretical implications

7.2.1. CBM paradigms as standalone interventions for unhealthy food behaviours

Collectively, the findings from chapters 3, 4 and 5 provided limited evidence to support the use of CBM paradigms as standalone intervention strategies to reduce unhealthy food preference and consumption behaviours. Given the mixed conclusions in relation to training efficacy across the literature, these findings fail to support previous work that found CBM to have a significant influence on food preferences (e.g., Chen et al., 2016; Hensels & Baines, 2016) and consumption (e.g., Haynes et al., 2015; Oomen et al., 2018) in both laboratory and online contexts, however, provide support for studies where CBM training was found to have little impact on unhealthy food consumption (e.g., Adams et al., (2017, Study 1), Bongers et al, 2018) or choice (e.g., Lebens et al., 2011) and studies raising concerns in relation to evidential value (Carbine & Larson, 2019).

As there is considerable variation in terms of CBM task design, it is difficult to directly compare studies across the literature (and draw conclusions in relation to overall training efficacy) as a number of factors may contribute toward training success or failure in terms of behavioural outcomes. The studies contained within this thesis used consistent task paradigms (in terms of number of trials and task stimuli) and utilised 50% contingency control groups within experimental designs, where control group participants completed active CBM training (i.e., withholding responses to 50% of unhealthy foods, respond to 50% unhealthy foods for cue-ICT and experiencing 50% unhealthy foods paired with negative images and 50% paired with positive images for EC). This ensured that participants in control groups were not being trained *towards* unhealthy foods, as previous work has demonstrated that food value can be increased by asking participants to consistently provide responses to images (Schonberg et al., 2014). The use of reversed contingency (i.e., respond to 100% unhealthy, inhibit to 100% healthy) control groups within CBM research may have resulted in inflated between group differences (Jones et al., 2016), and potentially account for some of the positive outcomes reported across the literature and the lack of research support for standalone CBM discovered within chapters 3 and 4.

Additionally, the results from chapter 4 revealed that there was no linear decrease in training effectiveness in line with the percentage of trials where unhealthy foods were either not responded to (for cue-ICT) or paired with negative images (for EC). As previous meta-analytic work had discovered a positive association between task performance and training effectiveness for cue-ICT (with increased performance more likely at higher cue-inhibition percentages) (Jones et al., 2016)), it was hypothesised that as responses became less predictable (in the lower contingency percentage groups), training effectiveness would decrease (as cue-inhibition associations would not be formed (Verbruggen & Logan, 2008)), however, this was not the case. This raises questions in relation to the impact of the actual task within CBM studies, as if CBM were truly an effective standalone intervention for unhealthy food behaviours, the number and type (in terms of responses and pairings with unhealthy foods) of trials experienced by participants should substantially influence training outcomes, as participant exposure to the stimulus and response (or associated image) is greater at higher contingencies, making the development of stimulus-associations more likely (Verbruggen et al., 2014b).

One final consideration in relation to independent training efficacy concerns the statistical power of studies across the literature. It is recommended that studies should be powered to detect the smallest meaningful effect size (Lakens & Evers, 2014), with previous work considering a small effect size within CBM fields to be meaningful as CBM is a low cost and relatively simple behavioural intervention (if effective) (Carbine & Larson, 2019). While the studies within this thesis were powered to detect a small to medium effect (d = .30), not all previous studies are adequately powered to detect smaller effects. A recent p-curve analysis (Carbine & Larson, 2019) highlighted that published effect sizes within cue-ICT studies are likely to be inflated, with the p curves from the analysis characterised by small average effect sizes (between d = .04 and .25) and low average power to detect those effects (ranging between 7-18%), with evidence for an underlying effect driven by the smallest p value (in addition to evidence of selective reporting). In contrast, for EC, while the average effect size is hypothesised to be larger (d = .52 (Hofmann et al., 2010)), there is an increased amount of variability in effect sizes between individual studies, ranging between d = .20 (Lebens et al., 2011) and d = 1.28 (Wang et al., 2017), with a lack of pre-registration making it difficult to ascertain whether selective reporting is prevalent across the literature (in addition to a number of studies finding no significant impact of training on behaviour (e.g., Hensels & Baines, 2011; Lebens et al., 2011)) or to identify the true magnitude of training effects. This may indicate (in combination with the lack of significant standalone training effects observed across adequately powered and pre-registered studies within chapters 3, 4 and 5) that the true underlying effect of CBM as a standalone intervention is not robust, with inflated effect sizes, underpowered studies and selective reporting making substantial contributions to the uncertainty surrounding CBM as a behaviour change intervention. As researchers begin to consistently adopt and advocate for open science approaches within health psychology (e.g., Hagger et al., 2021), questionable research practices should eventually be eliminated, increasing the quality of literature and the ability of researchers to evaluate the presence of true underlying effects within psychological research.

7.2.2. Individual differences within CBM

While the evidence to support CBM as a standalone intervention for unhealthy food consumption was limited, the studies within chapter 5 provided evidence to suggest that factors external to training (specifically belief) had a substantial influence on perceived training effectiveness, with a significant influence of training on unhealthy food value discovered, but *only* in participants who were presented with a manipulation message informing them of the potential benefits of the specific training paradigm. For cue-ICT, this significant change to unhealthy food value occurred irrespective of the actual training content (i.e., active or control cue-ICT). For EC, this effect appeared to be more complicated: while participants who received a positive manipulation message and active training had a reduction in unhealthy food value both immediately post training and one week post training, for participants in the positive message and control training group, while no significant reduction in unhealthy food value was found immediately post training, they had significantly lower unhealthy food value scores one week post training. Importantly, across both studies, participants who were not presented with the positive message prior to training displayed no changes to unhealthy food value which suggests that the presentation of the message had a substantial influence on training outcomes rather than the individual components of the CBM technique.

While these results demonstrated that both cue-ICT and EC appeared to be susceptible to the influence of the manipulation message (in terms of unhealthy food value), contingency and aim awareness is not commonly measured or controlled for throughout CBM literature, which may account for some of the mixed overall conclusions in relation to training efficacy. Previous work has demonstrated that contingency awareness can predict explicit unhealthy food evaluations in control group participants (Zerhouni et al., 2019) and meta-analytic work revealed that training effects were substantially larger in contingency aware participants (d = .60 compared to d = .20 (Hofmann et al., 2010)). Previous work has also discovered that a seemingly robust influence of EC training was mainly attributed to participants who were instructed to memorise the specific pairings presented during training, concluding that contrary to early beliefs, contingency awareness does not reduce training effectiveness (e.g., Hammerl & Fulcher, 2005), but is instead reliant on awareness (Kattner, 2012). This conclusion is supported by the results from chapter 5, as the only significant changes to unhealthy food value were observed within participants who received the manipulation message, irrespective of actual training content.

As EC is an arguably simpler task than cue-ICT in terms of its presentation (as the pairings are explicitly presented rather than response driven), this may account for some of the inconsistent outcomes observed between studies within this thesis as there may be increased aim awareness within EC groups. In chapter 4, the only significant difference was observed between the 100% and 50% (control) EC groups for explicit preference, with the 100% group making an increased number of healthy choices in comparison to the control group and in chapter 3, a significant difference was found between the active cue-ICT and EC groups for explicit choice, with the active EC group making an increased number of healthy choices compared to the active cue-ICT group. While belief in EC as a paradigm was not measured within these studies, the results from chapter 5 and previous work highlighting the role of awareness in EC paradigms (e.g., Hofmann et al., 2010; Zerhouni et al., 2019) may indicate that contingency awareness may have had an influence on these specific outcomes, however, future work would need to further investigate the role of non-manipulated belief and aim awareness in CBM contexts to ascertain the true influence on training outcomes.

An additional individual level factor hypothesised to influence training effectiveness is individual inhibitory control ability. While it is assumed that overall there are population level deficits in implicit processes (Franken & van de Wetering, 2015), it is argued that CBM should be most effective in individuals who may benefit most from training (i.e., those with poorer inhibitory control to food-related cues) (Jones et al., 2018). While the results of chapter 4 revealed that there was no significant effect of either cue-ICT or EC on unhealthy food value, the analysis also revealed that the pre-existing inhibitory ability of participants appeared to have no significant influence on training outcomes as inhibitory ability was not a significant covariate. This is in contrast to previous work that discovered that EC training effects were moderated by inhibitory control, with only participants poorer in inhibitory control consuming less snack foods after training (Haynes et al., 2015). While it is possible that inhibitory control could have some influence on training outcomes, this raises questions in relation to the samples selected within CBM work and participant motivation within research. Previous meta-analytic work outside of CBM contexts has demonstrated that high early outcome expectations (in relation to psychotherapy) are significantly associated with positive post-treatment outcomes (Constantino et al., 2018), and Beard et al., (2010) found that training expectations were correlated with changes in social anxiety symptoms, with high expectations linked to increased treatment effectiveness. While across the studies within the current thesis participants were not informed about the true purpose of the study prior to completion, this is not always the case across CBM work and on occasions, participants are specifically recruited based on pre-existing unhealthy eating behaviours, loss of control over eating or wanting to reduce their weight (e.g., Forman et al., 2016; Haynes et al., 2015; Lawrence et al., 2015a). These discrepancies in recruitment may have consequences for participant motivations within the sample and have an influence on CBM training outcomes.

