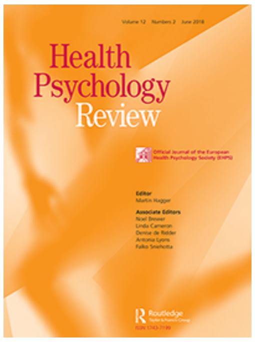

Health Psychology Review

ISSN: 1743-7199 (Print) 1743-7202 (Online) Journal homepage: https://www.tandfonline.com/loi/rhpr20

Implicit process interventions in eating behaviour: A meta-analysis examining mediators and moderators

Matthias B. Aulbach, Keegan Knittle & Ari Haukkala

To cite this article: Matthias B. Aulbach, Keegan Knittle & Ari Haukkala (2019): Implicit process interventions in eating behaviour: A meta-analysis examining mediators and moderators, Health Psychology Review, DOI: 10.1080/17437199.2019.1571933

To link to this article: https://doi.org/10.1080/17437199.2019.1571933

Accepted author version posted online: 24 Jan 2019.

Publisher: Taylor & Francis & Informa UK Limited, trading as Taylor & Francis Group

Journal: *Health Psychology Review*

DOI: 10.1080/17437199.2019.1571933

Implicit process interventions in eating behaviour: A meta-analysis examining mediators and moderators

Matthias B. Aulbach*, phone: +358 4578725277, matthias.aulbach@helsinki.fi

Keegan Knittle, phone: +358 294124896, keegan.knittle@helsinki.fi

Ari Haukkala, phone: +358 294124891, ari.haukkala@helsinki.fi

University of Helsinki
Faculty of Social Sciences, Social Psychology
Unioninkatu 37, 00170 Helsinki, Finland

Ari Haukkala and Matthias Aulbach have received funding from the Signe and Ane Gyllenberg Foundation and Matthias Aulbach has received funding from the Finnish Cultural Foundation.

*** Corresponding author**

Abstract

Dual-process models integrate deliberative and impulsive mental systems and predict dietary behaviours better than deliberative processes alone. Computerized tasks such as the Go/No-Go, Stop-Signal, Approach-Avoidance, and Evaluative Conditioning have been used as interventions to directly alter implicit biases. This meta-analysis examines the effects of these tasks on dietary behaviours, explores potential moderators of effectiveness, and examines implicit bias change as a proposed mechanism.

Thirty randomized controlled trials testing implicit bias interventions (47 comparisons) were included in a random-effects meta-analysis, which indicated small cumulative effects on eating-related behavioural outcomes (g = -0.17, CI_{95} = [-0.29; -0.05], p

= .01) and implicit biases (g = -0.18, CI_{95} = [-0.34; -0.02], p = .02). Task type moderated these effects, with Go/No-Go tasks producing larger effects than other tasks. Effects of interventions on implicit biases were positively related to effects on eating behaviour (B = 0.42, CI_{95} = [0.02; 0.81], p = .03).

Go/No-Go tasks seem to have most potential for altering dietary behaviours through implicit processes. While changes in implicit biases seem related to the effects of these interventions on dietary outcomes, more research should explore whether repeated exposure to implicit bias interventions may have any practical intervention value in real world settings.

Keywords: eating; impulsivity; meta-analysis; intervention; behaviour change; implicit cognition

Supplementary files, datasets and syntax files are available from the project's OSF page at: https://osf.io/d6hw8/

As of 2014, nearly 40% of adults worldwide were overweight, with another 13% being obese (World Health Organization, 2015). Overweight and obesity are major risk factors for chronic noncommunicable diseases such as cardiovascular disease, diabetes, and some cancers (World Health Organization, 2015), which are the leading causes of death worldwide and present considerable costs to society. As obesity and overweight are primarily caused by an imbalance between calories consumed and calories expended, interventions to improve dietary behaviours may help to improve the obesity epidemic (Hill, Catenacci, & Wyatt, 2005).

Many interventions to change dietary behaviours exist, and these primarily target conscious, deliberative processes and self-regulatory approaches to behaviour change (Hollands et al., 2016). Overall, these interventions produce small effects on dietary behaviours, and often include the behaviour change techniques (BCTs) providing information on the behaviour-health link, prompting intention formation and prompting self-monitoring of behaviour (Michie, Abraham, Whittington, McAteer, & Gupta, 2009). These effects on dietary behaviours are not always maintained however, and research has indicated that the theories upon which deliberative interventions are based may provide incomplete pictures of the determinants of eating behaviour. Theories such as the reasoned action approach (Fishbein & Ajzen, 2010) and the theory of planned behaviour (Ajzen, 1991), which propose deliberative routes to behaviour, predict around 30% of dietary behaviours (McEachan et al., 2016). The predictive power of these psychological models can be improved, however, by including variables that represent implicit processes, such as behavioural approach biases and attentional biases (Kemps, Tiggemann, & Hollitt, 2014; Wiers, Gladwin, Hofmann, Salemink, & Ridderinkhof, 2013). Implicit processes play an important role in predicting health behaviours, including eating behaviours (Hagger, Trost, Keech, Chan, & Hamilton, 2017), alcohol and drug use (Greenwald, Poehlman, Uhlmann, & Banaji, 2009), condom use (Keatley, Clarke, & Hagger, 2012), and physical activity (Rebar et al., 2016).

The ubiquity of food-related cues in modern societies make implicit processes particularly relevant in predicting eating behaviours. A recent study on the prediction of sugar consumption revealed that implicit evaluations of sugar, as measured with an Implicit Association Test, predicted sugar consumption comparably to reflective behavioural antecedents such as intentions (Hagger et al., 2017). This stresses the importance of implicit processes in the eating domain, especially in real world environments filled with food-related stimuli and cues (Hollands, Marteau, & Fletcher, 2016).

The role of implicit processes

Dual-process models integrate implicit and deliberative mental processes and assume that the interplay of these two intertwined systems of information processing guides behaviour. Generally, these theories propose one conscious, deliberate, reflective system that processes information slowly and carefully, and another implicit parallel system, which operates unintentionally, unconsciously, independently of resources, or uncontrollably (Bargh, 1994) (see Hahn & Gawronski, 2017 for an overview of problems with these conditions). The idea that implicit processes operate quickly and relatively effortlessly when compared to the slower and more resource-demanding deliberative system, implies that when motivation and cognitive resources are low, implicit processes will more often guide behaviour (Strack & Deutsch, 2004). For example, implicit evaluations of candy gain more influence on behaviour when working memory capacity is low (Hofmann, Gschwendner, Friese, Wiers, & Schmitt, 2008), when participants are under cognitive load (Friese & Hofmann, 2009), or under the influence of alcohol (Hofmann & Friese, 2008). Importantly, learning happens differently in the two systems: while the reflective system is capable of one-shot learning (e.g., when hearing nutritional information about certain foods) the impulsive system changes gradually through repetition (Strack & Deutsch, 2004).

Past research has shown that some characteristics of the impulsive system can keep people from adhering to a healthy diet, even when they have committed to it and when it is represented in their reflective system. There is evidence that people selectively direct their attention toward food cues (Kemps et al., 2014; Werthmann, Jansen, & Roefs, 2015), that it is easier to approach food stimuli (i.e. reach out towards them rather than move away from them) than neutral stimuli (Brignell, Griffiths, Bradley, & Mogg, 2009), and that it is more difficult to stop a triggered response towards food stimuli than neutral stimuli (Hofmann, Friese, & Roefs, 2009). These implicit biases toward food-related stimuli tend to be stronger in obese individuals (Kemps & Tiggemann, 2014) and weaker in individuals with restrictive eating disorders such as anorexia nervosa (Veenstra & de Jong, 2012). Approach biases toward food stimuli (relative to non-food stimuli) are associated with increased snack-intake and overweight (Kakoschke, Kemps, & Tiggemann, 2015) and are stronger for high-caloric than low-caloric foods (Havermans, Giesen, Houben, & Jansen, 2011).

These findings support the idea of an implicit system that influences behaviour, and the reflective-impulsive model postulates an associative network that links conceptual content (e.g. high caloric content of food) with motor programs (e.g. approaching the high-caloric food) (Strack & Deutsch, 2004). For example, perceiving a piece of chocolate activates the concept of "chocolate" and sets in motion a process of activation which spreads to related concepts, including an evaluation (e.g. "tasty") and a motor program to obtain and consume the chocolate (as expressed in biases e.g. in the Approach-Avoidance Task). The act of eating chocolate is thus preceded by activation of positive stimulus evaluations and activation of motor programs, both of which are reinforced by the subsequent rewards associated with consuming and enjoying the chocolate.

This conceptualization is closely related to the concept of habits which have been defined as 'behavioural patterns, based on learned context-behaviour associations, that are elicited automatically upon encountering associated contexts . . . acquired through context-dependent repetition' (Gardner, Abraham, Lally, & de Bruijn, 2012, p. 1). Habits may therefore be better altered by interventions that directly alter implicit processes through repeated exposures instead of relying on processes that act in the reflective system alone (van't Riet, Sijtsema, Dagevos, & de Bruijn, 2011). For example, changing associative links between stimuli and reactions (i.e. altering the activation spread happening upon encountering the stimulus) may break up habitual behavioural patterns and allow individuals to gain flexibility in their behaviour (van't Riet et al., 2011). This 'require[s] disrupting the cue-response association . . . or programming alternative responses to these cues' (Lally & Gardner, 2013, p. 140).

Targeting implicit processes

Three main behavioural computer-based tasks are typically used to target implicit processes: the Go/No-Go task, the Stop-Signal task, and the Approach-Avoidance task. All three tasks present food stimuli on a computer screen and require the participant to either respond or withhold a response, depending on the features of the encountered stimulus. While there are measurement and intervention versions of these tasks, we will first introduce the basic ideas of each before explaining how they can be used as interventions. Figures 1-3 illustrate the Go/No-Go, Stop-Signal, and Approach-Avoidance tasks, respectively.

The Go/No-Go task presents stimuli (i.e. food pictures) alongside a go- or no-go cue that is unrelated to the stimulus content (e.g., the frame around the picture turns either red or green). The participants' task is to respond as fast as possible to trials with a go-cue and to refrain from reacting on trials with a no-go cue. As a measurement tool, biases toward food stimuli can be calculated as the difference in reaction times and/or error rates between food- and non-food or healthy vs unhealthy food trials.

In the Stop-Signal task, participants are required to categorize pictures as fast as possible by pressing different buttons, except when the picture is accompanied by a stop-signal, in which case participants should withhold their responses. Compared to the Go/No-Go task, stop trials typically occur less frequently than no-go trials, and are made more difficult using a staircase procedure that alters the interval between the stimulus and the stop signal. This allows estimating the speed of the inhibition process compared to the reaction process (Verbruggen & Logan, 2008). Differences in the speed of the inhibition process between stimulus categories (food vs non-food; healthy vs unhealthy foods) thus indicate a cognitive bias towards one category or the other.

The Approach-Avoidance task also requires fast responses from participants to different sets of stimuli. Here, participants react to all stimuli with an approach (i.e. pull) or avoidance (i.e. push) reaction, usually with a computer joystick. Like in the Go/No-Go task, the content of the stimulus is typically unrelated to the required response (e.g. the tilt of the picture functions as the movement cue).

For measurement of biases towards unhealthy versus healthy foods, researchers use versions of these tasks which pair stimuli and critical trials (i.e. no-go, stop, avoid) evenly across groups of stimuli. Differences in reaction times or error rates between groups of stimuli (e.g. high vs low caloric food) serve as an estimation of the strength and direction of implicit biases (Kakoschke et al., 2015). These reaction time tasks rest on the assumption that stimuli activate motor programs that correspond to the participant's evaluation of the stimulus, or in other words, that positive evaluations automatically elicit approach tendencies (Eder, Elliot, & Harmon-Jones, 2013). In consequence, it is easier to approach appetitive stimuli than to avoid them or to inhibit a reaction towards them (Brignell et al., 2009; Hofmann et al., 2009).

[Figures 1-4 near here]

While the Go/No-Go task, Stop-Signal task, and Approach-Avoidance task have a longer tradition as measures of the strength of implicit processes, recent research has begun investigating possibilities to use modified versions of these tasks to alter the constructs that they have traditionally been used to measure. To achieve this, interventional versions of the tasks systematically pair stimuli with reactions that are incompatible with the automatically-activated motor program. For example, an Approach-Avoidance intervention might present pictures of unhealthy foods and require the participant to always (or more frequently) show an avoidance reaction towards them - a reaction that is incompatible with the automatic tendency to approach such stimuli. In this way, the tasks interrupt the automatic activation of a motor program to approach unhealthy foods, and attempt to reprogram new avoidance responses in relation to unhealthy food stimuli.

In Go/No-Go or Stop-Signal interventions, unhealthy food stimuli systematically appear with a signal not to react to the stimulus, again counteracting the automatically-activated motor program. Through repetition, unhealthy food stimuli become associated with stopping instead of going.

In summary, all three tasks systematically pair unhealthy foods with an incompatible action (avoid, inhibit) which, through repetitive activation of motor programs, alters the association between unhealthy foods and the response tendency. This intervention mechanism is directly related to behaviour change techniques from the BCTTv1 (Michie et al., 2013): Namely, techniques 8.1 through 8.4, behavioural rehearsal/practice, behaviour substitution, habit formation, and habit reversal.

These implicit process interventions have been tested in several different domains of health-related behaviour, including alcohol consumption in non-clinical (Sharbanee et al., 2014) and clinical samples (Wiers, Eberl, Rinck, Becker, & Lindenmeyer, 2011), smoking (Machulska, Zlomuzica, Rinck, Assion, & Margraf, 2016), and consumption of unhealthy food (Chen, Veling, Dijksterhuis, & Holland, 2016; Schumacher, Kemps, & Tiggemann, 2016), and have produced desired effects in changing the targeted behaviour, mostly after one laboratory-based session.

A related line of research has investigated the possibilities of reducing dietary intake through Evaluative Conditioning. In these interventions, conditioned stimuli (i.e. food stimuli) are repeatedly presented alongside or in close succession to positive or aversive unconditioned stimuli (e.g. positive or aversive body images). In computer-based interventions, this means that participants passively observe pictures on the computer screen (Lebens et al., 2011, see Figure 4 for an illustration). These interventions aim to alter implicit evaluations of conditioned stimuli as they become associated with the valence of unconditioned stimuli. Assuming that implicit evaluations guide consumption behaviour, pairing unhealthy foods with aversive unconditioned stimuli should reduce consumption of those foods. An important difference to the other three tasks is that no motor responses are performed in Evaluative Conditioning. A large meta-analysis has found medium effects of Evaluative Conditioning in a wide range of settings, e.g. fear conditioning or conditioned taste aversion (Hofmann et al., 2010).

