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Comparing the effects of inhibitory control training and evaluative conditioning for unhealthy food behaviours

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ABSTRACT

Cognitive Bias Modification (CBM) is hypothesised to reduce unhealthy food preference and consumption 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 using a mixed experimental design, 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 there no significant differences in terms of implicit preferences, ad-libitum food consumption or food choice. These results provide limited evidence to support the use of CBM as a psychological intervention for unhealthy food choice or consumption. Further work is needed to isolate mechanisms of effect for successful training and identify the most effective CBM protocols for implementation in future studies.

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 craving caused by 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

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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., 2013) 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., 2018; Houben & Jansen, 2011, 2015; Lawrence, O'Sullivan, et al., 2015, 2015b; Veling et al., 2013), 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: 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 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; Hensels, I, & Baines, 2016; Hollands et al., 2011; 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, resulting in a mixed design where participants completed one of five possible types of active or control training. As previous work has demonstrated that the provision of motor responses to food items can increase food value (e.g., Schonberg et al., 2014), the inclusion of both active and passive control groups allowed for the direct comparison of both types of control group to measure the extent to which control group design may have influenced perceived training efficacy across the literature. 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 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.

2. Method

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 required to be aged 18 +, self-report no history of eating disorders, not be taking medication that influences appetite, and have 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 ($d = 0.30$ (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., 2021); 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 $d = 0.31$, 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.

2.2. Measures

2.2.1. Implicit preference

The implicit association test (IAT, Greenwald et al., 1998) was used to measure relative implicit preference for healthy vs unhealthy food items. The IAT uses trial reaction times to calculate a measure of the strength of automatic associations between variables (e.g., healthy foods, positive words) and is frequently used as a proxy measure of training success within various food based CBM studies (e.g., Hensels et al., 2016; Hollands et al., 2011). 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.

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 (based on Hollands & Marteau, 2016). Food images consisted of 4 healthy (vegetable platter, cucumber sticks, apples, oranges) and 4 unhealthy (chips/crisps, fries, chocolate, cake) sweet and savoury items. All food images depicted food items presented against a plain white background (to avoid any contextual cues), with the same images presented to all participants. A healthy food choice was scored as +1, and an unhealthy food choice scored as 0, resulting in possible scores ranging between 0 (two unhealthy choices) and 2 (two healthy choices).

2.2.3. Food consumption and preference

Food consumption was assessed through a bogus *ad-libitum* taste test (see Robinson et al., 2017). All participants were presented with four identical bowls, each containing 100g of healthy (carrot sticks, grapes) and unhealthy (crisps/chips, cookies) foods (in addition to 500 ml 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 100 mm 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).

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. We followed similar guidance to Lawrence, O'Sullivan, et al. (2015) by determining unhealthy foods as those which are more energy dense (>4 kcal/g), and here unhealthy-foods are also foods that would be classed as 'high-calorie foods'.

Food images used within this task were selected based on previously conducted pilot work assessing the appeal of these images (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)), with block order counterbalanced based on participant number. Each image remained on screen for 1500 ms (or until a response was provided for go trials), and response feedback was provided after each trial (either 'correct' or 'incorrect' displayed for 250 ms). 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 ($r = 0.69$, $p < .001$).

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). Image pairs were either congruent (healthy food images followed by positive health outcome images, unhealthy food images followed by negative health outcome images) or incongruent (healthy food images followed by negative health outcome images, unhealthy food images followed by positive health outcome images). Participants completed either active (100% congruent trials) or control (50% congruent trials, 50% incongruent trials) 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 assessing both positive and negative health outcome images for appeal (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 1000 ms, 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 250 ms). Split half reliability analyses using reaction time data revealed high levels of internal reliability for this task ($r = 0.85$, $p < .001$).

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 250 ms).

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.

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, $\alpha = 0.84$, disinhibition $\alpha = 0.77$).

2.3. Procedure

Participants attended a weekday laboratory session lasting ~45 min at the University of Liverpool between the hours of 11am and 6pm, and were asked to refrain from eating for 1 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 (a wordsearch containing words unrelated to food) 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 Fig. 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) (see Fig. 2).

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.[2] 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). 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).

[2] Note – we originally planned to conduct a one-way ANOVA for food choice, however given the lack of variability in responses (0, 1 or 2) we also treat this data as categorical and use Chi-Squared analysis. This is a deviation from our pre-registered protocol.

3. Results

See Table 1 for descriptive statistics split by experimental group. Mean hunger across all groups was 4.61 (±2.30). There were no significant between group differences in Age, BMI, hunger or baseline IAT score (see supplementary materials).