It is also possible that inhibitory control may relate to other characteristics that are associated with training effectiveness as opposed to being predictive of training efficacy independently. Previous research by Jasinka et al., (2012) discovered that inhibitory control deficits were associated with various unhealthy eating practices including overeating in response to food cues and selecting foods on taste profiles (rather than health value), and in other work, while inhibitory control ability alone did not predict unhealthy food consumption, it was predicted by an interactive effect of inhibitory control and approach biases for food (Kakoschke et al., 2015). The influence of these additional factors (in combination with the results from chapter 4) may indicate that inhibitory control abilities alone do not have a direct influence on training efficacy, contributing to the uncertainty in relation to overall training efficacy within these individuals, and subsequently, the hypothesised susceptibility of these groups to CBM.

7.3. Mechanisms of action for CBM effects

7.3.1. Devaluation

The findings from the studies within chapters 3 and 4 provide no evidence to support the devaluation hypothesis in relation to CBM in food contexts, as no significant changes to healthy or unhealthy food value were observed when comparing pre and post training evaluations in either set of studies. While there was some evidence to support a devaluation hypothesis within the studies contained in chapter 5, it is important to note that the devaluation observed for unhealthy foods occurred in both the active and control ICT training groups. Additionally, the reduction in unhealthy food value in the EC study did not correspond to differences in food choice in the explicit preference task, and for the cue-ICT study, the evidence to support training induced choice differences was relatively weak (as the differences were not between the true control group and message groups). These results raise questions in relation to the hypothesised mechanism of action for CBM, as devaluation is thought to occur to resolve response conflict due to being asked to inhibit responses to appetitive stimuli, however, this was observed within 5 even where participants were not consistently inhibiting responses to stimuli during trials, and this reduction in unhealthy food value did not necessarily result in differences in explicit food preferences.

While previous work has found support for devaluation within CBM contexts (e.g., Chen et al., 2018b, Hensels & Baines, 2016), not all researchers have found evidence to support this hypothesised mechanism, even in studies where CBM resulted in positive behavioural outcomes. Meta-analytic work discovered that while ICT appeared to overall lead to a reduction in food consumption in the lab, there was no robust effect of cue-ICT on stimulus devaluation (Jones et al., 2016), and work by Hollands and Marteau (2016) demonstrated that while EC appeared to have an influence on unhealthy food choice, the main effect of training on implicit preference (i.e., the devaluation effect) was not significant. It has been suggested that the *type* of measure (i.e., implicit vs explicit measures of preference) used may influence the perceived devaluation effect (Jones et al., 2016), however, there was no evidence to support devaluation in either chapter 3 or 4 (which used the same task paradigms with implicit/explicit measures of preference) which, when combined with the mixed evidence to support devaluation across the literature, increases uncertainty in relation to the viability of this mechanism for behaviour change in CBM contexts.

7.3.2. Memory formation/association based accounts

The results from chapter 5 also raise questions for memory formation hypotheses within CBM contexts: associative learning theories state that behavioural changes are the result of associations formed between unhealthy food stimuli and either inhibit responses (cue-ICT) or valenced images (EC) through repeated exposure. While chapter 5 was the only chapter showing consistent CBM effects on unhealthy food value (when combined with a positive manipulation message), these effects did not appear to be reliant on the training content itself. The results from both the cue-ICT and EC elements of the chapter indicated that the observed influence of training on unhealthy food preference occurred irrespective of the training received, with significant reductions to unhealthy food value observed within groups who received control training in combination with a positive manipulation message.

Given that in the active control groups, 50% of responses were either respond to unhealthy food trials (cue-ICT) or unhealthy food/positively valenced image (EC), the formation of associations between stimuli and/or responses should not have been promoted within these groups, as 50%/50% control groups are thought to be no more or less beneficial for individuals with pre-existing biases (Kruijt & Carlbring, 2018).

Although these findings do not support the formation of associations through the mechanism of CBM training itself, it is important to consider the context in which these positive training outcomes were obtained. These significant reductions to unhealthy food value were only discovered where the positive manipulation message was presented prior to training: it is possible that by highlighting the required responses and pairings to participants through the message, their awareness of the actual task paradigms increased, reinforcing the links between target stimuli and responses/valenced stimuli. This could mean that associations hypothesised to form through training completion are actually developed explicitly through contingency awareness rather than task responses (where a manipulation message is not presented). This idea is also supported by the results from chapter 4, as were the development of associations essential to elicit CBM effects, a significant difference would have been revealed between the varying contingency percentage groups. Previous work has also demonstrated that participants completing active EC training reported increased negative and decrease positive associations with unhealthy foods (Lebens et al., 2011): it is possible that the simpler presentation of EC paradigms leads to increased participant awareness and the development of stimulus-image associations, resulting in behavioural differences. Future work is needed to further investigate the role of associations within CBM contexts to fully establish mechanisms of action where successful behavioural changes have been observed.

7.4. Measures of CBM behaviour change

While measures of food value and explicit choice are often used as measures of intervention success (due to the reduced expense and ease of administration compared to alternative more direct measures of consumption), the results from chapter 6 provided limited evidence to support the use of these measures as predictors of real world healthy and unhealthy food consumption. This further complicates attempts to draw conclusions in relation to overall CBM efficacy within eating behaviour contexts: where studies use these variables to evaluate the influence of training, their lack of predictive validity in terms of real-world food consumption is problematic as it may be that training does have an influence on food consumption, but not the individual proxy measures (or vice versa). This may help to explain poor translations observed between lab studies and clinical interventions within CBM contexts: although meta-analytic work discovered a robust effect of training on ad libitum food consumption in the lab (Jones et al., 2016), recent work has demonstrated that cue-ICT had no significant influence on real world food consumption or weight loss (despite a reduction to energy-dense food liking (Adams et al., 2021)), which may indicate these proxy measures are poor predictors of real world food behaviours. Experimental medicine (EM) approaches (Sheeran et al., 2017) emphasise the importance of factor validation to ensure variables lead to behavioural change: for CBM, the desired behavioural changes are typically reductions in unhealthy food consumption, and the results from study 6 suggest that measures of preference and value are poor predictors of consumption behaviours. This would indicate that path B in the EM framework (validation of association between target factor and behaviour change outcome) has not been successfully met, which may suggest that CBM interventions are not being evaluated appropriately, with the targeted intervention outcomes not linked to desirable and sustained behavioural change (Field et al., 2021).

Interestingly, the results from chapter 6 also revealed that the measures of food value and choice did not consistently relate to each other: while there was an association between IAT D' score and healthy food value, this association was small ($b = .001$) and there were no significant associations between IAT D' score, unhealthy food value or explicit choice. This finding indicates that while all measures are hypothesised to assess preferences for food items, it is unlikely that the same underlying construct is being measured by each variable. This supports ambiguous findings from previous work, where significant differences in food choice were not supported by a significant change to implicit preferences (e.g., Hollands & Marteau, 2016) or where changes to implicit food preferences were not observed alongside corresponding differences in explicit food choices (e.g., Lebens et al., 2011; Hensels & Baines, 2016). While the reason for these discrepancies is unclear, it may be related to the way in which tasks are presented. IATs are relatively long (and more difficult) tasks, with more complex analysis strategies in comparison to explicit choice tasks which are relatively short and allow participants to manipulate their responses relatively easily (i.e., selecting an explicitly healthy or unhealthy food item). It is argued that it is difficult to manipulate responses in an IAT, as the required (or desirable) response is less clear (Goodall, 2011) which may explain some of the disparity between measures. It is also important to note that hypothetical choice and value tasks have no real consequences for participants, as they do not have to consume (or not consume) the items presented, which might influence the validity of responses (Klein & Hilbig, 2019). This has implications for self-presentation, as it may be possible participants are manipulating their responses as an attempt at impression management (Vartanian, 2015) or to support (or refute) what they believed to be the aims of the study (Corneille & Lush, 2022). While these issues are concerning where measures are used interchangeably within CBM studies, the ability of these variables to predict self-reported food consumption was found to be poor in chapter 6. This (combined with limited between-measure concordance) raises questions related to what (if any) behaviours these measures are predictive of.

7.5. Strengths, limitations and future research directions

While the studies contained within this thesis were pre-registered, suitably powered, employed appropriate control groups and adopted consistent task protocols across studies (allowing for direct comparisons between studies and objective evaluations of training effects), they focused on acute changes to food consumption, value and preference, with measures typically taken before and after training (food value) or just after training (food preference/consumption). While previous work has discovered significant CBM effects after a single training session (e.g., Houben & Jansen, 2015; Jones et al., 2016; Kakoschke et al., 2017), it is possible that repeated administration of CBM may have a greater influence on measures of food choice and preference. Work by Lawrence et al., (2015a) discovered a significant effect of active cue-ICT on energy intake, food liking and weight when multiple cue-ICT training sessions were completed, and previous research has found that longitudinal cue-ICT studies tend to have larger sample sizes and higher statistical power (and show promising training effects) (Carbine et al., 2019). More recent work has discovered that multiple training sessions led to significant reductions to energy dense food liking and increases to healthy food liking, however, there were no significant differences between groups in terms of weight or food consumption (although this could be related to the short-term nature of the follow up (2 weeks)) (Adams et al., 2021). Future work should further investigate the influence of repeated CBM training over longer time periods using pre-registered, suitably powered and standardised study protocols to allow for direct comparison to previous work investigating acute training effects.