Mechanisms of behaviour change

To understand how these interventions result in behaviour change, it is important to distinguish between two processes that are likely to be involved. The first process in the interventions improves the capacity for response inhibition (i.e., the ability to stop a triggered response) (Logan, Cowan, & Davis, 1984), while the second process directly alters associative links between certain stimuli and reactions (Jones, Hardman, Lawrence, & Field, 2017). While the first strengthens a reflective resource that works "top-down", the second aims at the impulsive system and works "bottom-up". It is then important to understand the extents to which different implicit process interventions affect these "top-down" and "bottom-up" processes. While Allom and colleagues (2016) speculate that a stimulus-specific Stop Signal task might predominantly work in a "top-down" manner and the Go/No-Go task predominantly in a "bottom-up" manner, Jones and colleagues (2017) argue that the dividing line is rather between stimulus-specific vs generalized training. This means that interventions to train response inhibition can strengthen "top-down" response inhibition processes independently of concrete stimuli, while stimulus-specific response inhibition training create "bottom-up" associations between classes of stimuli and adaptive behavioural programs (e.g. stopping upon encountering unhealthy food stimuli). This view is supported by meta-analytic results by Jones et al., (2016) who demonstrated that the share of successful inhibitions on critical trials (which is higher in the Go/No-Go task than Stop Signal task) was a significant predictor of effect size, indicating that repeated successful pairing of the stimulus category and stopping is an important aspect of training. Wiers and colleagues express this idea as follows: 'One crucial aspect . . . is that the alternative response is triggered when needed, in a bottom-up fashion, by relevant stimuli' (Wiers et al., 2013, p. 201). It seems most likely that stimulus-specific training combines strengthening control resources with the formation of associative links between stimuli and reactions (Stice, Lawrence, Kemps, & Veling, 2016).

Research around the Behavior-Stimulus-Interaction theory (Veling, Holland, & van Knippenberg, 2008) indicates that initially positively evaluated stimuli are devalued after repeatedly stopping in response to them. This, together with neurocognitive findings of feedback mechanisms between motor regions and reward regions (Schonberg et al., 2014), supports the idea of bidirectional associative links between behaviour and stimulus evaluations as proposed by dual-process models such as the reflective-impulsive model (Strack & Deutsch, 2004). Findings from studies using the Approach-Avoidance task indicate that performing approach- or avoidance-related arm movements induces changes in implicit evaluations (Kawakami, Phills, Steele, & Dovidio, 2007; Woud, Becker, & Rinck, 2008) as do Evaluative Conditioning interventions (Hollands, Prestwich, Marteau, 2011), indicating that changes in stimulus evaluations are one of the mechanisms of behaviour change involved in all four tasks. Following the logic of reciprocal links, devalued stimuli should in turn elicit weaker approach tendencies since approach-avoidance behaviour is inherently evaluative (Eder, Müsseler, & Hommel, 2012).

While all four tasks potentially alter stimulus evaluations, it is important to note that Evaluative Conditioning is more likely to change evaluations "only", whereas the three behavioural tasks (Stop-Signal, Go/No-Go, Approach-Avoidance) should also change how stimuli automatically trigger motor programs.

The current meta-analysis

Earlier reviews and meta-analyses have independently examined the effectiveness of (1) the Go/No-Go task and the Stop-Signal task (Allom et al., 2016; Jones et al., 2016;

Turton, Bruidegom, Cardi, Hirsch, & Treasure, 2016), (2) Approach-Avoidance task interventions (Kakoschke, Kemps, & Tiggemann, 2017a) and (3) Evaluative Conditioning (Hofmann et al., 2010). However, despite their conceptual and methodological similarities, especially their shared focus on changes in implicit biases, their effectiveness has not been reviewed in combination.

Second, existing reviews in this area report on a wide range of unhealthy behaviours, including cigarette smoking and alcohol consumption, making it difficult to discern the extents to which their effects are uniform across behaviours, or how well interventions targeting implicit biases function in specific behavioural domains. For the development of interventions in the eating domain, it is crucial to understand which interventions produce optimal effects, under which circumstances, and for which populations for dietary behaviours specifically. Earlier meta-analyses have conducted moderator analyses for task and population characteristics only across health behaviour domains (eating, alcohol consumption, smoking), thus not allowing inferences about eating behaviour specifically. Distinguishing between different target behaviours is crucial as the interventions examined here are specific for a class of stimuli and are theorized to change bottom up processes.

Finally, investigations on mechanisms of behaviour change in the eating domain are scarce (for an exception see Jones (2016)). Behavior-Stimulus-Interaction theory states that repeatedly pairing a stimulus with a reaction that is incompatible with the automatically-triggered motor program subsequently leads to lower evaluations of that stimulus (Harm Veling et al., 2008). In the case of food stimuli, this lower evaluation, in turn, leads to less consumption of the trained food (Chen et al., 2016). Evaluative Conditioning also aims to change behaviour through changing stimulus evaluation (Hofmann et al., 2010). Therefore, this meta-analysis investigates the proposed mechanism of stimulus devaluation by examining the degree to which interventions have changed implicit biases towards food stimuli and how these changes relate to interventions' effects on dietary intake.

In sum, this study will address several shortcomings in the existing literature, and aims to synthesize the results of studies on computerized implicit process interventions for eating behaviour, to report on a proposed mechanism of change in the literature and to investigate moderating variables related to both features of the task and the studied samples.

Methods

This systematic review and meta-analysis was pre-registered in the PROSPERO register (https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=54485), and all methods were either pre-registered or suggested during the peer review process.

Information sources and search strategy

Searches were conducted through the electronic databases PsycInfo, Scopus, and Medline with relevant keywords, expanding search terms from earlier, related reviews (see Appendix A). As no previous reviews on this topic have included any studies published before 1990, publication date was limited to 1990 - present. Authors of related reviews were contacted for excluded articles of their own literature search which were then scanned according to eligibility criteria. The literature search was rerun before the final analyses in October 2018. Only studies published in English, Finnish, Dutch, Spanish or German and which had an English-language abstract were considered for inclusion. Searches were limited to human samples. In addition, reference sections of eligible articles and related reviews (Allom et al., 2016; Jones et al., 2016; Kakoschke, Kemps, & Tiggemann, 2017b; Turton et al., 2016) were screened for further eligible studies. Members of the European Health Psychology Society, the European Society for Clinical Nutrition and Metabolism, the International Society of Behavioral Nutrition and Physical Activity, the International

Society of Behavioral Medicine, and the European Association for the Study of Obesity were contacted for unpublished data.

Inclusion and exclusion criteria

Studies were considered for inclusion if they provided at least one session of the Go/No-Go task, the Stop-Signal task, Approach-Avoidance task training and/or Evaluative Conditioning utilizing food- or eating-related stimuli for the experimental group. Training could be delivered online and/or in a laboratory. Only randomized control trials that included an outcome measure related to eating behaviour were eligible for inclusion in the primary meta-analysis. These included the amount of consumed food in an ostensible taste test, snack choice in a free choice situation and/or food diary or questionnaire data delivered by participants. Studies which reported data on a food-related implicit bias measure, but did not report on any dietary outcome measures were eligible for inclusion in secondary meta-analyses examining implicit biases as an outcome. Sufficient statistical information for the computation of effect sizes had to be indicated in the article or supplemental materials or delivered by one of the authors on request.

Data extraction

Means and standard deviations of outcome variables were extracted to a Microsoft-Excel spreadsheet by the first author in consultation with the second author. Outcome measures were coded as primary or secondary according to the description in the article and were categorized as either taste test consumption behaviour, snack choice, or self-report data on questionnaires or food diaries. In addition, data on implicit bias measures at post-training were extracted for the analysis of implicit bias change as a possible mechanism of the training effect. We regarded different versions of the Implicit Association Task, the Approach-Avoidance task, or the Manikin task as implicit bias measures, following the logic that devaluation of stimuli should also lead to changes in approach behaviour patterns (as outlined above; note that these tasks were not part of the original pre-registration but were added during the search process). Coding was such that negative values indicate intended effects of the training (i.e. reduced food intake for the intervention group relative to the control group). For studies that did not report data necessary to calculate effect sizes ($k = 4$), additional data was requested from the authors. For studies which compared multiple relevant intervention groups to a single control group, each intervention versus control comparison was entered into the meta-analysis with the sample size of the control group divided by the number of treatment groups to which it had been compared. This method subdivides the total weight of a study by the number of relevant comparisons it includes, and yields reasonably independent comparisons that allow for examining possible sources of heterogeneity across intervention arms (Higgins, Deeks, & Altman, 2011).

Moderator Coding

Several potentially relevant moderating variables were coded for analysis where available from the article. These included variables related to the recruited samples, the task used in the study and the kind of outcome measure.

The nature of the training task (Approach-Avoidance task/Go/No-Go task/Stop-Signal task/Evaluative Conditioning) was coded according to the authors' description. In addition, several task properties were extracted: the total number of trials in the training, the percentage of avoid/no-go/stop/aversive image trials, the contingency of pairing avoid/no-go/stop/aversive trials with unhealthy food stimuli, and the kind of signal used to indicate the required reaction in the task. Additionally, we assessed whether the training was delivered in a laboratory session or online.

The type of control group was coded with respect to the kind of sham treatment the control group received. The three variations encountered were (1) a "counter-training", i.e. a reversed contingency between unhealthy food stimuli and stop/no-go/avoid trials (2) a "random training", which did not display any contingency between stimuli and required response, and (3) a training unrelated to food, i.e. using food-unrelated stimuli such as stationary objects.

The gender ratio, mean age, and mean body-mass index (BMI) (at baseline) were extracted from articles where available. Inclusion and exclusion criteria for study participants were extracted where reported. In addition, the use of control variables was coded, such as hunger and appetite levels. This could either be measured and used as a covariate in the data analysis of the study or controlled for by experimental procedures.

Statistical analysis

All meta-analyses were conducted with the **metafor** package (Viechtbauer, 2010) and publication bias was analysed with the **weightr** package (Coburn & Vevea, 2017) in R software (R Core Team, 2017). All analyses were pre-specified in the registration of this review or were suggested during the peer review process. Hedges' *g* was used as an effect size metric, representing the standardized mean difference between conditions. Hedges' *g* is a corrected version of Cohen's *d* and values of 0.2-0.5 can be interpreted as small, 0.5-0.8 as medium, and larger than 0.8 as large (Cohen, 1988; Lakens, 2013). According to recommendations for heterogeneous samples across studies, a random effects model was used (DerSimonian & Laird, 1986).

We calculated a 95% confidence interval (*CI*), Cochrane's Q and I^2 statistics as indicators of study heterogeneity for all effect sizes. A statistically significant test for Q (at the .05-level) indicates heterogeneity between included studies, and I^2 stands for the share of variation due to heterogeneity in relation to chance (Higgins & Thompson, 2002). Large heterogeneity indicates that included studies differ from each other in terms of their outcomes and warrants further analysis of possible moderating variables.

As analysing more than one outcome from the same set of studies without accounting for within-study covariance of the outcomes can create biased effect size estimates (Riley, 2009), we conducted a bivariate meta-analysis of dietary outcomes and implicit biases using the **rma.mv** function within **metafor**. These bivariate meta-analyses account for within-study covariance by breaking the overall correlation between the two outcomes down into within-studies and between-studies components, and yield effect sizes for each outcome and a between-study correlation coefficient (Riley, Abrams, Lambert, Sutton, & Thompson, 2007; Riley, Abrams, Sutton, Lambert, & Thompson, 2007). As only two studies reported actual within-studies correlations of these outcomes, our bivariate analyses were modelled at five different levels of within-studies correlations (0.1, 0.3, 0.5, 0.7, and 0.9).

The data and analysis code for this study are freely available from the project's Open Science Framework page (https://osf.io/d6hw8/)

Meta-regression

Moderators were analysed in mixed-effects meta-regression models, separately for each moderator. Categorical moderators (i.e. kind of task, kind of outcome, kind of control group, whether satiety was controlled or not, and whether training was delivered online) were dummy-coded and examined as binary variables. Continuous moderators (i.e. number of trials, share of signal trials, sample age, sample BMI) were used as such in the meta-regression. The test of moderation is a significance test of the *Q*-statistic against zero, such that a significant effect means that the moderator alters the effect of the intervention on the outcome. To maintain stability in moderator analyses, analyses were only conducted on potential moderators that were both present and absent in at least three studies.

Publication Bias

Publication bias (i.e. studies that report statistically significant results are more likely to be published than studies that do not) can result in overestimations of effect sizes in meta-analysis (Thornton & Lee, 2000). To assess the risk of publication bias in the literature, we constructed and analysed a funnel plot, showing the observed effect size on the x-axis and a measure of precision (i.e. the standard error) on the y-axis. More precise effect sizes should lie closer to the average effect size in the absence of publication bias. In addition, the distribution of found effect sizes should be symmetrical around the average effect size. Egger's regression analyses test for violations of symmetry, and a significant test statistic indicates the presence of publication bias.

Publication bias was then corrected for using the Trim-and-Fill method, which corrects any identified asymmetry by trimming outliers and filling in hypothetical effects that would need to exist to create a symmetrical funnel plot (Duval, 2005; Duval & Tweedie, 2000). Since the Trim-and-Fill method has been shown to under-correct publication bias (Carter, Schönbrodt, Gervais, & Hilgard, 2018), we additionally employed the weight-function model for publication bias as proposed by Vevea and Hedges (1995). It specifies a model for the selection of statistically significant effect sizes that "make it" into the literature and then corrects the estimated effect sizes accordingly. Weight-function models seem to perform more effectively than other methods under many circumstances (Carter et al., 2018).

Results

The search strategy identified 7752 studies in electronic databases and 22 studies through other sources, resulting in a total of 5894 studies after duplicates were removed. Title screening delivered 502 studies which were screened by abstract. We assessed 57 full-text articles for eligibility, of which 27 did not fulfil the inclusion criteria. The 27 articles were excluded for not having a control group that met the inclusion criteria, for not providing interventions that met the inclusion criteria, for not reporting on an appropriate outcome, or for not providing sufficient data for effect size calculation. This resulted in 30 articles included in the meta-analysis, which contributed 50 comparisons for the main outcomes. The PRISMA flow diagram in Figure 5 outlines this process, and details of all included studies are listed in Table 1.