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, $p < .001$, $\eta p2 = 0.20$), 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, $p = .802$, $\eta p2 = 0.01$), and no significant condition by time interaction (F (4, 124) = 0.42, $p = .797$, $\eta p2 = 0.01$) (see Fig. 3).

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 for full model reporting).

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 main effect of condition (F (4, 124) = 2.54, $p = .043$, $\eta p2 = 0.08$). 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 Fig. 4) ($p = .027$). No other groups differed significantly ($p > .05$ in all cases). Analysing this data categorically (0 vs 1 vs 2 food choices), using a chi-squared test demonstrated no significant effect ($\chi^2(8) = 10.21$, $p = .251$).

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, $p = .489$, $\eta p2 = 0.03$: see Fig. 5). 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, $p = .534$, $\eta p2 = 0.03$) (see Fig. 6). Nonparametric Kruskal-Wallis tests (based on the number of outlying data points across all conditions) did not substantially alter the findings (Healthy: $H(4) = 4.69$, $p = .32$; Unhealthy: $H(4) = 5.69$, $p = .22$).

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.

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

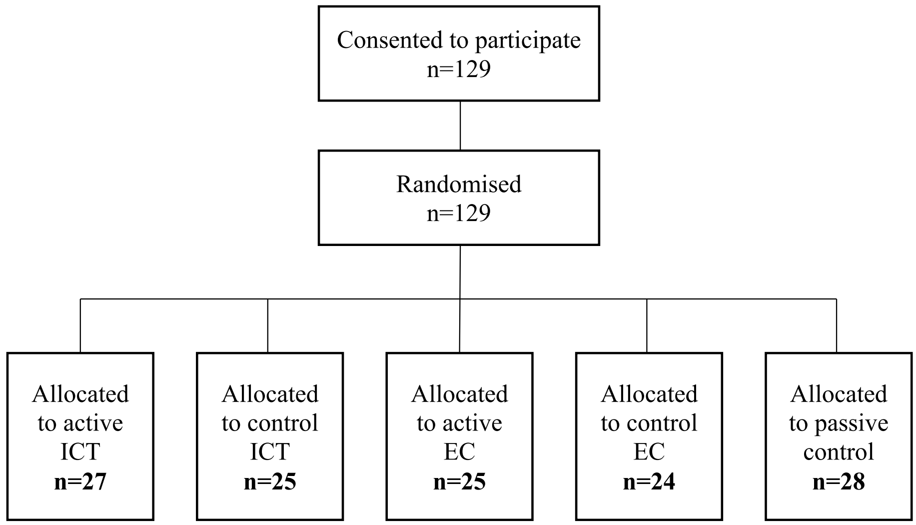

Fig. 1. A schematic flow diagram of participant recruitment and condition allocation.

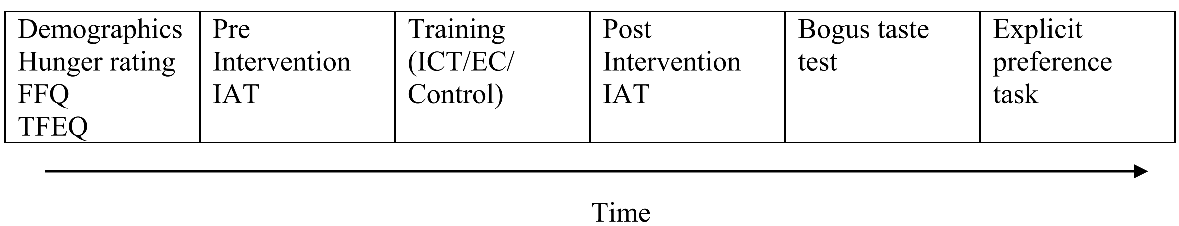

Fig. 2. A schematic diagram of the procedure for the initial lab session.

Table 1
Descriptive statistics for participant demographics split by condition. Values for age, BMI and hunger represent M (±SD).