An additional consideration for future work relates to the role of individual level factors within CBM paradigms. The results from the studies contained within this thesis indicate that factors external to training itself (e.g., belief (chapter 5)) can have a substantial influence on perceived training outcome, unlike variations to specific training protocols which do not appear to have an influence on training efficacy (e.g., chapter 4). The participants recruited within these studies were typically of healthy weight (average BMI ~ 24-25) and were not recruited based on any desire to lose or maintain weight/change eating behaviours. While this was an intentional decision to reduce the influence of weight stigma (by not specifically recruiting participants self-identifying as having overweight and obesity (Romano et al., 2018)) and ensure participant motivations/expectations were not influenced by information provided during recruitment (Boot et al., 2013), it may be that the lack of support found for CBM across these studies is related to the characteristics of the sample. Previous work recruiting participants looking to reduce snack food consumption showed that individuals in the ICT only group appeared to experience positive outcomes in terms of snack consumption (Forman et al., 2016) and Haynes et al., (2015) discovered positive EC training effects for individuals low in inhibitory control in a sample motivated to manage weight through healthy eating. It is possible that participant expectations may influence training outcomes (as work in other domains has demonstrated significant positive associations between expectancies and treatment efficacy (e.g., Beard et al., 2011, Smith et al., 2018)), obscuring the true influence of CBM as a standalone intervention. Further work is needed to disentangle training specific effects from participant expectation and motivation driven effects to fully (and objectively) evaluate CBM within food intervention contexts.

A final consideration for future CBM research is the measures used to evaluate intervention effectiveness. The studies within chapters 3, 4 and 5 utilised proxy measures of choice and preference (similarly to other CBM studies (e.g., Chen et al., 2018a, Hensels &

Baines, 2016; Lebens et al., 2011)), however, the results from 6 revealed that these measures are poor predictors of real-world food consumption. Given that CBM is designed to be an intervention to reduce unhealthy food behaviours (and subsequently, weight), the poor relations between preference measures and consumption behaviours indicate that CBM is not being evaluated effectively. Additionally, the studies within this thesis focused on snack food behaviours/consumption: although unhealthy snack food consumption has been associated with BMI (Cohen et al., 2010) and is often targeted in CBM studies (e.g., Bongers et al., 2018; Lawrence et al., 2015a; Wang et al., 2017)), it may be that research should focus on all types of foods consumed rather than solely snack food intake (as obesity is the result of excess calorie intake (Skidmore & Yarnell, 2004)), or adopt more complex analyses techniques accounting for both binary choices and reaction times (e.g., drift diffusion models (Lee & Usher, 2021)). Future work should attempt to further develop and validate measures closely associated with food behaviours, or adopt alternative, more objective measures of all types of food consumption (e.g., photographic food diaries, calorie intake diaries) to ensure any measured CBM effects are likely to lead to a change in real-world food behaviours before the development of large scale randomised controlled trials.

7.6. Concluding remarks

The overall aim of this thesis was to investigate cue-ICT and EC to evaluate their efficacy as non-invasive intervention strategies for unhealthy food behaviours. To do this, the studies within the thesis addressed previous limitations across the literature (e.g., inappropriate control groups, unstandardised task design) by developing a standardised experimental paradigm for cue-ICT and EC and studies were pre-registered and adequately powered. Overall, there was limited evidence to support CBM as a standalone intervention strategy, with the results revealing that factors external to training (i.e., belief in training efficacy) appeared to have a substantial influence on training outcomes. There was limited evidence to support devaluation as a mechanism of effect for CBM due to the lack of significant training effects discovered across the studies. There was however some evidence to support memory formation/association based hypotheses, although this may not be due to the actual CBM training protocols used within studies, but contextual factors surrounding training completion (and expectations). Finally, while proxy measures of food intake (such as preference and consumption) are frequently used to evaluate training efficacy, they do not appear to be robust predictors of real-world food consumption behaviours. Further research is needed to identify and isolate the role of individual differences within CBM paradigms, and to develop and validate new measures of food preference and choice that consistently and accurately relate to real world consumption behaviours.

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Appendices

8.1. Appendix A: Supplementary materials (Chapter 3)

Outliers

The main analyses were repeated with outliers (as identified through boxplots) for the respective dependent variables removed to assess their potential impact on the analyses.

H1 - Participants in the intervention groups (cue-specific ICT or EC) will show a reduction in implicit food preferences for unhealthy foods compared to those involved in either active or passive control conditions.

Removal of outliers did not substantially influence the outcome of the mixed ANOVA (with the independent variable as condition and the dependent variable of IAT score), with a main effect of time (F (1, 119) = 46.72, p < .001, ηp2 = 0.28) but no main effect of condition (F (4, 119) = 0.86, p = .493, ηp2 = 0.03) or condition by time interaction (F (4, 119) = 0.89, p = .473, ηp2 = 0.03).

H3 - Participants involved in the intervention groups (cue-ICT or EC) will consume less unhealthy food in an ad libitum tasting compared to active and passive control groups

When the analyses were repeated with outliers removed (one way ANOVAs with condition as the independent variable and healthy/unhealthy food consumption as the dependent variables) there were no meaningful changes to the analyses outcomes with no main effects found for healthy (F (4, 121) = 1.62, p = .173, ηp2 = 0.05) or unhealthy (F (4, 116) = 1.09, p = .364, ηp2 = 0.04) food consumption.

Exploratory Analyses

Bayesian Analysis

Bayes factors were calculated for each model to evaluate evidence in support of the null hypotheses, and are summarised in the tables below. Analyses were performed using JASP 0.11.1.

Supplementary Table 1. Bayes factors for mixed ANOVA model (IAT score).

	BF_{01}	BF_{10}
Condition	13.18	0.08
Time	0.0000006	155364.05
Condition * Time	142.86	0.05

Supplementary Table 2. Bayes factors for ANOVA model (Explicit Preference).

	BF_{01}	BF_{10}
Condition	1.00	1.00

Supplementary Table 3. Bayes factors for ANOVA models (Food Consumption).

Models	BF_{01}	BF_{10}
Healthy food consumption		
Condition	10.85	0.09
Unhealthy food consumption		
Condition	12.04	0.08

Food Liking

To assess the impact of training on measures of food liking, a one way ANOVA with condition as the independent variable (active ICT, control ICT, active EC, control EC, passive control) and average healthy food rating (mean liking of the two healthy food options as measured using the VAS) as the dependent variable was conducted. The results revealed that there was no main effect of condition on healthy food liking (F (4, 124) = 0.58, p = .676, $\eta p2$ = 0.02).

When the analysis was repeated using average unhealthy food rating (mean liking of the two unhealthy food options as measured using the VAS) as the dependent variable, again, there was no significant main effect of condition (F (4, 124) = 0.32, p = .861, $\eta p2$ = 0.01)

8.2. Appendix B: Supplementary materials (Chapter 4)

Example Images

Two example food images used within the training tasks (across both studies) are displayed below (supplementary figure 1).

Supplementary figure 1. Examples of healthy (left) and unhealthy (right) food images used within training tasks and food value measures.

Study 1

Participant characteristics

To ensure that the sample did not vary on demographic characteristics dependent on recruitment method (student sample VS prolific academic), two univariate ANOVAs were performed, with the IV as recruitment type (student sample or prolific academic) and DVs as age and BMI. Results are summarised in supplementary table 1.

Supplementary Table 1. ANOVA summary table for demographic analyses (sample characteristics compared on recruitment strategy).

	$df_{num}(df_{err})$	*F*	p	ηp^2
Age (y)	1(168)	0.16	.693	.001
BMI (kg/m^2)	1(157)	0.02	.882	<.001

Outliers

Hypothesis one (Participants in the highest cue-inhibition contingency group (100%) will show more pronounced food value changes post training compared to those in lower contingency groups (75%, 50% and 25%)) and Hypothesis three (Participants with poorer levels of inhibitory control pre training will show greater benefits from food specific cue-ICT).

To assess the influence of outliers on the results, the analyses were repeated with outliers (as identified through boxplots) removed. Removal of outliers did not result in any changes to the outcome of the ANCOVA (with healthy food VAS as the dependent variable and number of inhibition errors as the covariate), with no main effect of condition (F (3,155) = 0.40, p = .756, ηp^2 = .01), time (F (1,155) = 0.13, p = .724, ηp^2 = .001) or time by condition interaction (F (3,155) = 1.15, p = .331, ηp^2 = .02). This was also the case when median 'go' RT was used as the covariate, with no main effect of condition (F (3,155) = 0.44, p = .723, ηp^2 = .01), time (F (1,155) = 0.39, p = .532, ηp^2 = .003) or interaction (F (3,155) = 1.16, p = .325, ηp^2 = .02) observed.

As previously, when using unhealthy food VAS as the dependent variable and number of inhibition errors as the covariate, there was no significant main effect of condition (F (3,155) = 0.21, p = .886, ηp^2 = .004), or time (F (1,155) = 0.03, p = .875, ηp^2 < .001), and no condition by time interaction (F (3,155) = 0.55, p = .649, ηp^2=.01) when DV outliers were removed. Additionally, results did not differ when median 'go' RT was used as the covariate, with no main effect of condition (F (3,155) = 0.28, p = .839, ηp^2 = .005), time (F (1,155) = 0.35, p = .557, ηp^2 = .002) or a condition x time interaction (F (3,155) = 0.61, p = .612, ηp^2= .01).

Supplementary table 2. Descriptive statistics for mean VAS scores for healthy and unhealthy foods, both pre and post training (with outliers removed). Scores range from -100 to +100, with higher scores representing higher food value. Values are mean and SD.