[Figure 5 near here]

[Table 1 near here]

Main Results

As shown in the last line in Figure 6, the overall random-effects model revealed a small but significant effect of interventions on dietary outcomes across all studies (Hedges' g = -0.17, CI_{95} = [-0.29; -0.05], p = .007). Cochrane's Q was Q (df = 46) = 120.34, p < .0001 and I^2 = 61.43%, indicating moderate heterogeneity of effect sizes (Huedo-Medina, Sánchez-Meca, Marín-Martínez, & Botella, 2006). We identified 24 effect sizes regarding implicit biases towards unhealthy food stimuli as a possible mechanism for the effect of the training on actual consumption, 21 of which also reported a dietary outcome. The overall effect of interventions on the implicit bias measures was g = -0.18 (CI95 = [-0.34; -0.02], p = .02), indicating that the trainings produced beneficial changes in implicit biases towards the stimuli. The effect on dietary outcomes in the 21 of studies reporting those outcomes was not significantly different from zero (g = 0.08, CI95 = [-0.09; 0.24], p = .37).

Bivariate Analysis

All available effect sizes (i.e. 47 effect sizes for dietary outcomes and 24 effect sizes for implicit bias outcomes) were included in the multivariate meta-analysis. Only two published studies reported the within-study correlation between the two outcomes of interest (Hollands, Prestwich, and Marteau, 2011, Wang et al., 2017), .33 and .17, respectively.

Therefore, we conducted the analysis with five different within-study correlation coefficients (0.1, 0.3, 0.5, 0.7, and 0.9) to determine the effect of different within-study correlations on the outcomes. Since estimates did not differ largely for different within-study correlation coefficients (see Table 3), we report values from the model assuming a within-study correlation of .5. As shown in Table 3, these bivariate meta-analyses indicated that interventions had larger effects on implicit biases (g = -0.35, CI95 = [-0.52; -0.19] , p < .001) than what the univariate analyses had indicated (g = -0.18) but the same effect size for the dietary outcome (g = -0.17, CI_{95} = [-0.29; -0.05]).

Moderator analyses

To investigate potential sources of heterogeneity between studies, moderator analyses examined associations between study and sample characteristics and effect sizes. We also conducted subgroup analyses to explore tentative differences between groups of studies when the number of studies were low. Statistics on all moderator analyses can be found in Table 2.

Consumption Behaviour

The training tasks used were classified as either (1) Approach-Avoidance task (16 effect sizes), (2) Go/No-Go task (22 effect sizes), (3) Stop-Signal task (six effect sizes), (4) a combination of Approach-Avoidance task and Go/No-Go task (two effect sizes), or (5) Evaluative Conditioning (four effect sizes). The test of moderators yielded a significant result, Q (4) = 13.16, p = .01, indicating that the kind of task influences effect size, and a residual heterogeneity of I^2 = 55.06%. The analysis showed significant effects for Go/No-Go task only, g = -0.39, CI_{95} = [-0.57; -0.22], p < .001. To explore which of the tasks differ significantly from each other, we conducted pairwise comparisons between Approach-Avoidance task, Go/No-Go task, and Stop-Signal task. The tests indicated a significant difference between Go/No-Go task and Approach-Avoidance task (Δg = 0.48, p = .003), but none of the other pairwise tests reached significance. Figure 6 illustrates the different effect sizes for the different kinds of tasks.

[Figure 6 near here]

No other investigated variables moderated the effects of interventions on consumption behaviour. The results of all conducted moderator analyses, including pairwise comparisons, can be found in Table 2.

[Table 2 near here]

Implicit Bias

Moderator analyses on the implicit bias outcomes revealed a significant moderation by task to assess implicit bias, Q (3) = 12.11, p = .007, I^2 = 50.08% with only performance in the Approach Avoidance task being affected by the interventions (g = -0.46, CI_{95} = [-0.68; -0.25], p < .001). The effects on implicit biases were also moderated by the kind of control group (Q (2) = 7.02, p = .03, I^2 = 49.53%) with only "counter-training" control groups producing significant effects (g = -0.50, CI_{95} = [-0.78; -0.21], p = .001).

No other investigated variables moderated the effects of interventions on measures of implicit bias.

Proposed mechanism – implicit bias change

To test the influence of implicit bias change on consumption behaviour, we conducted a meta-regression with the effect size of implicit biases as a continuous moderator of the effect size for eating behaviour. This resulted in a statistically significant regression weight of B = .42 (CI_{95} = [.02; .81], z = 2.07, p = .04, k = 21), indicating an association between the magnitude of interventions' beneficial effects on implicit biases and dietary intake. See Figure 7 for an illustration of the results.

The bivariate meta-analysis yielded point estimates for the between-study correlations between .45 (for a within-study correlation of .9) and 1 (for a within-study correlation of .1) with wide confidence intervals.

[Figure 7 near here]

Risk of Bias

To assess publication bias in the literature, we examined a funnel plot (Figure 8) and performed an Egger's regression test. This test was significant ($z = -2.19$, $p = .03$), indicating publication bias (Egger, Smith, Schneider, & Minder, 1997). Performing the trim and fill method reduced the effect to $g = -0.02$ ($CI_{95} = [-0.15; 0.11]$, $p = .79$), indicating that there is no true overall effect of interventions on dietary outcomes after adjusting for publication bias (Duval, 2005; Duval & Tweedie, 2000). Figure 8 shows the funnel plot with the added hypothetical studies from the trim and fill method.

[Figure 8 near here]

Since the Go/No-Go task seemed most effective in our initial analysis, we also analysed the funnel plot for studies using Go/No-Go task only, using the same statistical methods as for the whole sample of effects. Egger's test turned out significant ($z = -2.43$, $p = .02$), indicating publication bias for this subset of studies as well. The trim and fill procedure delivered an effect size estimate of -.25 ($CI_{95} = [-.42; -.09]$, $p = .002$), indicating that there is still a small effect of Go/No-Go task interventions after correcting for publication bias.

The estimate from the weight function model (Vevea and Hedges, 1995) delivered an overall effect estimate of $g = -0.16$ ($CI_{95} = [-0.30; -0.01]$, $p = .04$), indicating similar results to the original model. Including the training task as a moderator led to the same results as the original model, both with and without including Evaluative Conditioning studies. Taken together, this indicates no significant publication bias.

Discussion

The current study meta-analysed 47 effect sizes from 30 independent studies of interventions targeting implicit processes in eating behaviour. The cumulative effect on dietary outcomes across tasks was small and significant, but no longer remained statistically significant after correcting for publication bias. Moderator analyses showed that the Go/No-Go task produced significant effects relative to active control groups on dietary outcomes, even after correcting for publication bias, indicating that systematically pairing unhealthy food stimuli with stopping of a response can reduce food intake. No other examined variables moderated the size of training effects on eating behaviours.

The effect sizes found here are similar to those of a previous meta-analysis which examined the effects of a wide range of dietary intervention studies (Michie et al., 2009), and slightly smaller than those reported in other meta-analyses which specifically examined the effects of implementation intentions on reducing fat intake (Vilà, Carrero, & Redondo, 2017) and reducing unhealthy eating patterns (Adriaanse, Vinkers, De Ridder, Hox, & De Wit, 2011). These studies are comparable to many studies testing implicit bias interventions as they typically deliver interventions in single sessions with short or non-existent follow-up periods and do not allow for any statements about longer-lasting behavioural effects (with Veling et al.'s (2014) being a notable exception). However, in a direct comparison of the Go/No-Go task and implementation intentions, van Koningsbruggen et al. (2014) found the two interventions to be equally effective.

While we found the effect attained through the Go/No-Go task training as a stand-alone intervention to be small, more research on combinations of different interventions seems promising: interactions between implicit food preferences and response inhibition predict weight gain and targeting both could therefore produce larger effects (Nederkoorn, Houben, Hofmann, Roefs, & Jansen, 2010). The potential of interventions on implicit processes may lie in the interaction with other interventions that focus on more deliberate self-regulatory strategies. A large study using experience-sampling methods found an interaction between different aspects of self-control, including response inhibition, food desires, attempts to resist those desires, and weight loss (Hofmann, Adriaanse, Vohs, & Baumeister, 2014). This indicates that improving different aspects of self-regulation and underlying desires at the same time might lead to larger effects than any of these interventions alone.

This study yields some initial evidence for the proposed mechanism of implicit bias change interventions: Namely, that changes in implicit biases toward unhealthy foods are associated with subsequent eating behaviours across studies (at least in controlled experimental settings)(Figure 7). These demonstrated links between changes in implicit biases and eating behaviours should be treated as tentative for several reasons. First, the effect size of interventions on implicit biases differed substantially between uni- (g = -0.18) and bivariate (g = -0.35) analyses, and it is difficult to know which estimate is more trustworthy. The reason for this uncertainty is a potential confounding between the outcomes reported by each study (i.e. only dietary behaviour, or both dietary behaviour and implicit bias change), the type of task used in an intervention (also, the type of measure used to assess implicit biases), and the differential effectiveness of these tasks on eating behaviour outcomes. Of the 47 included studies, 26 studies reported on dietary outcomes alone and delivered an average effect of -0.38 [-0.51; -0.34], while 21 studies reported both dietary outcomes and implicit bias change, and had a significantly smaller average effect of 0.08 [-0.09; 0.24] on dietary outcomes. Furthermore, 20 of the 26 studies (77%) reporting only dietary outcomes tested Go/No-Go training (the task with the largest effects on eating behaviour), and 15 of the 21studies (71%) that reported on both dietary and implicit bias outcomes tested Approach-Avoidance training (a task with null effects on eating behaviour). Therefore, when interpreting the “borrowed strength” in the bivariate meta-analysis, we must be aware that the estimate is based on (1) implicit bias outcomes from mainly Approach-Avoidance studies, (2) food intake outcomes from a mixed set of studies with the significant effect mainly driven by Go/No-Go studies, and (3) the correlation between the two outcomes estimated solely from the studies that reported both outcomes. Hence, we can only trust the estimate of implicit bias change from the bivariate meta-analysis insofar as we assume that both Approach/Avoidance and Go/No-Go task work through the same mechanism. In addition, this might be indicative of selective reporting in Go/No-Go studies, such that implicit biases that did not turn out to change significantly following training may not have been reported.

When interpreting the effects on implicit biases it must be noted that most studies measured and intervened on implicit biases with an Approach-Avoidance task and only when biases were measured with the Approach-Avoidance task was bias change observed. This indicates that the Approach-Avoidance task as an intervention can change approach biases which, however, seems not to result in behaviour change. This can also be seen in Figure 7: While most of the data points indicate decreased biases, only a minority of studies led to decreased dietary intake. It is therefore possible that the reported effects of bias reduction are an artefact of the measurement method, i.e. participants simply learned to perform the Approach-Avoidance task better through repetition. In order to clarify the mechanisms at play in the different tasks, systematic research is necessary, including different interventions and measurement techniques of implicit biases, such as the implicit association test (Greenwald, McGhee, & Schwartz, 1998). This also includes research into neural underpinnings of processes involved in the interventions under examination: a recent article showed relations between brain activation patterns related to response inhibition in a food- Go/No-Go task and eating behaviour (Carbine et al., 2017). This approach could clarify the mechanisms of behaviour change when applied to Go/No-Go task interventions while measuring these neural patterns.

Moderator analyses revealed that the Go/No-Go task had larger effects on outcomes than both the Stop-Signal task and the Approach-Avoidance task. Previous related meta-analyses have also found larger effects for the Go/No-Go task than the Stop-Signal task (Allom et al., 2016; Jones et al., 2016). The nearly-null cumulative effects of Approach-Avoidance tasks shown in this study are in contrast with an earlier review that indicated that the Approach-Avoidance task effectively changes eating behaviour (Kakoschke et al., 2017a) and with a large literature on other problematic consumption behaviours, especially alcohol consumption (Wiers et al., 2013). Unlike the review by Kakoschke et al. (2017a), our analyses are quantitative and have systematically investigated effects of possible moderators on the effects. We therefore have reason to trust our results and agree with Becker and colleagues (2017) that the optimistic conclusions from the earlier review were "premature and too optimistic" (Becker, Jostmann, & Holland, 2017; p. 293).

The difference in effectiveness between tasks poses the question of their conceptual differences. The Go/No-Go task typically displays the go or no-go cue at the same time as the stimulus, whereas the Stop-Signal task presents stop signals only after a certain, usually variable, delay (Verbruggen & Logan, 2008). This implies that the performance of a Stop-Signal task always requires activation of a response, which is then to be stopped, whereas this is not the case in the Go/No-Go task. These differential effects on behaviour support the idea that the processes involved might differ across tasks (Allom et al., 2016). Verbruggen and Logan (Verbruggen & Logan, 2009) have demonstrated that while the Go/No-Go task typically leads to automatic response inhibition, performance of the Stop-Signal task requires executive control. This is because the Stop-Signal task typically maps stimuli and response requirements inconsistently whereas the Go/No-Go task typically maps stimuli and no-go cues consistently, as was the case in the studies examined here. When, however, stimuli are consistently mapped onto stop signals, the Stop-Signal task can produce automatic inhibition too. Therefore, it might not be the Stop-Signal task *per se* that produces smaller effects, but rather its inconsistent mapping of stimuli and stop signals. However, we are not aware of any study that directly addressed the effect of contingency between a stop/no-go signal and the kind of stimulus.

When applying these considerations to the Approach-Avoidance task, we would expect the effect to be “automatic” in nature, as the pairing between stimulus and reaction is highly consistent and the reaction cue is presented alongside the stimulus, like in the Go/No-Go task. However, we did not find significant effects of the Approach-Avoidance task on eating behaviours. The main difference between the Approach-Avoidance task and the other two tasks lies in the fact that it always requires a response, and never the withholding of a response. Thus, it might be that the behavioural activation involved in the Approach-Avoidance task does not sufficiently differentiate between approach and avoidance behaviour. Another explanation is offered by a recent study by Lender and colleagues (2018) who measured larger approach-biases when food stimuli were relevant for the task than when they were not (i.e. participants reacted to the content of the picture rather than a distinct cue). Even though this study did not deliver an intervention, the same problem might apply to intervention studies examined here. Since almost none of the included studies delivered interventions with food stimuli as the reaction feature (i.e. they were task-relevant), this might have resulted in null effects.

However, given the successful application of Approach-Avoidance task in the alcohol domain (Wiers et al., 2011), its lack of effectiveness in the eating domain is surprising and warrants further research, especially since mechanisms of change are hypothesized to be the same. One possible explanation for the disparity could be that alcoholic drinks are a more specific category than unhealthy or high-caloric food which might influence later consumption.