Condition	Age (y)	Sex (M:F)	BMI	Hunger
Active ICT	22.85 (6.37)	3:24	24.64 (4.04)	4.48 (2.47)
Control ICT	22.16 (8.31)	3:22	24.15 (5.24)	4.72 (2.35)
Active EC	22.32 (6.50)	5:20	24.67 (3.93)	4.36 (1.96)
Control EC	22.71 (7.17)	6:18	25.79 (5.14)	4.58 (2.87)
Passive Control	22.50 (5.45)	3:25	23.87 (4.07)	4.89 (1.91)

consumption. The different types of training had no robust influence on food-choice, 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 et al., 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, O'Sullivan, et al., 2015), 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, Verbruggen, et al., 2015). 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, there was also no robust evidence that training had an effect on the number of unhealthy food items chosen. While there was no significant difference between the active and control conditions for each CBM technique, participants in the active EC condition made healthier explicit choices than those in the active ICT

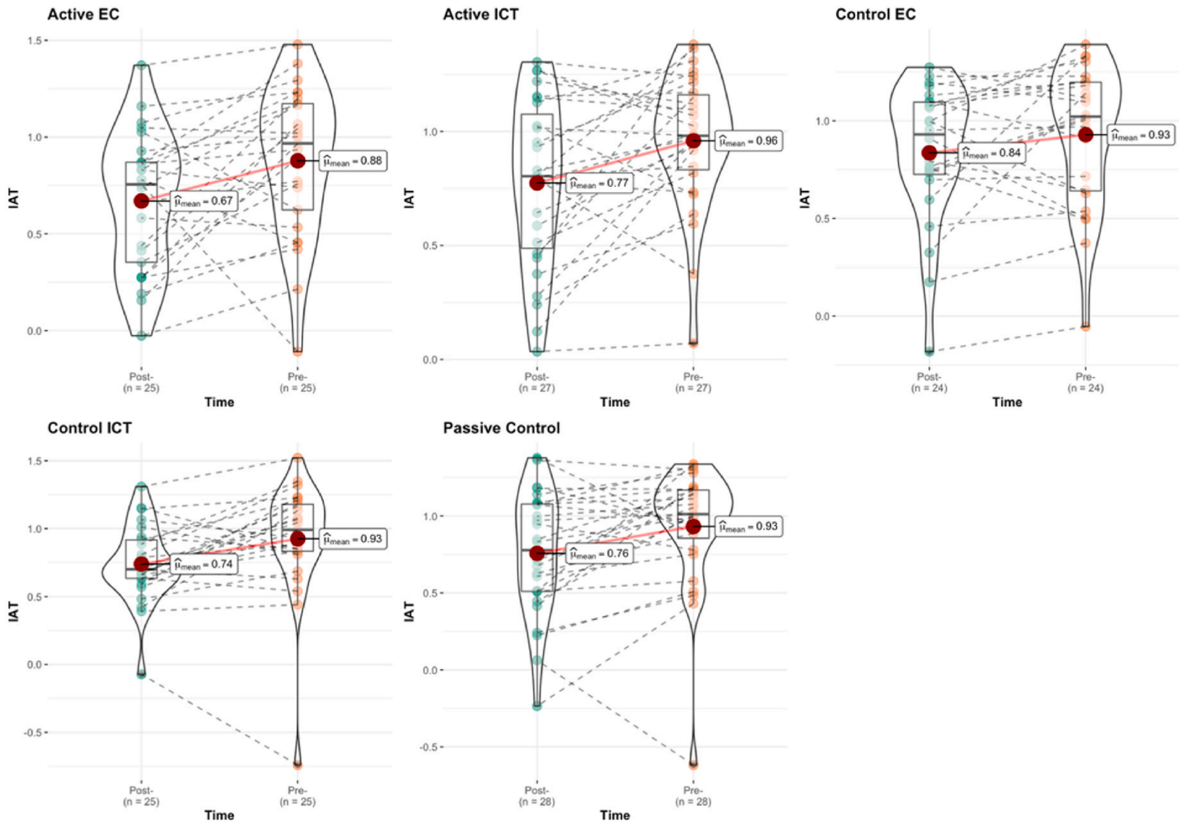

Fig. 3. IAT mean scores pre and post intervention. Higher scores represent increased preference for healthy foods, scores range between −2 and +2.

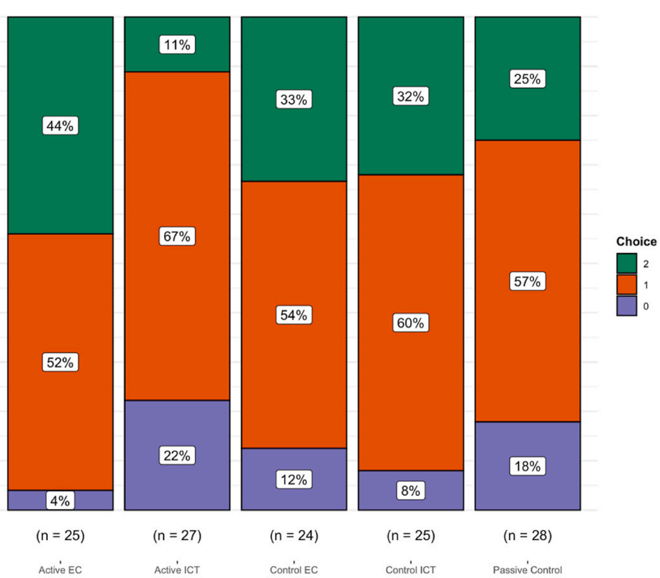

Fig. 4. A graph displaying explicit preference scores split by condition. A score of 0 represents two unhealthy choices, scores of 1 represent one healthy and one unhealthy choice, and scores of 2 represent two healthy choices.