	Healthy food VAS		Unhealthy food VAS	
Condition	Pre training	Post training	Pre training	Post training
25% Inhibition Unhealthy	21.40 (26.93)	21.38 (28.49)	22.70 (26.73)	22.46 (27.37)
50% Inhibition Unhealthy	25.26 (20.47)	26.26 (21.68)	15.77 (25.17)	17.09 (27.60)
75% Inhibition Unhealthy	26.27 (25.56)	24.80 (25.21)	21.22 (27.59)	19.52 (27.57)
100% Inhibition Unhealthy	24.30 (23.82)	27.25 (25.47)	19.17 (24.20)	18.81 (24.81)

Exploratory Analyses

Signal Detection measure of inhibitory control:

The initial analyses were repeated using signal detection (*d*) as a covariate, as opposed to the initial inhibitory ability measures (number of inhibition errors and median ‘go’ trial RT). The 4 (cue-inhibition contingency: 25%, 50%, 75% and 100%) x 2 (time: pre training, post training) ANCOVA revealed that there was no main effect of condition (F (3,165) = 0.61, p = .607, ηp^2 = .01), time (F (1,165) = 0.43, p = .516, ηp^2 = .003) or condition by time interaction (F (3,165) = 0.71, p = .546, ηp^2 = .01) for healthy food VAS ratings. This was also the case for unhealthy food VAS ratings, with no main effect of condition (F (3,165)

= 0.90, p = .442, ηp^2 = .02), time (*F* (1,165) = 0.93, p = .336, ηp^2 = .01) or interaction (*F* (3,165) = 1.16, p = .326, ηp^2 = .02) discovered.

The explicit preference analysis (one way ANCOVA, with condition as the independent variable (cue-inhibition contingency: 25%, 50%, 75% and 100%) and explicit preference score as the dependent variable) was also repeated using signal detection as the covariate. Again, no significant differences were found in explicit preferences based upon condition allocation (*F* (3,164) = 0.43, *p* = .733, ηp^2 = .01).

Generalisation

To assess potential generalisation of training effects to novel images, a 4 (cue-inhibition contingency: 25%, 50%, 75% and 100%) x 2 (time: pre training, post training) x 2 (generalisation: trained images, novel images) ANCOVA was conducted, using number of inhibition errors as the covariate and healthy food VAS as the DV. The analysis showed no main effect of condition (*F* (3,165) = 0.67, p = .573, ηp^2 = .01) or time (*F* (1,165) = 0.13, p = .720, ηp^2 = .001), however, a main effect of generalisation was revealed (*F* (1,165) = 4.18, p = .043, ηp^2 = .03) with participants rating training images higher overall (*Mean*= 30.09, *SE* = 2.32) than novel images (*Mean*= 22.49, *SE* = 2.44). There were no significant interactions between time and condition (*F* (3,165) = 0.73, p = .536, ηp^2 = .01), generalisation and condition (*F* (3,165) = 0.57, p = .635, ηp^2 = .01), generalisation and time (*F* (1,165) < .001, p = .991, ηp^2 < .01) or between time, condition and generalisation (*F* (3,165) = 2.31, p = .078, ηp^2 = .04).

There was no main effect of condition (*F* (3,165) = 0.69, p = .560, ηp^2 = .01), time (*F* (1,165) = 0.27, p = .602, ηp^2 = .002) or generalisation (*F* (1,165) = 0.91, p = .342, ηp^2 = .01) on healthy food VAS ratings when using median 'go' trial RT as the covariate. As previously, there were no significant interactions between time and condition (*F* (3,165) =

0.74, p = .531, ηp^2= .01), generalisation and condition (F (3,165) = 0.69, p = .560, ηp^2= .01), generalisation and time (F (1,165) = 0.21, p = .650, ηp^2= .001), or between time, condition and generalisation (F (3,165) = 2.34, p = .075, ηp^2= .04).

Finally, when using signal detection as the covariate, there was no main effect of condition (F (3,165) = 0.61, p = .607, ηp^2= .01) or time (F (1,165) = 0.43, p = .516, ηp^2= .003), but a main effect of generalisation (F (1,165) = 12.02, p = .001, ηp^2= .07). There were no significant interactions between time and condition (F (3,165) = 0.71, p = .546, ηp^2= .01), generalisation and condition (F (3,165) = 0.68, p = .563, ηp^2= .01), generalisation and time (F (1,165) = 0.13, p = .716, ηp^2= .001) or between time, condition and generalisation (F (3,165) = 2.42, p = .068, ηp^2= .04).

The above analyses were repeated using unhealthy food VAS ratings as the dependent variable, and no main effects of condition (F (3,165) = 0.67, p = .573, ηp^2= .01), time (F (1,165) = 0.13, p = .720, ηp^2= .001) or generalisation (F (1,165) = 0.65, p = .422, ηp^2= .004) were discovered when using number of inhibition errors as the covariate. There were also no significant interactions between time and condition (F (3,165) = 0.73, p = .536, ηp^2= .01), generalisation and time (F (1,165) = 1.48, p = .226, ηp^2= .01) or between time, condition and generalisation (F (3, 165) = 0.63, p = .596, ηp^2= .01). A significant interaction was found between generalisation and condition (F (3,165) = 2.69, p = .048, ηp^2= .05), however, post hoc analyses did not reveal any significant differences between individual groups (p > .05 in all cases).

When controlling for median 'go' RT, the results of the analysis did not differ, with no main effect of condition (F (3,165) = 0.69, p = .560, ηp^2= .01), time (F (1,165) = 0.27, p = .602, ηp^2=.002) or generalisation (F (1,165) = 1.08, p = .300, ηp^2= .01). There was no significant interaction between time and condition (F (3,165) = 0.74, p = .531, ηp^2= .01), generalisation and time (F (1,165) = 1.96, p = .163, ηp^2= .01) or between time, generalisation and condition (F (3,165) = 0.53, p = .663, ηp^2 = .01), however, there was a marginally significant interaction between generalisation and condition (F (3,165) = 2.69, p = .048, ηp^2 = .05), with post hoc analyses revealing no significant differences between groups (p > .05 for all cases).

Finally, using signal detection as the analysis covariate did not result in any changes to the results, with no main effect of condition (F (3,165) = 0.61, p = .607, ηp^2 = .01), time (F (1,165) = 0.43, p = .516, ηp^2 = .003) or generalisation (F (1,165) = 3.45, p = .065, ηp^2 = .02) discovered. Interactions between time and condition (F (3,165) = 0.71, p = .546, ηp^2 = .01), generalisation and time (F (1,165) = 1.88, p = .172, ηp^2 = .01) and time, generalisation and condition (F (3,165) = 0.63, p = .598, ηp^2 = .01) were not significant, and while a significant interaction between generalisation and condition was found (F (3,165) = 2.91, p = .036, ηp^2 = .05), post hoc analyses revealed no significant between group differences (p > .05).

Aim Awareness

To determine the extent to which aim awareness influenced training impact, responses from the funnelled debrief were used to classify participants as either 'aware' or 'unaware' in terms of the true experimental aims. A total of 33 participants correctly guessed the true aim of the study, correctly identifying that the purpose of the training was to manipulate their preferences for healthy and unhealthy items.

To establish the influence of aim awareness on training effectiveness, a 4 (cue-inhibition contingency: 25%, 50%, 75% and 100%) x 2 (time: pre or post intervention training) ANCOVA was conducted, with healthy VAS scores as the DV, number of inhibition errors as the covariate, and the data for the 33 participants who correctly identified the experimental aim excluded. The results revealed that there was no main effect of condition (F (3,128) = 1.83, p = .145, ηp^2 = .04), time (F (1,128) = 0.14, p = .706, ηp^2 = .001) and no interaction between time and condition (*F* (3,128) = 0.37, p = .778, ηp^2 = .01). This was also the case where median 'go' RT was used as the covariate, with no main effect of condition (*F* (3,128) = 1.57, p = .200, ηp^2 = .04), time (*F* (1,128) = 0.03, p = .864, ηp^2 <.001), or condition by time interaction (*F* (3,128) = 0.32, p = .831, ηp^2 = .01). There were also no significant differences where signal detection was used as the covariate (condition (*F* (3,128) = 1.70, p = .171, ηp^2 = .04), time (*F* (1,128) = .004, p = .949, ηp^2 <.001) condition by time interaction (*F* (3,128) = .33, p = .803, ηp^2 = .01).

The analyses were repeated using unhealthy food VAS scores as the DV, while excluding the 33 participants who correctly described the experimental aims. When number of inhibition errors were used as the covariate, there was no significant main effect of condition (*F* (3,128) = 0.59, p = .623, ηp^2 = .01), time (*F* (1,128) = 0.001, p = .976, ηp^2 < .001) or time by condition interaction (*F* (3,128) = 0.99, p = .400, ηp^2 = .02). The results did not differ when using median 'go' RT as the covariate (condition (*F* (3,128) = 0.72, p = .541, ηp^2 = .02), time (*F* (1,128) = .99, p = .322, ηp^2 = .01) condition by time interaction (*F* (3,128) = 0.86, p = .467, ηp^2 = .02)) or when using signal detection as the covariate (condition (*F* (3,128) = 0.66, p = .576, ηp^2 = .02), time (*F* (1,128) = 0.19, p = .668, ηp^2 = .001), condition by time interaction (*F* (3,128) = 1.03, p = .381, ηp^2 = .02)).

Explicit Preference

In addition to the main analyses, a chi square test was performed to analyse the associations between condition and explicit preference (due to the frequency basis of the measure). The results supported the main analyses, and revealed there to be no significant association between condition and explicit preferences χ^2(6, N=169) = 4.46, p = .615.