Including studies using Evaluative Conditioning procedures did not alter the general patterns of results and those interventions did not produce significant effects on dietary intake. This might be due to the passive nature of the task, as it only requires participants to passively perceive stimuli without reacting to them. It seems, therefore, that a behavioural component in the task is essential, possibly because it targets not just but, in addition, the direct link between a stimulus and a corresponding reaction. Our findings are in line with the idea that “conflicts are inherently aversive” (Dreisbach & Fischer, 2015, p. 256) and that this conflict can be resolved by adjusting the value of the encountered stimulus (Dreisbach & Fischer, 2015). Since Evaluative Conditioning does not elicit a control conflict, no value adjustment is triggered and, consequently, no behaviour change takes place. In this light, our findings also support those of Chen and colleagues (2016), which demonstrated that the Go/No-Go task is not merely a special case of Evaluative Conditioning, but rather that response inhibition is a necessary precursor to stimulus devaluation.

None of the other examined moderators had a significant effect on behavioural outcomes. While the effect sizes obtained through taste test procedures and snack choice paradigms were larger than those from questionnaire data, the moderation effect was not significant. This is surprising given that snack choice and taste test paradigms typically measure behaviour right after the intervention, whereas questionnaire data is collected after a certain delay. Also, an earlier meta-analysis that also included alcohol consumption did find a moderator effect for the way of outcome measurement (Allom et al., 2016). This indicates that there are too few studies with questionnaire-based outcome measurements. This lack is particularly problematic since questionnaires probably capture real-life eating behaviour better than laboratory measures and could better estimate the longevity of effects.

Future research should ideally combine different outcome measures to get a more detailed picture of effects.

The type of control group was unrelated to the size of the obtained effect. This is surprising, as “counter-training”, wherein subjects react to unhealthy food stimuli while stopping to control stimuli, should theoretically increase the association between unhealthy food stimuli and approach behaviour. Other types of controls, such as non-contingent pairing of food and stop/no-go/avoid or control training with food-unrelated stimuli, should have no effect on these associations.

A substantial share of studies did not report controlling for participants’ satiety (for 21 of 50 effect sizes), either statistically or with instructions for participants not to eat some hours before participation. This is potentially problematic as biases towards high-caloric food are stronger when individuals are hungry (Loeber, Grosshans, Herpertz, Kiefer, & Herpertz, 2013). Therefore, training not to approach high-calorie food should be more effective for hungry individuals as the impulse that needs to be overcome is stronger. Our moderator analyses found no difference between studies controlling for satiety and those that did not, but our analyses could not test this on an individual participant level. Future research should examine the influence of hunger specifically by systematically varying satiety. Studies that do not explicitly examine the effect of hunger should at a minimum control for hunger, perhaps by standardizing the hunger levels of the participants.

We found only few interventions delivered online to make substantial statements about their effectiveness. However, given the potential for repeated training delivery, online training (including smartphone-delivered training) seems like a promising avenue for future research. A recent study that tested different forms of Go/No-Go and Stop-Signal training outside the laboratory via the internet to decrease alcohol consumption found that the training does not increase effectiveness when added to an intervention including self-monitoring of consumption (Jones et al., 2018). Due to its design, however, this study could not make statements about the computer training as a stand-alone intervention.

In line with related meta-analyses (Allom et al., 2016; Jones et al., 2016) but contrary to theoretical predictions, we did not find a significant effect of the number of trials. The reflective-impulsive model claims that associations in the impulsive system form through repetition, and that the strength of the association depends (among other things) on the amount of repetition (Strack & Deutsch, 2004). Therefore, larger effects would be expected from more intense training. However, the reflective-impulsive model also predicts a recency effect, wherein recently activated associations guide behaviour more strongly than those activated longer ago (Strack & Deutsch, 2004). This indicates that effects of interventions targeting the impulsive system might be more due to priming effects than to re-training of associations, which implies that effects should not be long lasting and rather fragile. This fits with our finding that studies using questionnaire measurements of dietary behaviour produced smaller effects than studies that utilized laboratory-based measures. However, this might be due to other issues of food intake measurement (Westerterp & Goris, 2002). In any case, the respective effects of recency and repetition should be tested more rigorously, e.g. by examining training effects after different time intervals.

The share of critical trials (i.e. trials that required stopping, No-Go, or avoidance) did not influence intervention effects. This is in line with the findings of Jones and colleagues (2016) who found no effect of the absolute amount of critical trials in inhibitory control training. In a direct test of the number of pairings of food stimuli with No-Go cues, one study did not find differences between participants that received either 4, 12, or 24 pairings (H. Veling, Aarts, & Stroebe, 2013). While some authors have argued that the share of critical trials needs to be low to induce a dominant response tendency (Allom & Mullan, 2015), our findings do not support this notion. However, Go/No-Go task and Approach-

Avoidance task always deliver 50% critical trials and only the Stop-Signal task varies in the share of critical trials. Further research could examine systematically how the variation in the share of critical trials affects effectiveness.

Strengths and Limitations

Amongst the strengths of this meta-analysis are the examination of a wide range of moderator variables and the inclusion of a proposed mechanism of behaviour change. We adhered to PRISMA guidelines for reporting in systematic reviews and pre-registered our search strategy, data extraction, and all analyses. Most importantly, this meta-analysis combined several strands of research that earlier reviews have only examined isolated from one another, i.e. Approach-Avoidance training, Evaluative Conditioning, and Go/No-Go and Stop-Signal training. Their conceptual similarity (altering implicit associations) and interaction in predicting dietary behaviour warrants combining them in analysis.

This study has several limitations, mostly related to the available literature. First, the samples under investigation in the articles included mainly consist of young, predominantly female, mostly normal-weight students. Second, most studies did not follow up their participants but relied on immediate assessment. These two points limit external validity of the finding, as we cannot determine the extent to which effects generalize to different populations or persist over time. Third, some of the potential moderator variables were confounded, such as the kind of task and the share of critical trials. This makes it impossible to disentangle the effects of either one of the variables. Related to this, statistical power was rather low for many of the moderator analyses, indicating that there are potentially important aspects of the interventions which have not been studied, such as comparing different outcome measures and control groups, and trials delivering online training. Future research should systematically vary different design features to further determine conditions for optimal outcomes.

In summary, there is too little systematic variation of potentially moderating variables such as participant age and body-mass index, the number of total share of critical trials, or precise task demands in the literature and research could progress faster, if these shortcomings were addressed systematically to better understand processes involved and create optimal versions of interventions on implicit processes.

Conclusion

The present meta-analysis summarizes research on interventions targeting implicit processes in eating behaviour, and shows that such interventions, in particular the Go/No-Go Task, can measurably affect participants' eating behaviour. Moderator analyses did not identify any study designs, or participant characteristics associated with outcomes. Although the Approach-Avoidance Task reduces implicit biases towards unhealthy foods, insufficient data were available to determine whether bias reduction also occurs in the Go/No-Go task or the Stop-Signal task. Combined with medium remaining heterogeneity and a lack of knowledge about long-term effects of repeated training, this indicates the need for more systematic research into how such interventions impact on behaviour before they can be recommended for use in practice.

Declaration of conflict of interest statement

The authors declare no conflict of interest.

References

Adams, R. C. (2014). Training Response Inhibition to Reduce Food Consumption. Retrieved from http://orca.cf.ac.uk/70025/2/2015adamsphd.pdf

Adriaanse, M. A., Vinkers, C. D. W., De Ridder, D. T. D., Hox, J. J., & De Wit, J. B. F. (2011). Do implementation intentions help to eat a healthy diet? A systematic review and meta-analysis of the empirical evidence. *Appetite*, *56*(1), 183–193. https://doi.org/10.1016/J.APPET.2010.10.012

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Allom, V., & Mullan, B. (2015). Two inhibitory control training interventions designed to improve eating behaviour and determine mechanisms of change. *Appetite*, *89*, 282–290. https://doi.org/10.1016/j.appet.2015.02.022

Allom, V., Mullan, B., & Hagger, M. S. (2016). Does inhibitory control training improve health behaviour? A meta-analysis. *Health Psychology Review*, *10*(2), 168–186. https://doi.org/10.1080/17437199.2015.1051078

Bargh, J. A. (1994). The four horsemen of automaticity: awareness, intention, efficiency, and control in social cognition. In R. S. Wyer & T. K. Skrull (Eds.), *Handbook of social cognition* (pp. 1–40). Hills: Erlbaum.

Becker, D., Jostmann, N. B., & Holland, R. W. (2017). Does approach bias modification really work in the eating domain? A commentary on Kakoschke et al. (2017). *Addictive Behaviors*. https://doi.org/10.1016/j.addbeh.2017.02.025

Brignell, C., Griffiths, T., Bradley, B. P., & Mogg, K. (2009). Attentional and approach biases for pictorial food cues. Influence of external eating. *Appetite*, *52*(2), 299–306. https://doi.org/10.1016/j.appet.2008.10.007

Campbell, M., Fitzpatrick, R., Haines, A., Kinmonth, A. L., Sandercock, P., Spiegelhalter, D., & Tyrer, P. (2000). Framework for design and evaluation of complex interventions to improve health Framework for trials of complex interventions. *British Medical Journal*, *321*(7262), 694–6. https://doi.org/10.1136/bmj.321.7262.694

Carbine, K. A., Christensen, E., LeCheminant, J. D., Bailey, B. W., Tucker, L. A., & Larson, M. J. (2017). Testing food-related inhibitory control to high- and low-calorie food stimuli: Electrophysiological responses to high-calorie food stimuli predict calorie and carbohydrate intake. *Psychophysiology*, *54*(7), 982–997. https://doi.org/10.1111/psyp.12860

Carter, E. C., Schönbrodt, F. D., Gervais, W. M., & Hilgard, J. (2018). Correcting for bias in psychology: A comparison of meta-analytic methods. Retrieved from osf.io/rf3ys

Chen, Z., Veling, H., Dijksterhuis, A., & Holland, R. W. (2016). How does not responding to appetitive stimuli cause devaluation: Evaluative conditioning or response inhibition? *Journal of Experimental Psychology: General*, *145*(12), 1687–1701. https://doi.org/10.1037/xge0000236

Coburn, K. M., & Vevea, J. L. (2017). Estimating Weight-Function Models for Publication Bias. Retrieved from https://cran.r-project.org/package=weightr

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Earlbaum Associates.

DerSimonian, R., & Laird, N. (1986). Meta-Analysis in Clinical Trials*. *Statistics in Medicine*, *188*, 177–188. https://doi.org/10.1016/0197-2456(86)90046-2

Dreisbach, G., & Fischer, R. (2015). Conflicts as Aversive Signals for Control Adaptation. *Current Directions in Psychological Science*, *24*(4), 255–260. https://doi.org/10.1177/0963721415569569

Duval, S. (2005). The Trim and Fill Method. In H. R. Rothstein, A. J. Sutton, & M. Borenstein (Eds.), *Publication Bias in Meta-Analysis: Prevention, Assessment and Adjustments* (pp. 127–144). Chichester: John Wiley & Sons.

Duval, S., & Tweedie, R. Trim and Fill: A Simple Funnel-Plot-Based Method of Testing and

Adjusting for Publication Bias in Meta-Analysis, 56 Biometrics § (2000). International Biometric Society. Retrieved from http://www.jstor.org/stable/2676988

Eder, A. B., Elliot, A. J., & Harmon-Jones, E. (2013). Approach and avoidance motivation: Issues and advances. *Emotion Review*. https://doi.org/10.1177/1754073913477990

Eder, A. B., Müsseler, J., & Hommel, B. (2012). The structure of affective action representations: temporal binding of affective response codes. *Psychological Research*, *76*(1), 111–118. https://doi.org/10.1007/s00426-011-0327-6

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple , graphical test measures of funnel plot asymmetry. *Bmj*, *315*(7109), 629–34. https://doi.org/10.1136/bmj.315.7109.629

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behavior: The reasoned action approach*. *New York: Psychology Press*. Taylor & Francis. https://doi.org/10.4324/9780203937082

Friese, M., & Hofmann, W. (2009). Control me or I will control you: Impulses, trait self-control, and the guidance of behavior. *Journal of Research in Personality*, *43*(5), 795–805. https://doi.org/10.1016/j.jrp.2009.07.004

Gardner, B., Abraham, C., Lally, P., & de Bruijn, G. J. (2012). Towards parsimony in habit measurement: Testing the convergent and predictive validity of an automaticity subscale of the Self-Report Habit Index. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 102. https://doi.org/10.1186/1479-5868-9-102

Greenwald, A. G., Mcghee, D. E., & Schwartz, J. L. K. (1998). *Measuring Individual Differences in Implicit Cognition: The Implicit Association Test*. *Journal of Personality and Social Psychology* (Vol. 74). Retrieved from http://faculty.fortlewis.edu/burke_b/Senior/BLINK replication/IAT.pdf

Greenwald, A. G., Poehlman, T. A., Uhlmann, E. L., & Banaji, M. R. (2009). Understanding and using the Implicit Association Test: III. Meta-analysis of predictive validity. *Journal of Personality and Social Psychology*, *97*(1), 17–41. https://doi.org/10.1037/a0015575

Hagger, M. S., Trost, N., Keech, J., Chan, D. K. C., & Hamilton, K. (2017). Predicting sugar consumption: Application of an integrated dual-process, dual-phase model. *Appetite*, (April). https://doi.org/10.1016/j.appet.2017.04.032

Hahn, A., & Gawronski, B. (2017). Implicit Social Cognition. In J. T. Wixted (Ed.), *The Stevens' handbook of experimental psychology and cognitive neuroscience* (4th ed., pp. 395–427). New York, NY: Wiley. https://doi.org/10.1016/B978-0-08-097086-8.24066-X

Havermans, R. C., Giesen, J. C. A. H., Houben, K., & Jansen, A. (2011). Weight, gender, and snack appeal. *Eating Behaviors*, *12*(2), 126–130. https://doi.org/10.1016/j.eatbeh.2011.01.010

Higgins, J. P., Deeks, J., & Altman, D. (2011). Chapter 16: Special topics in statistics. In G. S. Higgins JPT (Ed.), *Cochrane Handbook for Systematic Reviews of Interventions* (Version 5.). The Cochrane Collaboration. Retrieved from www.handbook.cochrane.org

Higgins, J. P., & Thompson, S. G. (2002). Quantifying heterogeneity in a meta-analysis. *Statistics in Medicine*, *21*(11), 1539–1558. https://doi.org/10.1002/sim.1186