condition (although this was only evident with parametric analysis). 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, with cue-ICT paradigms encouraging rapid responses to stimuli in comparison to EC paradigms which has minimum trial durations (as both stimuli images have to be displayed before participants can make a response). This may have consequences for participant performance: 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, resulting in differences between the two training groups. Despite this potential explanation, this finding was only evident using parametric analysis techniques and should be interpreted with caution.

While the forced-choice task is a well-utilised measure within CBM research (e.g., Hensels et al., 2016; Hollands et al., 2011; Veling et al., 2013), 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)). It is also possible that participants did not readily identify our categories of 'healthy' and 'unhealthy' foods, which were based on nutritional content. Research suggests nutritional knowledge is poor (Gruber et al., 2022) and associated with demographic variables (e.g. Socioeconomic status: Parmenter et al., 2000), which may have contributed to our (lack of) findings. 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

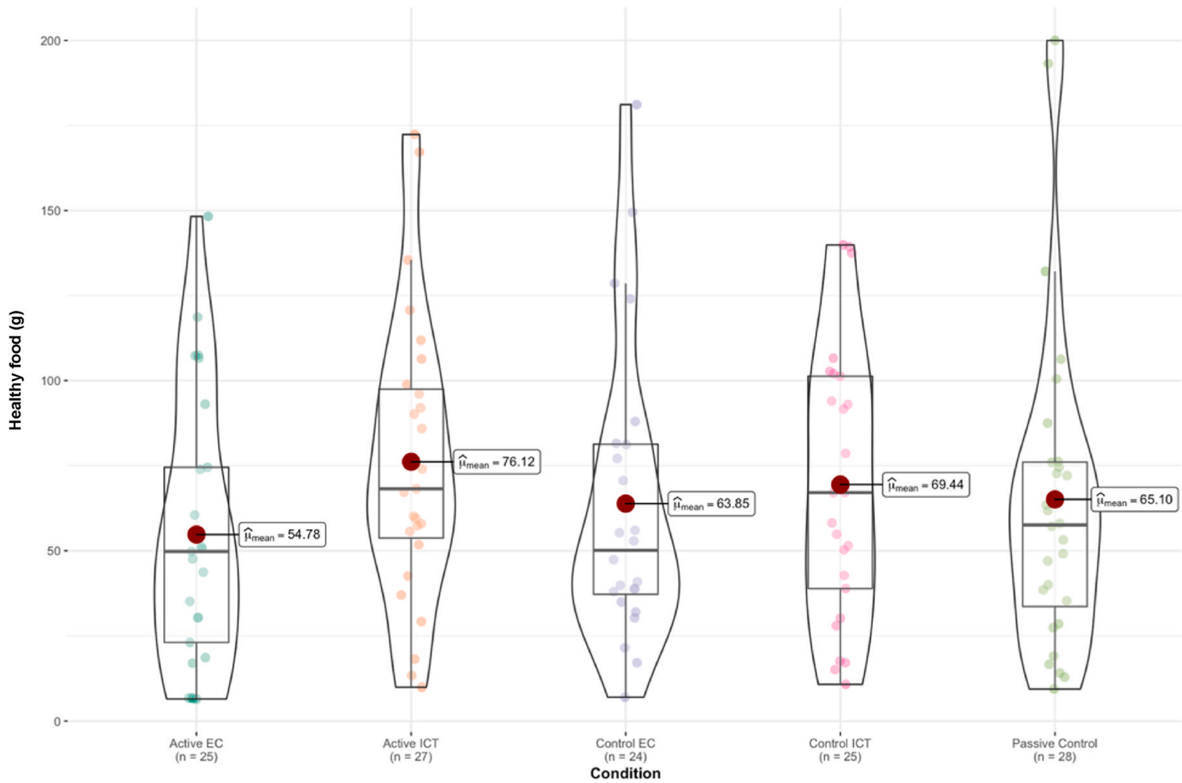

Fig. 5. Healthy food (grams) consumed as a result of experimental condition.