Bayesian Analysis

Bayes factors were calculated for each model to quantify evidence in support of the null hypotheses, and are summarised in the tables below. Analyses were performed using JASP 0.11.1.

Supplementary Table 3. Bayes factors for mixed ANCOVA models (healthy food VAS).

Models	BF_{01}	BF_{10}
Covariate: Inhibition errors		
Condition	5.67	0.18
Time	13.05	0.08
Condition * Time	28.47	0.03
Covariate: Median 'go' RT		
Condition	4.64	0.22
Time	12.37	0.08
Condition * Time	23.54	0.03

Supplementary Table 4. Bayes factors for mixed ANCOVA models (unhealthy food VAS).

Models	BF_{01}	BF_{10}
Covariate: Inhibition errors		
Condition	1.42	0.70
Time	3.34	0.30
Condition * Time	5.27	0.19
Covariate: Median 'go' RT		

Condition	4.10	0.24
Time	8.96	0.11
Condition * Time	17.73	0.06

Supplementary Table 5. Bayes factors for ANCOVA models (explicit food preference)

Models	BF_{01}	BF_{10}
Covariate: Inhibition errors		
Condition	32.21	0.01
Covariate: Median 'go' RT		
Condition	108.62	0.01

Study 2

Outliers

Hypothesis one (Participants who experience unhealthy food images paired with 100% negative images will show greater changes in food value post training compared to those where unhealthy stimuli are paired with fewer negative images (75%, 50% and 25%)) and Hypothesis three (Participants with lower levels of inhibitory control pre-study will benefit more from food based evaluative conditioning online training).

To assess the influence of outliers on the results, the analyses were repeated with outliers for the dependent variables removed. When using inhibition errors as the covariate (and healthy food VAS as the dependent variable), a significant main effect of condition (F (3,283) = 3.22, p = .023, ηp^2 = .03) was revealed, however, the main effect of time (F (1,283) = 0.36, p = .551, ηp^2 = .001) and the time by condition interaction (F (3,283) = 0.84, p = .474,

$\eta p^2 = .01$) were not significant. This was also the case when median 'go' RT was used as the covariate, with a main effect of condition (F (3,283) = 3.35, p = .019, $\eta p^2 = .03$), but no main effect of time (F (1,283) = 0.12, p = .727, $\eta p^2 < .001$) and no significant condition by time interaction (F (3,283) = 0.73, p = .533, $\eta p^2 = .01$).

When DV outliers were removed (and inhibition errors used as the covariate), the analysis revealed no significant main effect of time (F (1,283) = 2.87, p = .091, $\eta p^2 = .01$) or condition (F (3,283) = 2.59, p = .053, $\eta p^2 = .03$), and no significant time by condition interaction (F (3,283) = 0.81, p = .487, $\eta p^2 = .01$). The results were identical when using median 'go' RT as the covariate, with no main effect of condition (F (3,283) = 2.46, p = .063, $\eta p^2 = .03$), time (F (1, 283) = 2.10, p = .148, $\eta p^2 = .01$) or time by condition interaction (F (3,283) = 0.71, p = .544, $\eta p^2 = .01$).

Supplementary Table 6. Descriptive statistics for mean VAS scores for healthy and unhealthy foods, both pre and post training (with outliers removed). Scores range from -100 to +100, with higher scores representing higher food value. Values are mean and SD.

	Healthy food VAS		Unhealthy food VAS	
Condition	Pre training	Post training	Pre training	Post training
25% Congruent Trials	31.20 (31.13)	33.95 (26.10)	23.51 (31.29)	21.21 (34.42)
50% Congruent Trials	38.62 (22.96)	37.54 (26.75)	28.16 (33.11)	25.37 (37.17)
75% Congruent Trials	36.51 (26.55)	41.15 (27.90)	29.18 (31.77)	21.16 (33.09)
100% Congruent Trials	39.11 (29.73)	47.09 (28.28)	22.88 (29.62)	11.34 (35.62)

Exploratory Analyses

Signal Detection

The initial analyses were repeated using signal detection (*d*) as a covariate, as opposed to the initial inhibitory ability measures (number of inhibition errors and median 'go' trial RT). The 4 (congruent trials: 100%, 75%, 50% and 25%) x 2 (time: pre training, post training) ANCOVA showed that while there was a significant main effect of condition (F (3,292) = 2.71, p = .046, ηp^2= .03), there was no main effect of time (F (1,292) = 1.76, p = .185, ηp^2= .01) and no significant condition by time interaction (F (3,292) = 0.77, p = .510, ηp^2= .01) for healthy food VAS scores.

For unhealthy food VAS scores, using signal detection as the covariate resulted a significant main effect of condition (F (3,292) = 2.88, p = .037, ηp^2= .03), however, there was no significant main effect of time (F (1,292) = 3.38, p = .067, ηp^2= .01), and no significant condition by time interaction (F (3,292) = 0.62, p = .602, ηp^2= .01).

The explicit preference analysis (one way ANCOVA, with condition as the independent variable and explicit preference score as the dependent variable) was also repeated using signal detection as the covariate. As previously, there was a significant effect of condition (F (3,289) = 4.18, p = .006, ηp^2= .04) with the 100% and 50% groups differing in explicit preference score (p = .027).

Generalisation

To assess the potential for generalisation to novel stimuli through training, a 4 (congruent trials: 100%, 75%, 50% and 25) x 2 (time: pre training, post training) x 2 (generalisation: trained images, novel images) ANCOVA was conducted, using number of inhibition errors as the covariate and healthy food VAS as the DV. The analysis revealed that while there was no main effect of time (F (1,292) = 0.77, p = .380, ηp^2= .003), there was a weak significant main effect of condition (F (3,292) = 2.72, p = .045, ηp^2 = .03) and also of generalisation (F (1,292) = 32.22, p <.001, ηp^2 = .10), with participants rating images used in training higher (M = 42.34, SE = 1.51) than novel images (M = 34.18, SE = 1.65). There were no significant interactions between time and condition (F (3,292) = 0.74, p = .530, ηp^2 = .01), generalisation and condition (F (3,292) = 0.80, p = .497, ηp^2 = .01) time and generalisation (F (1,292) = 0.03, p = .854, ηp^2 <.001) or time, condition and generalisation (F (3,292) = 1.18, p = .318, ηp^2 = .01).

When median 'go' RT was used as the covariate, there was a significant main effect of condition (F (3,292) = 2.90, p = .035, ηp^2 = .03), however, there was no significant main effect of time (F (1,292) <.001, p = .998. ηp^2 <.001) or generalisation (F (1,292) = .02, p = .880, ηp^2 < .001). There were also no significant interactions between time and condition (F (3,292) = 0.75, p = .524, ηp^2 = .01), generalisation and condition (F (3,292) = 0.87, p = .456, ηp^2 = .01), time and generalisation (F (1,292) = 1.82, p = .178, ηp^2 = .01) or time, condition and generalisation (F (3,292) = 1.26, p = .289, ηp^2 = .01).

Finally, when using signal detection as the covariate, the analysis revealed significant main effects of generalisation (F (1,292) = 31.16, p < .001, ηp^2 = .10) and condition (F (3,292) = 2.71, p = .046, ηp^2 = .03) however there were no main effects of time (F (1,292) = 1.76, p = .185, ηp^2 = .01) and no interactions between time and condition (F (3,292) = 0.77, p = .510, ηp^2 = .01), generalisation and condition (F (3,292) = 0.78, p = .508, ηp^2 = .01), time and generalisation (F (1,292) = .12, p = .729, ηp^2 < .001) or time, condition and generalisation (F (3,292) = 1.21, p = .307, ηp^2 = .01).

The above analyses were repeated using unhealthy food VAS ratings as the dependent variable, and when using number of inhibition errors as the covariate, there was a main effect of condition (F (3,292) = 2.72, p = .045, ηp^2 = .03), however, there were no main effects of time (F (1,292) = 0.77, p = .380, ηp^2 = .003) or generalisation (F (1,292) = 0.40, p = .528, ηp^2

= .001). There were also no significant interactions between time and condition (F (3,292) = .74, p = .530, ηp^2 = .008), generalisation and condition (F (3,224) = 2.07, p = .104, ηp^2 = .02) time and generalisation (F (1,292) = .004, p = .948, ηp^2 < .001) or time, condition and generalisation (F (3,292) = 0.87, p = .455, ηp^2 = .01).

When median 'go' RT was used as the covariate, the results were as above, with a significant main effect of condition (F (3,292) = 2.90, p = .035, ηp^2 = .03). The main effects of time (F (1, 292) < .001, p = .998, ηp^2 < .001) and generalisation (F (1,292) = .03, p = .858, ηp^2 < .001) were not significant, and interactions between time and condition (F (3,292) = 0.75, p = .524, ηp^2 = .01), generalisation and condition (F (3,292) = 2.03, p = .110, ηp^2 = .02) time and generalisation (F (1,292) = 0.59, p = .444, ηp^2 = .002) and time, condition and generalisation (F (3,292) = 0.89, p = 447, ηp^2 = .01) were also not significant.

Finally, when signal detection was used as the covariate, the results mirrored those of the previous analyses, with a main effect of condition (F (3,292) = 2.71, p = .046, ηp^2 = .03) and no significant main effects of time (F (1,292) = 1.76, p = .185, ηp^2 = .01) or generalisation (F (1,292) = 0.16, p = .692, ηp^2 = .001). The interactions between time and condition (F (3,292) = 0.77, p = .510, ηp^2 = .01), generalisation and condition (F (3,292) = 2.06, p = .106, ηp^2 = .02) time and generalisation (F (1,292) = 0.06, p = .800, ηp^2 < .001) and time, condition and generalisation (F (3,292) = 0.87, p = .455, ηp^2 = .01) were not significant.