Hill, J. O., Catenacci, V., & Wyatt, H. R. (2005). Obesity: Overview of an Epidemic. *Psychiatr Clin N Am*, *28*, 1–23. https://doi.org/10.1016/j.psc.2004.09.010

Hofmann, W., Adriaanse, M., Vohs, K. D., & Baumeister, R. F. (2014). Dieting and the self-control of eating in everyday environments: An experience sampling study. *British Journal of Health Psychology*, *19*(3), 523–539. https://doi.org/10.1111/bjhp.12053

Vevea, J. L., & Hedges, L. V. (1995). A general linear model for estimating effect size in the presence of publication bias. *Psychometrika*, *60*(3), 419–435. https://doi.org/10.1007/BF02294384

Hofmann, W., & Friese, M. (2008). Impulses got the better of me: alcohol moderates the influence of implicit attitudes toward food cues on eating behavior. *Journal of Abnormal Psychology*, *117*(2), 420–427. https://doi.org/http://dx.doi.org/10.1037/0021-843X.117.2.420

Hofmann, W., Friese, M., & Roefs, A. (2009). Three ways to resist temptation: The independent contributions of executive attention, inhibitory control, and affect regulation to the impulse control of eating behavior. *Journal of Experimental Social Psychology*, *45*(2), 431–435. https://doi.org/10.1016/j.jesp.2008.09.013

Hofmann, W., Gschwendner, T., Friese, M., Wiers, R. W., & Schmitt, M. (2008). Working memory capacity and self-regulatory behavior: Toward an individual differences perspective on behavior determination by automatic versus controlled processes. *Journal of Personality and Social Psychology*, *95*(4), 962–977. https://doi.org/10.1037/a0012705

Hollands, G. J., Marteau, T. M., Fletcher, P. C., Hollands, G. J., Marteau, T. M., & Non-, P. C. F. (2016). Non-conscious processes in changing health- related behaviour : a conceptual analysis and framework. *Health Psychology Review*, *7199*(March), 14. https://doi.org/10.1080/17437199.2015.1138093

Hollands, G. J., Prestwich, A., & Marteau, T. M. (2011). Using Aversive Images to Enhance Healthy Food Choices and Implicit Attitudes: An Experimental Test of Evaluative Conditioning. *Health Psychology*, *30*(2), 195–203. https://doi.org/10.1037/a0022261

Huedo-Medina, T. B., Sánchez-Meca, J., Marín-Martínez, F., & Botella, J. (2006). Assessing heterogeneity in meta-analysis: Q statistic or I^2 index? *Psychological Methods*, *11*(2), 193–206. https://doi.org/10.1037/1082-989X.11.2.193

Jones, A., Di Lemma, L. C. G. G., Robinson, E., Christiansen, P., Nolan, S., Tudur-Smith, C., & Field, M. (2016). Inhibitory control training for appetitive behaviour change: A meta-analytic investigation of mechanisms of action and moderators of effectiveness. *Appetite*, *97*, 16–28. https://doi.org/10.1016/j.appet.2015.11.013

Jones, A., Hardman, C. A., Lawrence, N., & Field, M. (2017, May). Cognitive training as a potential treatment for overweight and obesity: A critical review of the evidence. *Appetite*.

https://doi.org/10.1016/j.appet.2017.05.032

Jones, A., McGrath, E., Robinson, E., Houben, K., Nederkoorn, C., & Field, M. (2018). A randomized controlled trial of inhibitory control training for the reduction of alcohol consumption in problem drinkers. *Journal of Consulting and Clinical Psychology, 86*(12), 991-1004. http://dx.doi.org/10.1037/ccp0000312

Kakoschke, N., Kemps, E., & Tiggemann, M. (2015). Combined effects of cognitive bias for food cues and poor inhibitory control on unhealthy food intake. *Appetite*, *87*, 358–364. https://doi.org/10.1016/j.appet.2015.01.004

Kakoschke, N., Kemps, E., & Tiggemann, M. (2017a). Approach bias modification training and consumption: A review of the literature. *Addictive Behaviors*, *64*(August), 21–28. https://doi.org/10.1016/j.addbeh.2016.08.007

Kakoschke, N., Kemps, E., & Tiggemann, M. (2017b). Impulsivity moderates the effect of approach bias modification on healthy food consumption. *Appetite*, *117*, 117–125. https://doi.org/10.1016/j.appet.2017.06.019

Kawakami, K., Phills, C. E., Steele, J. R., & Dovidio, J. F. (2007). (Close) Distance Makes the Heart Grow Fonder: Improving Implicit Racial Attitudes and Interracial Interactions Through Approach Behaviors. *Journal of Personality and Social Psychology*, *92*(6), 957–971. https://doi.org/10.1037/0022-3514.92.6.957

Keatley, D., Clarke, D. D., & Hagger, M. S. (2012). Investigating the predictive validity of implicit and explicit measures of motivation on condom use, physical activity and healthy eating. *Psychology & Health*, *27*(5), 550–569. https://doi.org/10.1080/08870446.2011.605451

Kemps, E., & Tiggemann, M. (2014). Approach Bias for Food Cues in Obese Individuals. *Psychology & Health*, *0446*(October), 1–25. https://doi.org/10.1080/08870446.2014.974605

Kemps, E., Tiggemann, M., & Hollitt, S. (2014). Biased attentional processing of food cues and modification in obese individuals. *Health Psychology*, *33*(11), 1391–1401.

https://doi.org/10.1037/hea0000069

Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: a practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*, 863. https://doi.org/10.3389/fpsyg.2013.00863

Lally, P., & Gardner, B. (2013, May). Promoting habit formation. *Health Psychology Review*. Taylor & Francis Group. https://doi.org/10.1080/17437199.2011.603640

Lawrence, N. S., Javaid, M., VanBeurden, S., Greaves, C., Chambers, C., & Verbruggen, F. (2016). The acceptability and effectiveness of online food response inhibition training for weight loss in a large public sample. *British Association for Psychopharmacology Conference*.

Lebens, H., Roefs, A., Martijn, C., Houben, K., Nederkoorn, C., & Jansen, A. (2011). Making implicit measures of associations with snack foods more negative through evaluative conditioning. *Eating Behaviors*, *12*(4), 249–253. https://doi.org/10.1016/j.eatbeh.2011.07.001

Lender, A., Meule, A., Rinck, M., Brockmeyer, T., & Blechert, J. (2018). Measurement of food-related approach–avoidance biases: Larger biases when food stimuli are task relevant. *Appetite*, *125*, 42–47. https://doi.org/10.1016/j.appet.2018.01.032

Loeber, S., Grosshans, M., Herpertz, S. C. S., Kiefer, F., & Herpertz, S. C. S. (2013). Hunger modulates behavioral disinhibition and attention allocation to food-associated cues in normal-weight controls. *Appetite*, *71*, 32–39. https://doi.org/10.1016/j.appet.2013.07.008

Logan, G. D., Cowan, W. B., & Davis, K. A. (1984). On the ability to inhibit simple and choice reaction time responses: A model and a method. *Journal of Experimental Psychology: Human Perception and Performance*, *10*(2), 276–291. https://doi.org/10.1037/0096-1523.10.2.276

Machulska, A., Zlomuzica, A., Rinck, M., Assion, H.-J., & Margraf, J. (2016). Approach bias modification in inpatient psychiatric smokers. *Journal of Psychiatric Research*, *76*, 44–51. https://doi.org/10.1016/j.jpsychires.2015.11.015

McEachan, R., Taylor, N., Harrison, R., Lawton, R., Gardner, P., & Conner, M. (2016). Meta-

Analysis of the Reasoned Action Approach (RAA) to Understanding Health Behaviors. *Annals of Behavioral Medicine*, *50*(4), 592–612. https://doi.org/10.1007/s12160-016-9798-4

Michie, S., Abraham, C., Whittington, C., McAteer, J., & Gupta, S. (2009). Effective techniques in healthy eating and physical activity interventions: A meta-regression. *Health Psychology*, *28*(6), 690–701. https://doi.org/10.1037/a0016136

Michie, S., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., … Wood, C. E. (2013). The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: Building an international consensus for the reporting of behavior change interventions. *Annals of Behavioral Medicine*, *46*(1), 81–95. https://doi.org/10.1007/s12160-013-9486-6

Nederkoorn, C., Houben, K., Hofmann, W., Roefs, A., & Jansen, A. (2010). Control yourself or just eat what you like? Weight gain over a year is predicted by an interactive effect of response inhibition and implicit preference for snack foods. *Health Psychology*, *29*(4), 389–393. https://doi.org/10.1037/a0019921

R Core Team. (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.r-project.org/

Rebar, A. L., Dimmock, J. A., Jackson, B., Rhodes, R. E., Kates, A., Starling, J., & Vandelanotte, C. (2016). A Systematic Review of the Effects of Non-Conscious Regulatory Processes in Physical Activity. *Health Psychology Review*, *7199*(August), 1–86. https://doi.org/10.1080/17437199.2016.1183505

Riley, R. D. (2009). Multivariate meta-analysis: The effect of ignoring within-study correlation. *Journal of the Royal Statistical Society. Series A: Statistics in Society*, *172*(4), 789–811. https://doi.org/10.1111/j.1467-985X.2008.00593.x

Riley, R. D., Abrams, K. R., Lambert, P. C., Sutton, A. J., & Thompson, J. R. (2007). An evaluation of bivariate random-effects meta-analysis for the joint synthesis of two correlated outcomes.

Statistics in Medicine, *26*(1), 78–97. https://doi.org/10.1002/sim.2524

Riley, R. D., Abrams, K. R., Sutton, A. J., Lambert, P. C., & Thompson, J. R. (2007). Bivariate random-effects meta-analysis and the estimation of between-study correlation. *BMC Medical Research Methodology*, *7*, 3. https://doi.org/10.1186/1471-2288-7-3

Schonberg, T., Bakkour, A., Hover, A. M., Mumford, J. A., Nagar, L., Perez, J., & Poldrack, R. A. (2014). Changing value through cued approach: An automatic mechanism of behavior change. *Nature Neuroscience*, *17*(4), 625–630. https://doi.org/10.1038/nn.3673

Schumacher, S. E., Kemps, E., & Tiggemann, M. (2016). Bias modification training can alter approach bias and chocolate consumption. *Appetite*, *96*(October), 219–224. https://doi.org/10.1016/j.appet.2015.09.014

Sharbanee, J. M., Hu, L., Stritzke, W. G. K., Wiers, R. W., Rinck, M., & MacLeod, C. (2014). The effect of approach/avoidance training on alcohol consumption is mediated by change in alcohol action tendency. *PLoS ONE*, *9*(1), e85855. https://doi.org/10.1371/journal.pone.0085855

Stice, E., Lawrence, N. S., Kemps, E., & Veling, H. (2016). Training motor responses to food: A novel treatment for obesity targeting implicit processes. *Clinical Psychology Review*, *49*, 16–27. https://doi.org/10.1016/j.cpr.2016.06.005

Strack, F., & Deutsch, R. (2004). Reflective and impulsive determinants of social behavior. *Personality and Social Psychology Review : An Official Journal of the Society for Personality and Social Psychology, Inc*, *8*(3), 220–247. https://doi.org/10.1207/s15327957pspr0803_1

Thompson, J. R., Minelli, C., Abrams, K. R., Tobin, M. D., & Riley, R. D. (2005). Meta-analysis of genetic studies using Mendelian randomization-a multivariate approach. *STATISTICS IN MEDICINE Statist. Med*, *24*, 2241–2254. https://doi.org/10.1002/sim.2100

Thornton, A., & Lee, P. (2000). Publication bias in meta-analysis: its causes and consequences. *Journal of Clinical Epidemiology*, *53*, 207–216. Retrieved from https://www.jclinepi.com/article/S0895-4356(99)00161-4/pdf

Turton, R., Bruidegom, K., Cardi, V., Hirsch, C. R., & Treasure, J. (2016). Novel methods to help develop healthier eating habits for eating and weight disorders: A systematic review and meta-analysis. *Neuroscience and Biobehavioral Reviews*, *61*(December), 132–155. https://doi.org/10.1016/j.neubiorev.2015.12.008

van't Riet, J., Sijtsema, S. J., Dagevos, H., & de Bruijn, G. J. (2011). The importance of habits in eating behaviour. An overview and recommendations for future research. *Appetite*. https://doi.org/10.1016/j.appet.2011.07.010

van Koningsbruggen, G. M., Veling, H., Stroebe, W., & Aarts, H. (2014). Comparing two psychological interventions in reducing impulsive processes of eating behaviour: Effects on self-selected portion size. *British Journal of Health Psychology*, *19*(4), 767–782. https://doi.org/10.1111/bjhp.12075

Veenstra, E. M., & de Jong, P. J. (2012). Attentional bias in restrictive eating disorders. Stronger attentional avoidance of high-fat food compared to healthy controls? *Appetite*, *58*(1), 133–140. https://doi.org/10.1016/J.APPET.2011.09.014

Veling, H., Aarts, H., & Stroebe, W. (2013). Using stop signals to reduce impulsive choices for palatable unhealthy foods. *British Journal of Health Psychology*, *18*(2). https://doi.org/10.1111/j.2044-8287.2012.02092.x

Veling, H., Holland, R. W., & van Knippenberg, A. (2008). When approach motivation and behavioral inhibition collide: Behavior regulation through stimulus devaluation. *Journal of Experimental Social Psychology*, *44*(4), 1013–1019. https://doi.org/10.1016/j.jesp.2008.03.004

Veling, H., van Koningsbruggen, G. M. G. M., Aarts, H., & Stroebe, W. (2014). Targeting impulsive processes of eating behavior via the internet. Effects on body weight. *Appetite*, *78*(March), 102–109. https://doi.org/10.1016/j.appet.2014.03.014

Verbruggen, F., & Logan, G. D. (2008). Response inhibition in the stop-signal paradigm. *Trends in*

Cognitive Sciences, *12*(11), 418–424. https://doi.org/10.1016/J.TICS.2008.07.005

Verbruggen, F., & Logan, G. D. (2009). Automaticity of cognitive control: Goal priming in response-inhibition paradigms. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *35*(5), 1381–1388. https://doi.org/10.1037/a0016645

Vevea, J. L., & Hedges, L. V. (1995). A general linear model for estimating effect size in the presence of publication bias. *Psychometrika*, *60*(3), 419–435. https://doi.org/10.1007/BF02294384

Viechtbauer, W. (2010). Conducting Meta-Analyses in R with the metafor Package. *Journal of Statistical Software*, *36*(3), 1–48. https://doi.org/10.1103/PhysRevB.91.121108