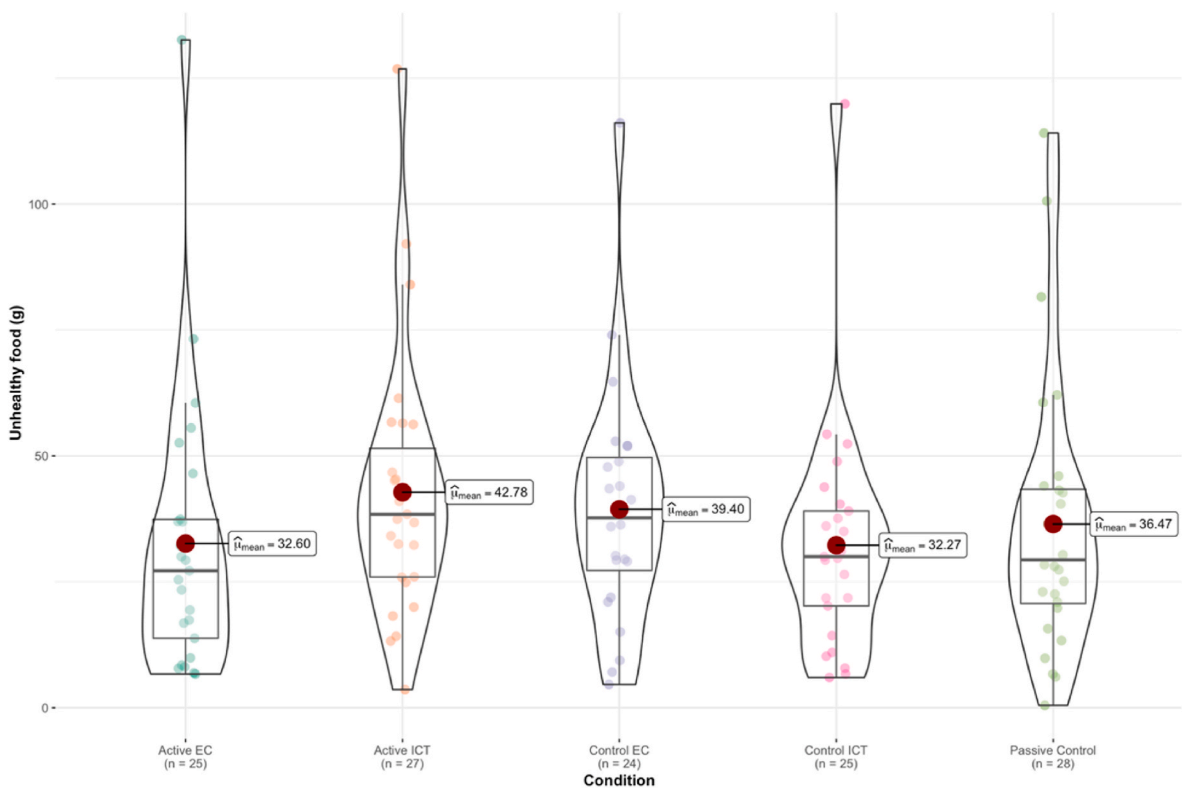

Fig. 6. Unhealthy food (grams) consumed as a result of experimental condition.

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 h 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.

A final consideration relates to the brief nature of the training task: while previous work has demonstrated that a single session of cue-ICT can have a positive influence on health-related behaviours (e.g., Allom et al., 2016; Jones et al., 2016), it may be that the one-off nature of the training session had implications for training outcomes. Previous work has demonstrated that multiple ICT training sessions delivered via a smartphone app resulted in improved healthy food choices (Kakoschke et al., 2018) and work by Lawrence, O'Sullivan, et al. (2015) found that multiple CBM training sessions resulted in significant reductions to unhealthy food liking, energy intake and weight (after 6 months). Future work should investigate the effects of multiple training sessions on choice and preference related outcomes to further explore the role of training paradigm(s) in CBM and identify the point at which maximum training efficacy is reached (and whether multiple sessions of CBM are required for training to influence behaviour).

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.

Ethical statement

The study conducted as part of this manuscript was approved by the University of Liverpool Health and Life Sciences Research Ethics Committee prior to research commencement (reference number 2926). All participants provided consent prior to study participation, and were fully debriefed (and provided with appropriate support information/ researcher contact details) at the end of the study.

Declaration of competing interest

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability

Data is freely available through the pre-registration link included within the manuscript

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.appet.2023.106529.

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