Aim Awareness

To determine the extent to which aim awareness influenced training impact, responses from the funnelled debrief were used to classify participants as either 'aware' or 'unaware' in terms of the true experimental aims. A total of 70 participants correctly guessed the true aim of the study, identifying that the purpose of the training was influence their food preferences dependent upon the image pairings (healthy food -> positive health outcome) presented.

To investigate this, a 4 (congruent trials: 100%, 75%, 50% and 25%) x 2 (time: pre training, post training) ANCOVA was conducted, with healthy VAS scores as the DV, number of inhibition errors as the covariate, and data for the 70 participants who were able to identify the experimental aim excluded. The results revealed that there was no main effect of condition (F (3,111) = 0.64, p = .590, ηp^2 = .02), time (F (1,111) = 0.33, p = .570, ηp^2 = .003) and no interaction between time and condition (F (3,111) = 0.61, p = .612, ηp^2 = .02). The results were similar when using median 'go' RT as the covariate, with no main effect of condition (F (3,111) = 0.96, p = .414, ηp^2 = .03), time (F (1,111) = 0.12, p = .735, ηp^2 =.001), or condition by time interaction (F (3,111) = 0.65, p = .587, ηp^2 = .02). There was a significant effect of median 'go' RT (F (1,111) = 4.46, p = .037, ηp^2 = .04), however, further analyses did not reveal any associations (p>.05). Where signal detection was used as the covariate, there were no significant main effects or interactions (condition (F (3,111) = 0.64, p = .590, ηp^2 = .02), time (F (1,111) = 0.48, p = .492, ηp^2 = .004) condition by time interaction (F (3,111) = 0.62, p = .603, ηp^2 = .02).

The analyses were repeated using unhealthy food VAS scores as the DV, again, excluding the 70 participants who were able to identify the experimental aims. When number of inhibition errors were used as the covariate, there was no significant main effect of condition (F (3,111) = 2.65, p = .052, ηp^2 = .07), time (F (1,111) = 3.55, p = .062, ηp^2 = .03) or time by condition interaction (F (3,111) = 0.21, p = .887, ηp^2 = .01). When using median 'go' RT as the covariate, there was no significant main effect of time (F (1,111) = 0.92, p = .340, ηp^2 = .01) and no time by condition interaction (F (3,111) = 0.11, p = .953, ηp^2 = .003). There was a weak significant main effect of condition (F (3,111) = 2.70, p = .049, ηp^2 = .07), however, post hoc analyses revealed no significant differences between groups (p>.05 in all cases, Finally, when using signal detection as the covariate there was no significant main effect of time (F (1,111) = 2.69, p = .104, ηp^2 = .02) or a condition by time interaction (F (3,111) = 0.18, p = .910, ηp^2 = .01). There was a significant main effect of condition (F (3,111) = 2.98, p = .034, ηp^2 = .01) and there was also a significant time by signal detection interaction, with a positive association between signal detection and pre training VAS (β = 5.81, p = .004).

Explicit Preference

As with the first study, a chi square test was performed to analyse the associations between condition and explicit preference due to the limits of the explicit preference measure. The results supported the main analyses, and revealed there was a significant association between condition and explicit preferences $\chi^2(6, N=294) = 13.60$, p = .034. Post hoc analyses (using Fisher's exact approach with Bonferroni correction (Shan & Gerstenberger, 2017)) indicated that participants in the 100% percentage group made two unhealthy food choices less frequently than expected by chance (adjusted residual = -3.07, p = .002).

Bayesian Analysis

Bayes factors were calculated for each model to quantify evidence in support of the null hypotheses, and are summarised in the tables below. Analyses were performed using JASP 0.11.1.

Supplementary Table 7. Bayes factors for mixed ANCOVA models (healthy food VAS).

Models	BF_{01}	BF_{10}
Covariate: Inhibition errors		

Condition	20.92	0.05
Time	7.83	0.13
Condition * Time	126.31	0.01
Covariate: Median 'go' RT		
Condition	9.70	0.10
Time	4.65	0.21
Condition * Time	51.93	0.02

Supplementary Table 8. Bayes factors for mixed ANCOVA models (unhealthy food VAS).

Models	BF_{01}	BF_{10}
Covariate: Inhibition errors		
Condition	3.08	0.33
Time	0.32	3.51
Condition * Time	46.24	0.02
Covariate: Median 'go' RT		
Condition	21.10	0.05
Time	1.77	0.57
Condition * Time	462.17	0.002

Supplementary Table 9. Bayes factors for ANCOVA models (explicit food preference).

Models	BF_{01}	BF_{10}

Covariate: Inhibition errors		
Condition	1.60	0.62
Covariate: Median ‘go’ RT		
Condition	2.26	0.44

8.3. Appendix C: Supplementary materials (Chapter 5)

Study 1

To ensure that there were no significant differences in participant demographics based upon recruitment method, two univariate ANOVAs were conducted, with the IV of recruitment strategy (community (and student) sample/prolific academic) and the DVs of Age (years) and BMI (kg/m^2). Results are reported in supplementary table 1.

There was also no significant association between recruitment type and condition randomisation (Chi Square: ($\chi 2$ = (6, N=129) = 4.94, p = .176)).

Supplementary Table 1. ANOVA summary table for demographic analyses (sample characteristics compared on recruitment strategy).

	$df_{num}(df_{err})$	*F*	p	ηp^2
Age (y)	1 (128)	2.44	.121	.02
BMI (kg/m^2)	1 (126)	0.64	.425	.01

Supplementary Table 2. Descriptive statistics for participant demographics split by condition. Values represent M (±SD).

Condition	Age (y)	Sex (M:F)	BMI
ICT Message + ICT	28.64 (12.22)	15:18	24.24 (3.55)
ICT Message + Control Training	27.89 (10.14)	16:19	25.12 (5.79)
Control Message + ICT	29.53 (15.34)	10:28	25.67 (6.00)
Control Message + Control Training	29.17 (13.68)	11:12	24.95 (5.86)

Inhibitory Control Training task – reliability and task performance

Split-half reliability analyses (using go trial reaction time) revealed that the task had high levels of internal reliability ($r = .87$, $p < .001$). Participant engagement was good, with a mean error percentage of 2.07% for go trials, 2.18% for no go trials, with an overall error percentage across go and no-go trials of 2.13%.

Descriptive Statistics

Supplementary Table 3. Descriptive statistics for mean VAS scores for healthy and unhealthy foods, both pre and post manipulation. Scores range from -100 to +100, with higher scores representing higher food value. Values are mean ± SD.

	Healthy food VAS		Unhealthy food VAS	
Condition	Pre manipulation	Post manipulation	Pre manipulation	Post manipulation
ICT Message + ICT	39.81 (26.78)	39.49 (24.91)	30.08 (34.52)	17.67 (39.39)
ICT Message + Control Training	39.74 (28.19)	44.74 (29.26)	40.96 (29.56)	31.73 (32.71)
Control Message + ICT	28.37 (31.03)	30.31 (30.95)	22.74 (30.73)	20.82 (31.19)
Control Message + Control Training	45.14 (21.91)	45.04 (23.86)	29.76 (34.81)	27.85(37.80)

Supplementary Table 4. Mean and standard deviation for explicit preference score per condition. Higher scores represent increased healthy choices

Condition	Mean explicit preference (± SD)
ICT Message + ICT	1.27 (0.52)
ICT Message + Control Training	1.26 (0.66)
Control Message + ICT	0.79 (0.62)
Control Message + Control Training	1.09 (0.67)

Exploratory Analyses

Outliers

Hypothesis one (Participants who receive a positive message related to ICT effectiveness and active ICT will show greater changes in food value in comparison to other training groups) and Hypothesis three (Participants who receive a positive message (and active training) or a positive message (and control training) will show greater changes in food value and make healthier explicit choices, compared to a group with no positive message and control training).

To assess the influence of outliers on the results, the main analyses were repeated with outliers (as identified through boxplots) removed. While no outliers were identified for the unhealthy food value measure, removal of outliers for the healthy food value measure analysis (4 (condition) x 2 (time) ANOVA) resulted in no change to the analysis outcome, with no significant main effect of time (F (1, 123) = 3.18, p = .077, ηp^2= .03), condition (F (3,123) = 1.21, p = .309, ηp^2=.03) or time by condition interaction (F (3, 123) = 1.88, p = .137, ηp^2= .04) revealed.

Explicit Preference

Due to the nature of the explicit preference data, a chi square test was also conducted to analyse the associations between condition and explicit preference. The results revealed a significant association between condition and explicit preference ($\chi2 = (6, N=129) = 15.73$, $p = .015$). Post hoc analyses (Fishers exact approach using Bonferroni correction ((Shan & Gerstenberger, 2017) revealed that this was due to participants in the control message and ICT group making an increased number of unhealthy choices (adjusted residual = 3.04, $p = .004$) and a decreased number of healthy choices (adjusted residual = -2.53, $p = .014$) than expected by chance.

Study 2

Evaluative conditioning task – reliability

Split half reliability analyses (using reaction time data) indicated that the task had high levels of internal reliability ($r = .80$, $p < .001$). Task performance was also good, with an average error percentage of 2.20% across all trials.