Vilà, I., Carrero, I., & Redondo, R. (2017). Reducing fat intake using implementation intentions: A meta-analytic review. *British Journal of Health Psychology*, *22*(2), 281–294. https://doi.org/10.1111/bjhp.12230

Wang, Y., Wang, G., Zhang, D., Wang, L., Cui, X., Zhu, J., & Fang, Y. (2017). Learning to dislike chocolate: Conditioning negative attitudes toward chocolate and its effect on chocolate consumption. *Frontiers in Psychology*, *8*(AUG), 1468. https://doi.org/10.3389/fpsyg.2017.01468

Werthmann, J., Jansen, A., & Roefs, A. (2015). Worry or craving? A selective review of evidence for food-related attention biases in obese individuals, eating-disorder patients, restrained eaters and healthy samples. In *Proceedings of the Nutrition Society* (Vol. 74, pp. 99–114). https://doi.org/10.1017/S0029665114001451

Westerterp, K. R., & Goris, A. H. C. (2002). Validity of the assessment of dietary intake: problems of misreporting. *Current Opinion in Clinical Nutrition and Metabolic Care*, *5*(5), 1363–1950. https://doi.org/10.1097/00075197-200209000-00006

Wiers, R. W., Eberl, C., Rinck, M., Becker, E. S., & Lindenmeyer, J. (2011). Retraining Automatic Action Tendencies Changes Alcoholic Patients' Approach Bias for Alcohol and Improves

Treatment Outcome. *Psychological Science*, *22*(4), 490–497. https://doi.org/10.1177/0956797611400615

Wiers, R. W., Gladwin, T. E., Hofmann, W., Salemink, E., & Ridderinkhof, K. R. (2013). Cognitive bias modification and cognitive control training in addiction and related psychopathology: Mechanisms, clinical perspectives, and ways forward. *Clinical Psychological Science*, *1*(2), 192–212. https://doi.org/10.1177/2167702612466547

World Health Organization. (2015). WHO; Overweight and Obesity. Retrieved December 8, 2016, from http://www.who.int/gho/ncd/risk_factors/overweight/en/

Woud, M. L., Becker, E. S., & Rinck, M. (2008). Implicit evaluation bias induced by approach and avoidance. *Cognition and Emotion*, *22*(6), 1187–1197. https://doi.org/10.1080/02699930801906843

Appendix A

The following terms were searched on PsycINFO, Medline, and Scopus for the meta-analysis "Effects of training implicit action tendencies and response inhibition in the eating domain - a meta-analysis".

(go no go OR go nogo OR go no-go OR stop signal OR stop-signal OR response inhibition OR inhibitory control OR cognitive bias modification OR implicit association OR joystick OR approach avoidance OR approach-avoidance OR impulse control OR self-control training OR evaluative conditioning OR evaluative learning OR affective conditioning OR affective learning OR attitude learning)

AND

(snack OR fruit OR vegetable OR fat OR sugar OR sweet* OR palatable OR chocolate OR consumption OR high-calorie OR unhealthy OR overeating OR intake OR food choice* OR diet OR calorie* OR salt* OR taste test* OR tendenc*)

PsycINFO, Medline, and Scopus were searched with the relevant keywords. Titles, keywords, and abstracts of the records were searched with the terms using the AND modifier. Since there are no publications on these topics before 1990 to our knowledge, the publication date was limited to 1990 - present. Authors of related reviews were contacted for excluded articles of their own literature search which were then scanned according to eligibility criteria. The literature search was re-run before the final analysis. Only studies published in English, Finnish, Dutch, Spanish or German (accompanied by an English abstract were considered for inclusion.

[Table 4 near here]

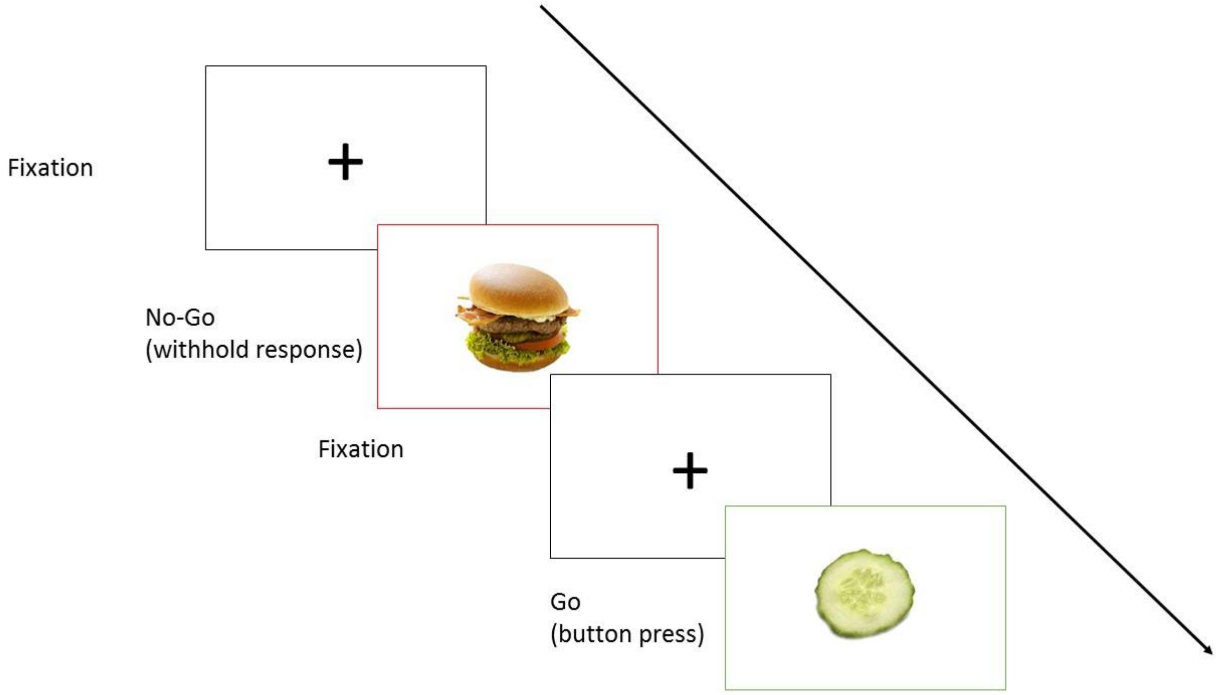

Figure 1 Course of a trial in a typical Go/No-Go Task. First, the participant's attention is directed to the center of the screen with a fixation cross. Next, the stimulus appears together with a Go or No-Go cue. In this example, the Go/No-Go cue is the color of the frame. Participants are told to withhold their response when the frame is red and to respond as fast as possible when the frame green. (Food images from Blechert, Meule, Busch, & Ohla, 2014)

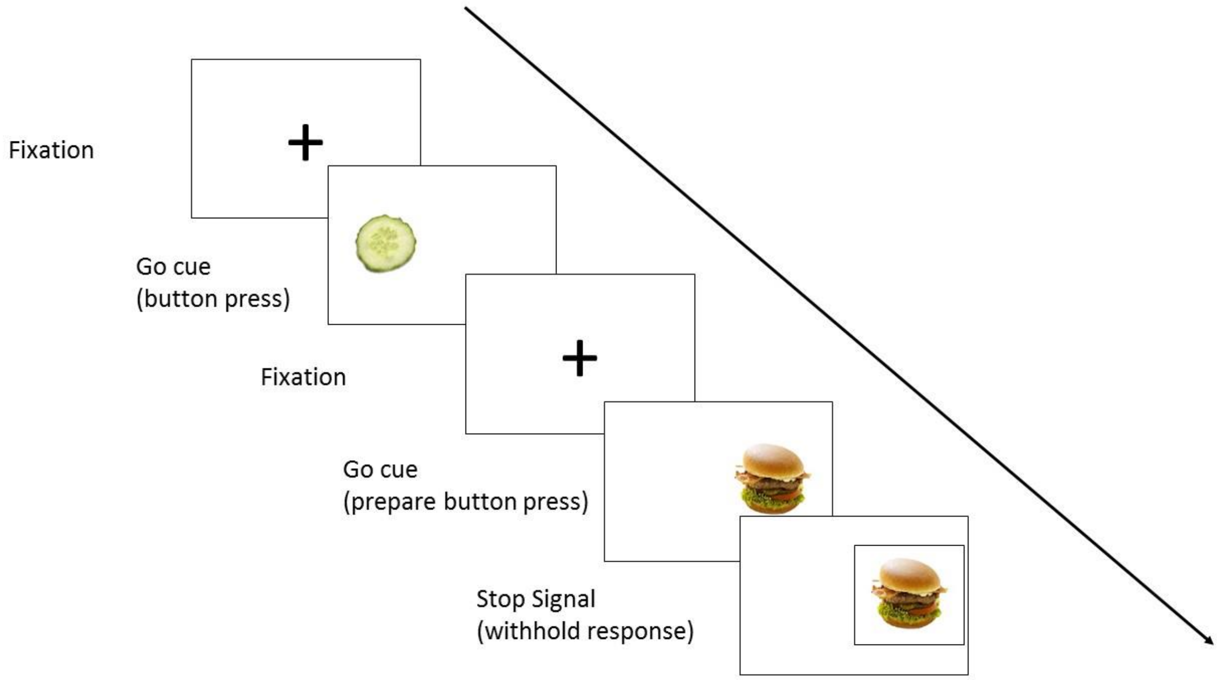

Figure 2 Course of two trials of a typical food Stop-Signal Task (first a go, second a stop trial). First, the participant's attention is directed to the center of the screen with a fixation cross. Next, a stimulus appears and the participant's task is to react as fast as possible. However, in some trials, a stop signal will appear after a certain interval which requires the participant to withhold the response. In the case in the second trial of the picture, the stop signal is the frame that appears around the stimulus after a variable delay. (Food images from Blechert et al., 2014)

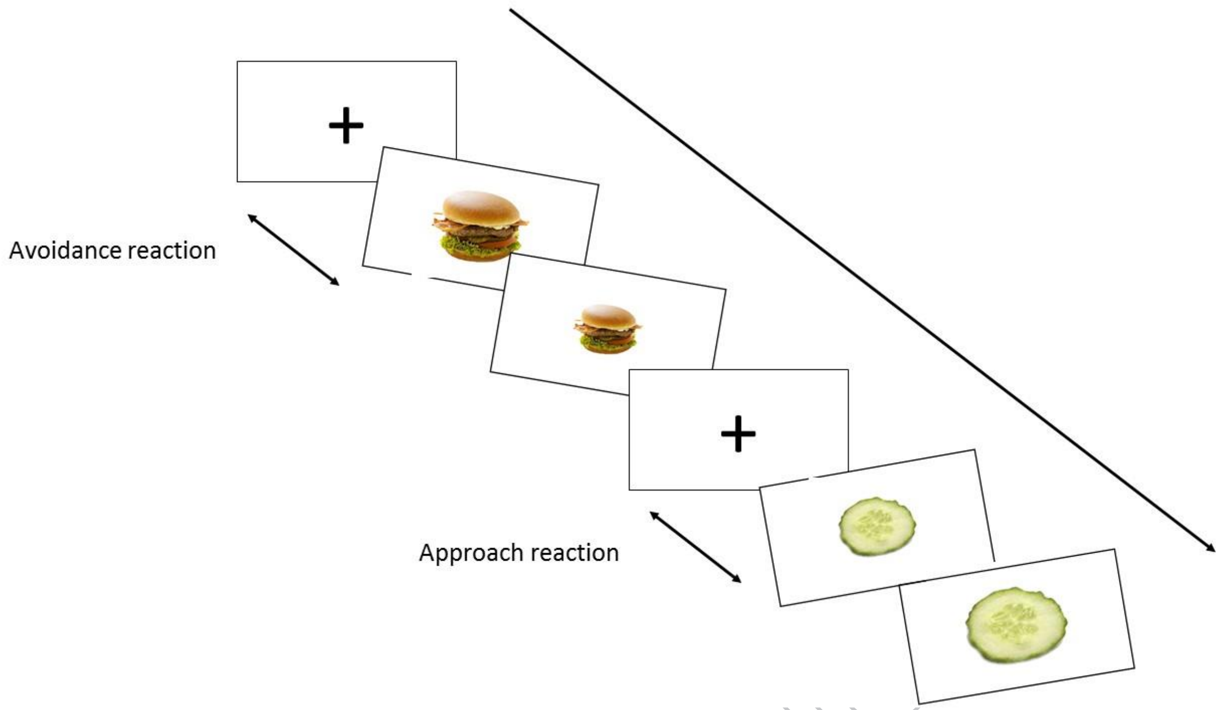

Figure 3 Course of two trials of a typical Approach-Avoidance Task. First, the participant's attention is directed to the center of the screen with a fixation cross. Next, the stimulus appears and the participants' task is to react as fast as possible and the kind of reaction (approach vs avoidance) depends on the cue. In this case, the tilt of the picture is the approach/avoidance cue. Food images from Blechert et al., 2014)

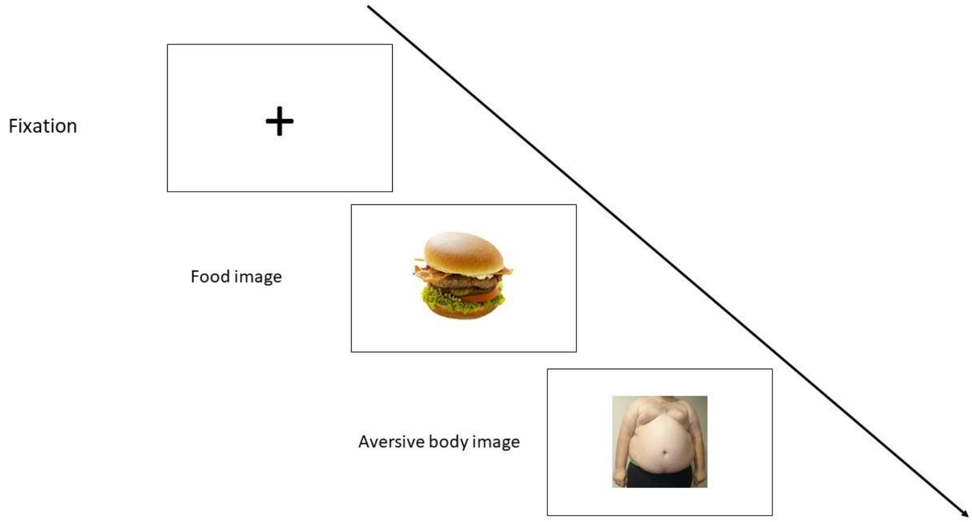
Fixation
+
Food image
Aversive body image