Descriptive Statistics

Supplementary Table 5. Descriptive statistics for participant demographics split by condition. Values represent M (±SD).

Condition	Age (y)	Sex (M:F)	BMI
EC Message + EC Training	31.14 (11.91)	17:12	24.32 (3.96)
EC Message + Control Training	26.94 (7.74)	23:14	25.17 (6.85)

Control Message + EC Training	28.08 (8.85)	22:10	24.58 (4.46)
Control Message + Control Training	29.98 (9.59)	24:17	25.50 (5.86)

Supplementary Table 6. Descriptive statistics for additional measures (TFEQ-R18 (Subscales: Cognitive Restraint, Uncontrolled Eating, Emotional Eating), SDRS-5 and BISS) split by condition. Values are mean ± SD.

	TFEQ-R18 – Cognitive Restraint	TFEQ-R18 – Uncontrolled Eating	TFEQ-R18 – Emotional Eating	SDRS-5	BISS
EC Message + EC Training	13.24 (3.63)	20.21 (5.20)	6.59 (2.13)	0.76 (0.92)	11.38 (2.90)
EC Message + Control Training	12.76 (3.26)	21.18 (5.71)	6.63 (2.80)	0.63 (0.82)	11.97 (3.86)
Control Message + EC Training	13.19 (3.37)	20.89 (4.81)	7.03 (2.36)	0.62 (0.92)	11.59 (3.40)
Control Message + Control Training	14.05 (3.66)	19.43 (4.20)	6.76 (2.03)	0.56 (0.92)	11.37 (3.67)

Supplementary Table 7. Descriptive statistics for mean VAS scores for healthy and unhealthy foods, both pre, post, and one week post manipulation. Scores range from -100 to +100, with higher scores representing higher food value. Values are mean ± SD.

	Healthy food VAS			Unhealthy food VAS		
Condition	Pre manipulation	Post manipulation	One week post manipulation	Pre manipulation	Post manipulation	One week post manipulation
EC Message + EC Training	30.77 (34.59)	40.52 (28.82)	39.04 (26.57)	33.80 (33.59)	13.71 (49.56)	19.37 (42.58)
EC Message + Control Training	34.64 (30.13)	38.87 (31.94)	36.61 (24.57)	28.08 (37.24)	20.16 (38.41)	18.68 (30.63)
Control Message + EC Training	31.06 (26.27)	37.91 (27.34)	38.51 (26.32)	25.34 (29.02)	21.59 (32.65)	23.54 (31.59)
Control Message + Control Training	30.07 (28.84)	36.42 (30.76)	37.78 (28.25)	23.80 (26.71)	23.40 (30.97)	26.05 (27.37)

Supplementary Table 8. Mean and standard deviation for explicit preference score per condition both post manipulation and one week post manipulation. Higher scores represent increased healthy choices.

Condition	Post manipulation	One week post manipulation
EC Message + EC Training	1.22 (0.80)	1.13 (0.63)
EC Message + Control Training	1.33 (0.58)	1.05 (0.59)
Control Message + EC Training	1.21 (0.56)	0.93 (0.65)
Control Message + Control Training	1.10 (0.66)	1.13 (0.63)

Exploratory Analyses

Outliers

Hypothesis one (Participants who are provided with a positive EC message in addition to active EC training will show greater changes in food value in comparison to other training groups) and Hypothesis three (Manipulation related effects will still be evident one week after training has been completed)

To assess the impact of outliers on the results, the analyses (4 (condition) x 3 (time) ANOVA) were repeated with outliers for the dependent variables (healthy/unhealthy food value) removed. The removal of outliers had no influence on the original outcomes for healthy (time (F (2, 194) = 12.41, p <.001, ηp^2 = .11), condition (F (3, 97) = 0.20, p = .895, ηp^2 = .01), time*condition (F (6, 194) = 0.61, p = .720, ηp^2 = .02)) or unhealthy (time (F (2, 192) = 9.89, p < .001, ηp^2 = .09), condition (F (3, 96) = 0.27, p = .844, ηp^2 = .01), time*condition (F (6, 192) = 3.65, p = .002, ηp^2 = .10)) food value.

Explicit Preference

Identically to study one, due to the nature of the explicit preference data, a chi square test was performed to further analyse the associations between condition and explicit preference. The analyses revealed that there was no significant association between condition and baseline session explicit preference ($\chi 2$ = (6, N=139) = 7.39, p = .286).

Potential Mechanisms

To investigate potential explanatory mechanisms, the unhealthy food value analyses were repeated using belief in science, social desirability and cognitive restraint as covariates. Individual inclusion of these variables within the model resulted in no meaningful changes to the overall analysis interpretation (see supplementary table 9).

Supplementary Table 9. ANOVA summary table for each covariate analysis

Covariate	$df_{num}(df_{err})$	*F*	p	ηp^2
BISS				
Time	1 (135)	0.18	.672	.001
Condition	3 (135)	0.03	.994	.001
Time * Condition	3 (135)	6.27	.001	.12
SDRS				
Time	1 (135)	14.58	<.001	0.10
Condition	3 (135)	0.04	.990	.001
Time * Condition	3 (135)	6.12	.001	.12
TFEQ (CR)				
Time	1 (135)	6.36	.013	.05
Condition	3 (135)	0.08	.970	.002

Time * Condition	3 (135)	6.06	.001	.12

Analysing healthy and unhealthy food value using 2 (time) x 2 (message) x 2 (training) ANOVA, for study 1 (ICT).

Supplementary table 10: ANOVA summary table for the 2 (time) x 2 (message) x 2 (training type (active or placebo) analysis with healthy food value as the dependent variable

	$df_{num}(df_{err})$	*F*	p	ηp^2
Time	1(125)	3.12	.080	.02
Message	1(125)	0.58	.448	.01
Training	1(125)	3.51	.064	.03
Time * Message	1(125)	0.60	.441	.01
Time * Training	1(125)	0.79	.376	.01
Time * Training * Message	1(125)	3.99	.048	.03

While the interaction between time, training and message was marginally significant for the healthy food VAS scores, this appeared to be the result of participants who received control training and the manipulation message scoring higher on healthy food VAS post training.

Supplementary table 11: ANOVA summary table for the 2 (time) x 2 (message) x 2 (training type (active or placebo) analysis with unhealthy food value as the dependent variable

	$df_{num}(df_{err})$	*F*	p	ηp^2
Time	1(125)	26.44	<.001	.18
Message	1(125)	0.67	.416	.01

Training	1(125)	2.72	.101	.02
Time * Message	1(125)	12.94	<.001	.09
Time * Training	1(125)	0.42	.519	.003
Time * Training * Message	1(125)	0.41	.523	.003

Analysing healthy and unhealthy food value using 2 (time) x 2 (message) x 2 (training) ANOVA, for study 2 (EC).

Supplementary Table 12: ANOVA summary table for the 2 (time) x 2 (message) x 2 (training type (active or placebo) analysis with healthy food value as the dependent variable

	$df_{num}(df_{err})$	*F*	p	ηp^2
Time	1(135)	34.21	<.001	.20
Message	1(135)	0.14	.713	.001
Training	1(135)	0.10	.755	.001
Time * Message	1(135)	0.01	.914	<.001
Time * Training	1(135)	0.96	.329	.01
Time * Training * Message	1(135)	.002	.964	<.001

Supplementary Table 13: ANOVA summary table for the 2 (time) x 2 (message) x 2 (training type (active or placebo) analysis with unhealthy food value as the dependent variable

	$df_{num}(df_{err})$	*F*	p	ηp^2
Time	1(135)	21.96	<.001	.14
Message	1(135)	.10	.756	.001

Training	1(135)	.02	.893	<.001
Time * Message	1(135)	10.77	<.001	.07
Time * Training	1(135)	6.75	.010	.05
Time * Training * Message	1(135)	3.69	.057	.03

Analysis of the significant interaction revealed that this difference was due to participants in the active training group having significantly lower unhealthy food VAS scores post training ($p<.001$). There was no significant difference in the control group ($p = .132$), however, we would urge caution in the interpretation of this finding due to the manipulation of expectations within this study (see Boot et al., 2013).

Manipulation Messages

ICT – Positive Message

'Please read the below information. You will be asked questions about this information, so please take the time to study it carefully.

Inhibitory Control Training (ICT) is a type of cognitive training that teaches you to withhold responses to unhealthy food. It does this by making you withhold responses to images of these foods, whilst quickly responding to images of healthy foods during a reaction time task. It is suggested that this type of training reduces how pleasurable you find unhealthy foods and improves your ability to resist eating unhealthily.

Research has shown that this type of training is extremely effective, and has led to reductions in unhealthy food consumption in laboratory studies (Houben & Jansen, 2010; Jones et al., 2016). It is suggested that this type of training can be used as a healthy eating intervention, and due to the online nature of training, it is accessible to large numbers of people.'

EC – Positive Message

'Please read the below information. You will be asked questions about this information, so please take the time to study it carefully.

Evaluative Conditioning (EC) is a type of cognitive training that teaches you to withhold responses to unhealthy food. It does this by showing you images of unhealthy foods alongside images of negative health outcomes, and images of healthy food items alongside images of positive health outcomes. It is suggested that this type of training reduces how pleasurable you find unhealthy foods and improves your ability to resist eating unhealthily. Research has shown that this type of training is extremely effective, and has led to reductions in unhealthy food consumption in laboratory studies (Hollands et al., 2011; Haynes et al., 2015). It is suggested that this type of training can be used as a healthy eating intervention, and due to the online nature of training, it is accessible to large numbers of people.'