Figure 4 Course of a trial in Evaluative Conditioning. The food image is followed by an aversive body image (body image downloaded from Wikimedia)

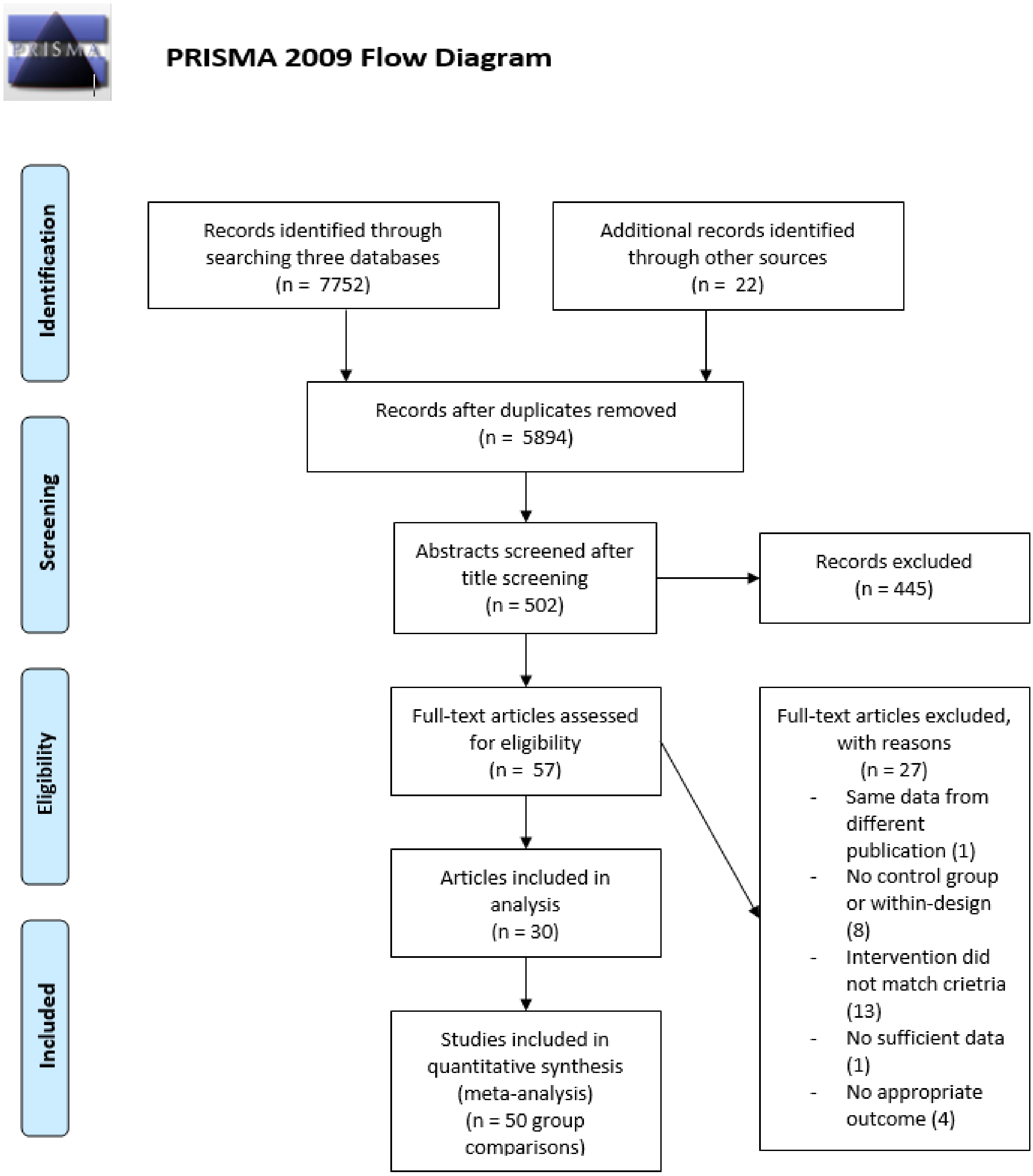

Figure 5 Flow diagram for the search and inclusion for studies in the meta-analysis (Moher, Liberati, Tetzlaff, Altman, & Group, 2009).

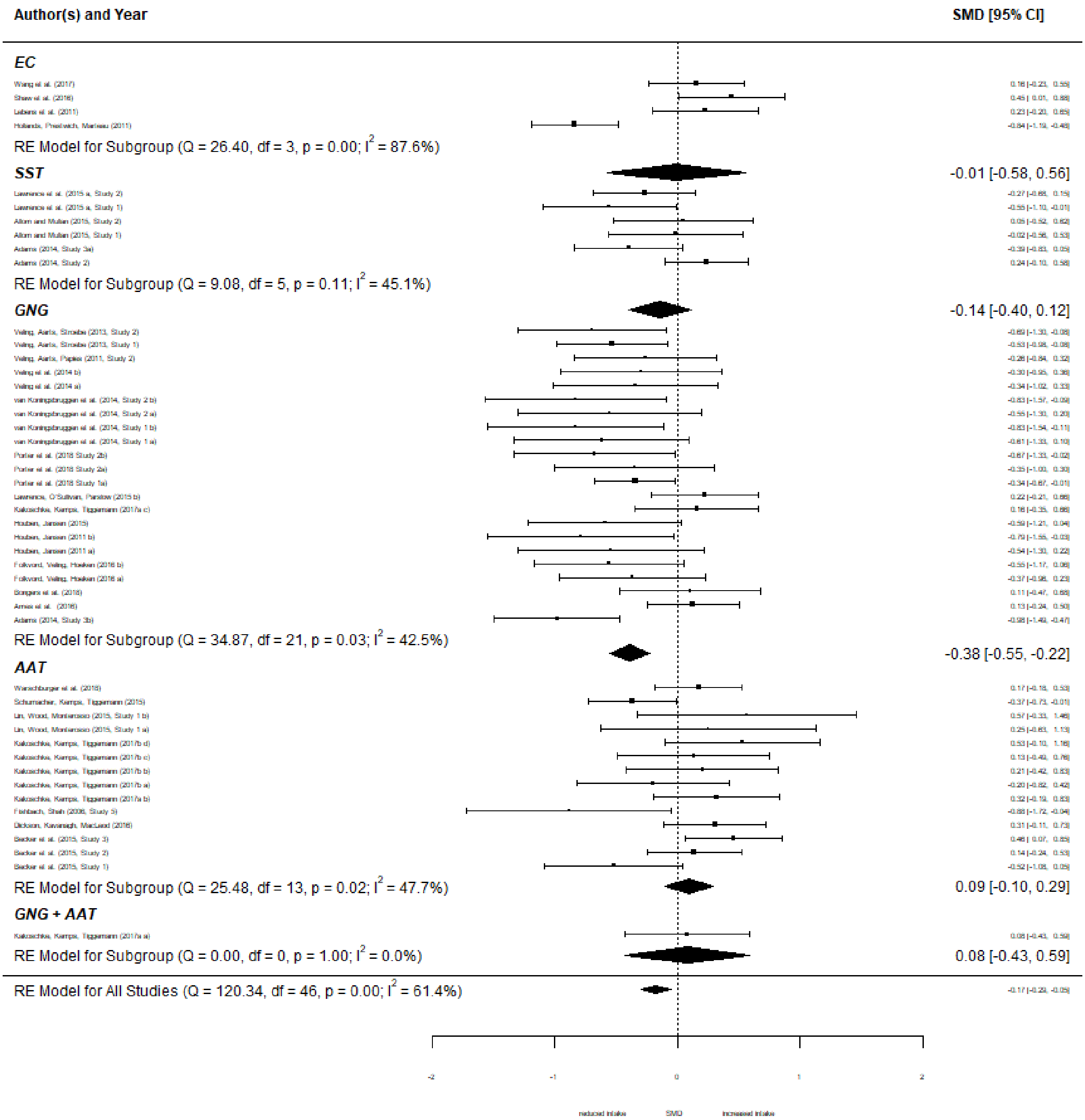

Figure 6 Forest plot for the effect sizes divided by the task used in the respective study (EC vs SST vs GNG vs AAT vs GNG+AAT).

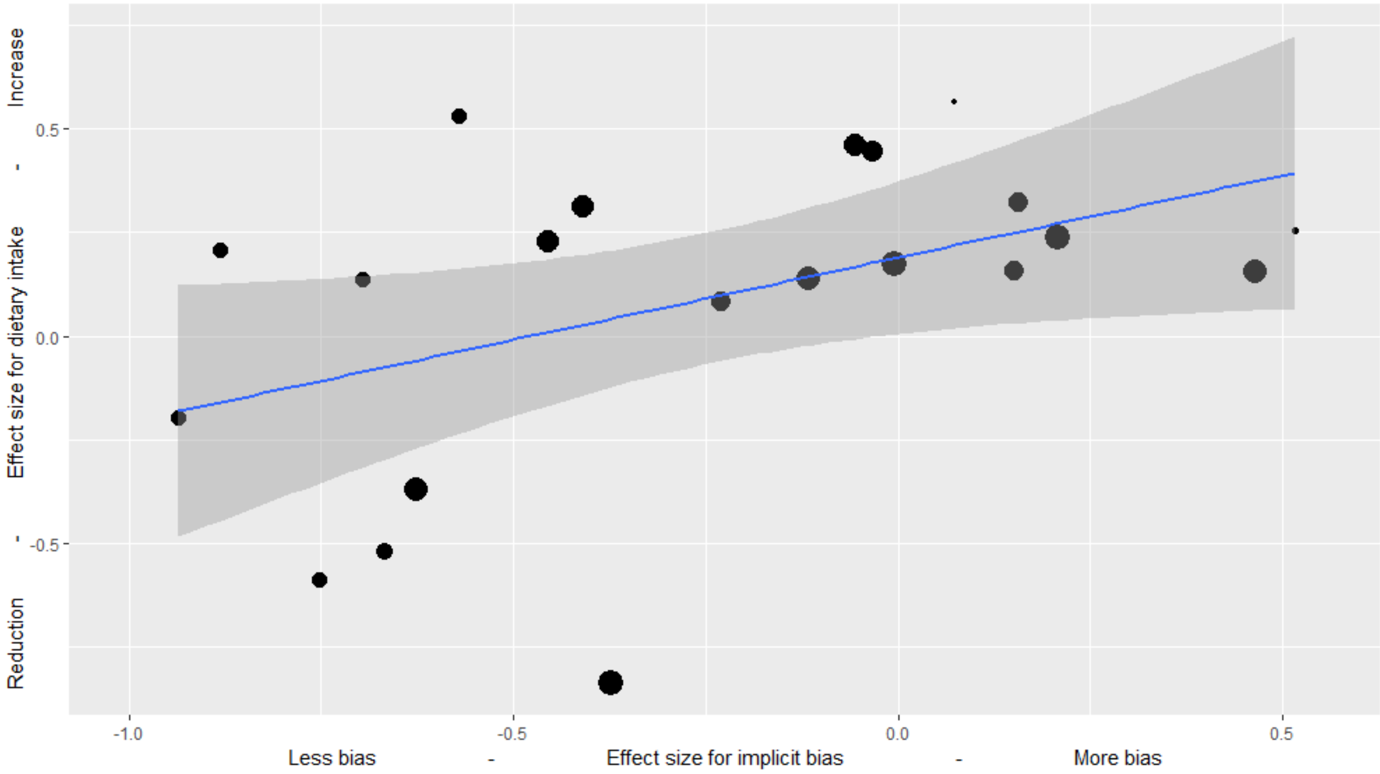

Figure 7 Regression of the intervention effect on implicit evaluations (x-axis) on the intervention effects on dietary intake (y-axis). The size of the data points reflects their weight in the meta-regression. The grey band indicates a 95% confidence interval to the blue regression line.

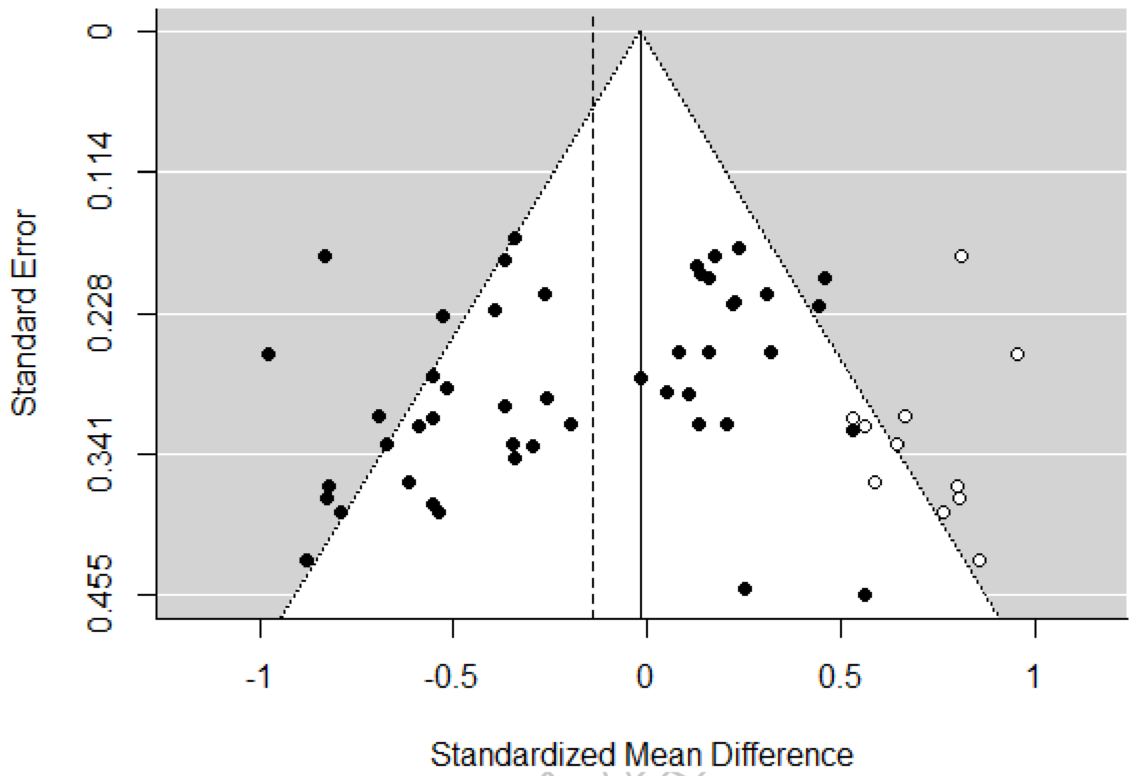

Figure 8 Funnel Plot with published studies in black and effects added by the trim and fill method in white. The dashed line indicates the estimated effect without the trim-and-fill method; the solid line indicates the estimated effect from the trim-and-fill method.

Authors & year of publication	**Participants total (controls)**	**mean age**	**Percent female**	**controlled satiety**	**Task**	**Control group**	**Online Training**	**Number of trials**	**Share critical trials**	**Consumption outcome used in meta-analysis**
Adams (2014, Study 2)	132 (65)	23.03	93	1	SST	No contingent pairing food/critical trial	0	480	0.25	Ad-lib consumption in taste test
Adams (2014, Study 3a)	81 (39)	21.24	93	1	SST	No contingent pairing food/critical trial	0	288	0.25	Ad-lib consumption in taste test
Adams (2014, Study 3b)	66 (32)	22.08	91	1	GNG	No contingent pairing food/critical trial	0	288	0.5	Ad-lib consumption in taste test
Allom and Mullan (2015, Study 1)	51 (25)	20.43	80	0	SST	No contingent pairing food/critical trial	1	1920	0.25	Food diary data
Allom and Mullan (2015, Study 2)	47 (23)	22.97	78	0	SST	No contingent pairing food/critical trial	1	1920	0.25	Food diary data

Ames et al. (2016)	112 (56)	16.06	66	1	GNG	Food-unrelated stimuli	0	180	0.5	Ad-lib consumption in taste test
Becker et al. (2015, Study 1)	50 (26)	20.47	100	0	AAT	No contingent pairing food/critical trial	0	360	0.5	Food diary data
Becker et al. (2015, Study 2)	104 (52)	20.77	100	0	AAT	No contingent pairing food/critical trial	0	360	0.5	Food diary data
Becker et al. (2015, Study 3)	103 (51)	21.94	100	0	AAT	No contingent pairing food/critical trial	0	400	0.5	Ad-lib consumption in taste test
Bongers et al. (2018)	47 (23)	19.68	100	1	GNG	No contingent pairing food/critical trial	0	640	0.5	consumption in taste test
Dickson, Kavanagh, MacLeod (2016)	90 (45)	NA	72	0	AAT	Reversed contingency	0	440	0.5	Ad-lib consumption in taste test
Ferentzi et al. (2018)	129 (65)	48	49	1	AAT	No contingent pairing	0	920	0.5	NA
Fishbach, Shah (2006, Study 5)	24 (12)	NA	100	0	AAT	Reversed contingency	0	120	0.5	Snack choice
Folkvord, Veling, Hoeken (2016 a)	52 (16)	8.9	53	0	GNG	Food-unrelated stimuli	0	132	0.5	Ad-lib consumption in taste test

Folkvord, Veling, Hoeken (2016 b)	48 (16)	8.9	53	0	GNG	Food-unrelated stimuli	0	132	0.5	Ad-lib consumption in taste test
Hollands, Prestwich, Marteau (2011)	132 (66)	24.2	77	0	EC	Food-unrelated stimuli	0	100	1	Snack choice
Houben, Jansen (2015)	41 (20)	20.13	100	1	GNG	Reversed contingency	0	320	0.5	Ad-lib consumption in taste test
Houben, Jansen (2011 a)	31 (20)	20.08	100	1	GNG	Reversed contingency	0	320	0.5	Ad-lib consumption in taste test
Houben, Jansen (2011 b)	33 (22)	20.08	100	1	GNG	No contingent pairing food/critical trial	0	320	0.5	Ad-lib consumption in taste test
Kakoschke, Kemps, Tiggemann (2017a a)	80 (20)	20.61	100	1	GNG_AAT	No contingent pairing food/critical trial	0	320	0.5	Ad-lib consumption in taste test
Kakoschke, Kemps, Tiggemann (2017a b)	80 (20)	20.61	100	1	AAT	No contingent pairing food/critical trial	0	200	0.5	Ad-lib consumption in taste test
Kakoschke, Kemps, Tiggemann (2017a c)	80 (20)	20.61	100	1	GNG	No contingent pairing food/critical trial	0	200	0.5	Ad-lib consumption in taste test
Kakoschke, Kemps, Tiggemann (2017b a)	40 (20)	20.08	100	1	AAT	Reversed contingency	0	240	0.5	Ad-lib consumption in taste test

Kakoschke, Kemps, Tiggemann (2017b b)	40 (20)	19.99	100	1	AAT	No contingent pairing food/critical trial	0	240	0.5	Ad-lib consumption in taste test
Kakoschke, Kemps, Tiggemann (2017b c)	40 (20)	20.47	100	1	AAT	Reversed contingency	0	240	0.5	Ad-lib consumption in taste test
Kakoschke, Kemps, Tiggemann (2017b d)	40 (20)	20.38	100	1	SST	No contingent pairing food/critical trial	0	240	0.5	Ad-lib consumption in taste test
Lawrence et al. (2015 a, Study 1)	54 (25)	24.00	59	1	SST	No contingent pairing food/critical trial	0	480	0.33	Ad-lib consumption in taste test
Lawrence et al. (2015 a, Study 2)	90 (46)	24.12	74	1	SST	No contingent pairing food/critical trial	0	512	0.25	Ad-lib consumption in taste test
Lawrence, O'Sullivan, Parslow (2015 b)	83 (42)	50.46	65	0	GNG	Food-unrelated stimuli	1	1080	0.5	Ad-lib consumption in taste test
Lebens et al. (2011)	85 (44)	34.19	100	0	EC	No contingent pairing food/critical trial	1	144	0.5	Snack choice

Lin, Wood, Monterosso (2015, Study 1 a)	23 (8)	NA	83	1	AAT	Reversed contingency	0	60	0.5	Ad-lib consumption in taste test
Lin, Wood, Monterosso (2015, Study 1 b)	23 (8)	NA	83	1	AAT	Reversed contingency	0	60	0.5	Ad-lib consumption in taste test
Maas et al. (2015)	77 (39)	20.3	76	0	AAT	No contingent pairing food/critical trial	0	480	0.5	NA
Porter et al. (2018, Study 1a)	145 (72)	7.66	52	1	GNG	No contingent pairing food/critical trial	0	128	0.5	Snack choice
Porter et al. (2018, Study 2a)	40 (25)	7.53	48	1	GNG	No contingent pairing food/critical trial	0	160	0.5	Snack choice
Porter et al. (2018, Study 2b)	42 (27)	7.53	48	1	GNG	Food-unrelated stimuli	0	160	0.5	Snack choice
Schumacher, Kemps, Tiggemann (2015)	120 (60)	19.7	100	1	AAT	Reversed contingency	0	240	0.5	Ad-lib consumption in taste test
Shaw et al. (2016)	84 (41)	21.8	NA	1	EC	Food-unrelated stimuli	0	120	0.5	Ad-lib consumption in taste test

van Koningsbruggen et al. (2014, Study 1 a)	35 (12)	21.8	54	0	GNG	No contingent pairing food/critical trial	0	72	0.5	Ad-lib consumption in taste test
van Koningsbruggen et al. (2014, Study 1 b)	36 (12)	21.17	63	0	GNG	No contingent pairing food/critical trial	0	72	0.5	Ad-lib consumption in taste test
van Koningsbruggen et al. (2014, Study 2 a)	31 (11)	21.17	63	0	GNG	No contingent pairing food/critical trial	0	72	0.5	Ad-lib consumption in taste test
van Koningsbruggen et al. (2014, Study 2 b)	35 (11)	21.17	63	0	GNG	No contingent pairing food/critical trial	0	72	0.5	Ad-lib consumption in taste test
Veling, Aarts, Papies (2011, Study 2)	46 (22)	21.16	61	0	GNG	No contingent pairing food/critical trial	0	72	0.5	Ad-lib consumption in taste test
Veling, Aarts, Stroebe (2013, Study 1)	79 (38)	21.38	62	0	GNG	Reversed contingency	0	96	0.5	Snack choice
Veling, Aarts, Stroebe (2013, Study 2)	45 (21)	21.5	61	0	GNG	Reversed contingency	0	96	0.5	Snack choice

Veling et al. (2014 a)	38 (13)	23.09	84	1	GNG	Food-unrelated stimuli	1	800	0.5	Food diary data
Veling et al. (2014 b)	42 (13)	22.22	91	1	GNG	Food-unrelated stimuli	1	800	0.5	Food diary data
Verbeken et al. (2018)	36 (15)	12	53	0	GNG_AAT	No contingent pairing food/critical trial	0	1872	0.5	NA
Wang et al. (2017)	102 (50)	21.99	100	1	EC	No contingent pairing food/critical trial	0	100	0.5	Ad-lib consumption in taste test
Warschburger et al. (2018)	129 (78)	13.09	54	1	AAT	No contingent pairing food/critical trial	0	360	0.5	Food diary data

Table 1: List of included studies

Categorical moderators		k	g	se	LL	UL	p Diff	Raw Diff	SE Diff	LL Diff	UL Diff	Diff (95% CI)	p Diff < 0.05
AAT	No	33	-0.27	0.07	-0.41	-0.13	< .001	0.36	0.13	0.11	0.61	0.36 (0.11 ; 0.61)	1
	Yes	14	0.09	0.11	-0.12	0.30							
GNG	No	25	0.01	0.08	-0.14	0.16	.001	-0.40	0.12	-0.63	-0.17	-0.40 (-0.63 ; -0.17)	1
	Yes	22	-0.39	0.09	-0.56	-0.22							
SST	No	41	-0.17	0.07	-0.31	-0.04	.90	0.02	0.18	-0.33	0.38	0.02 (-0.33 ; 0.38)	0
	Yes	6	-0.15	0.17	-0.48	0.18							
GNG + AAT	No	45	-0.17	0.06	-0.30	-0.05	.55	0.26	0.42	-0.57	1.08	0.26 (-0.57 ; 1.08)	0
	Yes	2	0.08	0.42	-0.74	0.90							
EC	No	43	-0.19	0.07	-0.32	-0.06	.17	0.21	0.42	-0.24	0.57	0.21 (-0.24 ; 0.57)	0
	Yes	4	-0.02	0.19	-0.40	0.36							

Taste test outcome	No	15	-0.29	0.11	-0.50	-0.08	.15	0.19	0.13	-0.07	0.45	0.19 (-0.07 ; 0.45)	0
	Yes	32	-0.10	0.08	-0.25	0.04							
Snack Outcome	No	39	-0.10	0.06	-0.22	0.03	.01	-0.38	0.15	-0.68	-0.08	-0.68 (-0.68 ; -0.08)	1
	Yes	8	-0.48	0.14	-0.75	-0.20							
Questionnaire outcome	No	40	-0.18	0.07	-0.32	-0.05	.56	0.10	0.17	-0.24	0.44	0.10 (-0.24 ; 0.44)	0
	Yes	7	-0.08	0.16	-0.40	0.23							
Control group "counter training"	No	36	-0.15	0.07	-0.29	-0.01	.53	-0.10	0.15	-0.40	0.21	-0.10 (-0.40 ; 0.21)	0
	Yes	11	-0.24	0.14	-0.51	0.02							
Control group no contingency	No	20	-0.23	0.10	-0.43	-0.04	.38	0.11	0.13	-0.14	0.36	0.11 (-0.14 ; 0.36)	0
	Yes	27	-0.12	0.08	-0.28	0.04							
Control group non-food stimuli	No	38	-0.15	0.07	-0.29	-0.02	.67	-0.07	0.16	-0.38	0.24	-0.07 (-0.38 ; 0.24)	0

	Yes	9	-0.22	0.14	-0.50	0.05							
Satiety controlled	No	19	-0.26	0.10	-0.45	-0.07	.23	0.15	0.13	-0.10	0.40	0.15 (-0.10 ; 0.40)	0
	Yes	28	-0.11	0.08	-0.26	0.05							
online	No	41	-0.19	0.07	-0.32	-0.06	.28	0.20	0.19	-0.16	0.57	0.20 (-0.16 ; 0.57)	0
	Yes	6	0.01	0.17	-0.33	0.35							
Continuous moderators	range	mean	regression weight	se	LL	UL	p						
number of trials	60-1920	388.6	0.00	0.00	0.00	0.00	0.18						
share of signal trials	0.25-1.00	0.48	-0.73	0.50	-1.71	0.26	0.15						
sample age	7.53-50.5	20.9	0.01	0.01	-0.01	0.03	0.16						
sample BMI	17.6-34.4	22.9	0.06	0.03	-0.01	0.12	0.09						

Table 2: Moderator Analyses for consumption outcome (k: number of studies; g: corrected standardized mean difference; se: standard error, LL, UL: lower and upper level of the 95% confidence interval; p diff: p-value for the test of the difference between the two groups of studies; Raw diff: raw value difference between the two groups of studies; SE diff: standard error of the difference between the two groups of studies; LL diff, UL diff: lower and upper level of the 95% confidence interval of the difference score; Diff (95% CI): difference between the two groups of studies and its 95% confidence interval; p Diff <.05: indication whether the difference score is significantly different from zero at 5% level.

Within-study correlation	*g* (dietary outcome) [95% - CI]	*p* (dietary outcome)	*g* (implicit bias) [95% - CI]	*p* (implicit bias)	Between-study correlation [95% - CI]
0.1	-.17 [-.30; -.05]	.006	-.34 [-.49; -.18]	<.0001	.71 [.44; 1]
0.3	-.17 [-.29; -.05]	.007	-.34 [-.51; -.18]	<.0001	.60 [-.07; 93]
0.5	-.17 [-.29; -.04]	.008	-.35 [-.52; -.19]	<.0001	.49 [-.20; .84]
0.7	-.16 [-.29; -.04]	.009	-.36 [-.53; -.20]	<.0001	.38 [-.32; .77]
0.9	-.16 [-.28; -.04]	.010	-.37 [-.54; -.20]	<.0001	.26 [-.45; .69]

Table 3: Results of the multivariate models with three different within-study correlation coefficients

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	1, 2
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	1-11
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	11-12
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	12
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	13
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	13
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	45
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	13
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	14
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	15

Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	-
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	16
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	16-17

Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	17-18
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	17-18
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	18
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	33
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	-
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	18, 34
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	18-20, 35
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	22, 36
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	20-22, 37-38
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	23-30

Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	30-31
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	23-32
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	32

Table 4: PRISMA statement

From: Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med 6(7): e1000097. doi:10.1371/journal.pmed1000097