Control Message (used in both studies)

'Please read the below information. You will be asked questions about this information, so please take the time to study it carefully.

Measles is a highly infectious viral illness, which in rare cases, can be fatal. The initial symptoms include cold like symptoms, sore red eyes and high temperatures, with a distinctive red-brown blotchy rash appearing a few days later. While there is no treatment for this illness, there is a vaccination available (Measles, Mumps, Rubella (MMR)), with one dose up to 93% effective, and two doses up to 97% effective (CDC, 2020; NHS, 2018).

While overall cases of Measles have reduced, recently, there have been large outbreaks of the disease across the world. It is suggested that this is due to a lack of uptake for the vaccination. A paper published in 1998 stated that there was a link between the MMR vaccination and Autism, which resulted in parents not permitting their children to be vaccinated. This paper was retracted in 2010 due to issues discovered within the study design, and more recent research has found there to be no relationship between MMR vaccinations and Autism (Hviid et al., 2019).'

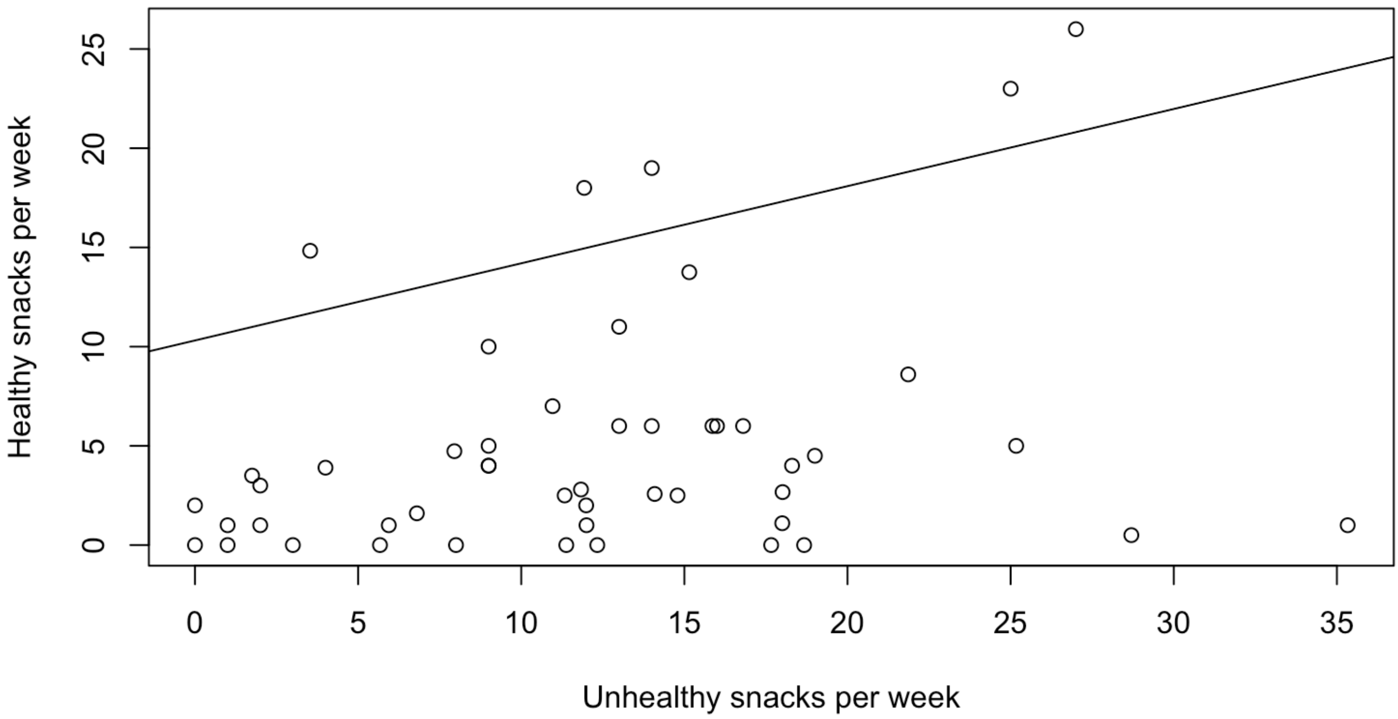
8.4. Appendix D: Supplementary materials (Chapter 6)

Supplementary table 1. Mean values (±SD) of assessment-level variables across 7-assessment days.

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Food Preference							
IAT D'	0.53 (0.38)	0.46 (0.40)	0.36 (0.41)	0.35 (0.38)	0.31 (0.40)	0.27 (0.37)	0.29 (0.39)
Explicit Choice	0.90 (0.71)	0.95 (0.67)	0.91 (0.74)	0.90 (0.69)	0.91 (0.72)	0.92 (0.67)	0.90 (0.73)
Food Value							
Unhealthy food VAS	7.43 (34.27)	1.98 (40.14)	1.90 (42.80)	-4.28 (40.42)	-3.56(41.65)	-3.07(42.25)	3.62 (40.79)
Healthy food VAS	12.06 (30.51)	12.40 (32.06)	9.80 (33.33)	8.73 (33.36)	9.34 (35.84)	10.61 (34.32)	4.26 (34.52)

Legend: ICC = intraclass correlation coefficient (the association between observations within individuals). IAT D' scores range between -2 (strong preference for unhealthy foods) and +2 (strong preference for healthy foods). Explicit choice scores range between 0 (2 unhealthy choices) and +2 (2 healthy choices). Food value scores range from -100 (not at all appealing) to +100 (extremely appealing).

Supplementary figure 1. Line plot of the association between healthy and unhealthy snacks per week, by participant



Full model reporting (Unhealthy Snacking occasions)

healthy_binary ~ iat_center + unhealthy_val_center + healthy_val_center + choice_center + BMI + Gender1M2F + Age + IAT_bs + Healthy_bs + Unhealthy_bs + Explicit_bs + Session_overall + (1 | Participant_num)

Optimizer = 'bobyqa'

AIC	BIC	logLik	deviance	df.resid
521.9	583.7	-247.0	493.9	596

Random effects variance = 2.02
Random effects Std. Dev = 1.48

Variance inflation factors

Low Correlation

Parameter	VIF	Increased SE
iat_center	1.09	1.04
unhealthy_val_center	1.14	1.07
healthy_val_center	1.07	1.03
choice_center	1.07	1.03
BMI	1.22	1.10
Gender1M2F	2.04	1.43
Age	2.30	1.52
IAT_bs	1.61	1.27
Healthy_bs	2.61	1.62
Unhealthy_bs	3.75	1.94
Session_overall	1.14	1.07

Moderate Correlation

Parameter	VIF	Increased SE
Explicit_bs	5.05	2.25

Full model reporting (Healthy Snacking occasions)

unhealthy_binary ~ iat_center + unhealthy_val_center + healthy_val_center + choice_center + IAT_bs + Healthy_bs + Unhealthy_bs + Explicit_bs + BMI_center + Gender1M2F + Age_center + Session_overall + (1 | Participant_num)
Data: EMA

Optimizer = 'bobyqa'

AIC	BIC	logLik	deviance	df.resid
760.1	821.8	-366.0	732.1	596

Random effects variance = 0.80

Random Effects Std. Dev = 0.90

Low Correlation

Parameter	*VIF*	*Increased SE*
iat_center	*1.09*	*1.04*
unhealthy_val_center	*1.11*	*1.05*
healthy_val_center	*1.05*	*1.02*
choice_center	*1.06*	*1.03*
IAT_bs	*1.67*	*1.29*
Healthy_bs	*3.16*	*1.78*
Unhealthy_bs	*3.88*	*1.97*
BMI_center	*1.20*	*1.09*
Gender1M2F	*1.90*	*1.38*
Age_center	*2.13*	*1.46*
Session_overall	*1.12*	*1.06*

Moderate Correlation

Parameter	*VIF*	*Increased SE*
Explicit_bs	*5.79*	*2.41*

Do measures of food value predict unhealthy snack portions?

Eleven snacking reports were outliers according to a box plot (number of portions > 3.71). As such we windzorised these to the next highest value (3.70). The two level model (occasions > participants) was a significantly better fit than a single level model ($X^2(1) = 6.98$, $p < .01$). The variance partition coefficient was .147, indicating that 14.7% of variance was at attributable to the individual level and 85.3% at the occasion level. There was multicollinearity present within the model (Explicit choice between subjects VIF = 6.15), therefore we removed this predictor. There was also some evidence of non-linearity of residuals, therefore results should be interpreted with caution. There were no significant predictors of number of snacks consumed. See supplementary table 2.

Supplementary table 2. Multi-level model predicting the number of snacks consumed.

	Coefficient	95% CI	T stat.
Intercept	2.179	0.092, 3.423	
Demographics and time			
Age	-.013	-.034, .008	1.103
BMI	.000	-.048, .049	0.010
Sex	-.116	-.493, .265	0.551
Time	-.014	-.033, .005	1.453
Within-subject			
D' Score	.107	-.424, .507	0.558
Explicit Choice	-.008	-.180, .169	-0.092
Unhealthy VAS	-.003	-.008, .001	1.237
Healthy VAS	.003	-.004, .005	0.134
Between-subject			
D' Score	0.329	-.424, 1.068	0.792
Unhealthy VAS	-.002	-.007, .002	1.005
Healthy VAS	.001	-.007, .002	0.411

Legend: Sex (male ref. category)