AKADÉMIAI KIADÓ

Journal of Behavioral Addictions

10 (2021) 3, 482–497

Special Section on Overweight, obesity and eating disorders in relation to addiction

DOI:
10.1556/2006.2021.00020

FULL-LENGTH REPORT

Awareness drives changes in reward value which predict eating behavior change: Probing reinforcement learning using experience sampling from mobile mindfulness training for maladaptive eating

VÉRONIQUE A. TAYLOR[1†*], ISABELLE MOSELEY[1†], SHUFANG SUN[1], RYAN SMITH[2], ALEXANDRA ROY[1], VERA U. LUDWIG[1,3] and JUDSON A. BREWER[1]

[1] Mindfulness Center, Brown School of Public Health and Warren Alpert Medical School, Brown University, 121 South Main Street, Providence, RI 02903, USA

[2] Laureate Institute for Brain Research, 6655 South Yale Ave, Tulsa, OK 74136, USA

[3] Department of Neuroscience, Perelman School of Medicine & Wharton Neuroscience Initiative, University of Pennsylvania, 106 Steinberg-Dietrich Hall, 3620 Locust Walk, Philadelphia, PA 19104, USA

Received: October 15, 2020 • Revised manuscript received: January 21, 2021 • Accepted: March 6, 2021
Published online: July 15, 2021

ABSTRACT

Background and aims: Maladaptive eating habits are a major cause of obesity and weight-related illness. The development of empirically-based approaches, such as mindfulness training (MT) that target accurate mechanisms of action to address these behaviors is therefore critical. Two studies were conducted to examine the impact of MT on maladaptive eating and determine the involvement of reinforcement learning mechanisms underlying these effects. *Methods:* In Study1, maladaptive eating behaviors were assessed using self-report questionnaires at baseline and 8 weeks after an app-based MT intervention ($n = 46$). A novel mindful eating craving tool was embedded in our intervention to assess: eating behaviors (intake frequency/magnitude), and reward (contentment ratings) experienced after eating. Using a well-established reinforcement learning (Rescorla-Wagner) model, expected reward values (EV) were estimated as a function of contentment levels reported after eating. In Study2 ($n = 1{,}119$), craving tool assessments were examined in an independent sample using the app in a real-world naturalistic context. *Results:* Study 1's results revealed a significant decrease in EV and eating behaviors across craving tool uses. In addition, changes in reward values predicted decreases in eating behaviors. Finally, Study 1's results revealed significant pre-post intervention reductions in self-reported eating behaviors. In Study2, we observed a significant decrease in EV, but not in eating behaviors, across craving tool uses. Study 2 also revealed a predictive relationship between EV and eating behaviors. *Discussion and conclusions:* These results support the implementation of MT to prevent and treat maladaptive eating behaviors, which target reinforcement learning processes as mechanisms of action.

KEYWORDS

maladaptive eating, craving-related eating, mobile mindfulness training, reinforcement learning, computational modeling, reward value

[†]These authors contributed equally to this work.

[*]Corresponding author.
E-mail: veronique_taylor@brown.edu

AKJournals

Maladaptive eating behaviors, such as eating in the absence of hunger, are one of the major causes of obesity (Dietz, 1983), an epidemic and an established risk factor for hazardous psychological consequences (e.g. low self-esteem), physical disease (e.g. cardiovascular disease, diabetes), and mortality (Pi-Sunyer, 2002; Reilly et al., 2003; Thompson, Edelsberg, Colditz, Bird, & Oster, 1999). Thus, the development of behavioral change interventions that are empirically supported and target specific mechanisms of action is of critical importance to address, prevent and treat health-detrimental eating habits.

Currently, popular available treatment approaches primarily focus on strengthening cognitive self-regulatory behaviors (eg. goal-setting, intentional avoidance of cues triggering food craving/over-eating, dietary restraint) (Barte et al., 2010; Butryn, Webb, & Wadden, 2011; Wu, Gao, Chen, & van Dam, 2009). In addition, while treatments under the framework of cognitive behavioral therapy have shown success on reducing binge eating episodes and eating habit management in the short term (Vocks et al., 2010) more empirical support on the long-term maintenance of these effects is needed (Dingemans, Bruna, & van Furth, 2002). Cognitive-behavioral therapy treatments are also not shown to produce successful weight loss (Grilo et al., 2011; Vocks et al., 2010). The low long-term success rates of such approaches (Dombrowski, Knittle, Avenell, Araujo-Soares, & Sniehotta, 2014; Maclean, Bergouignan, Cornier, & Jackman, 2011) may stem from the fact that attempts at top-down regulation over behaviors rooted in lower-level reward-based systems are unlikely to persist (Lowe, 2003), as they do not actually modify reward valuation processes motivating these behaviors. On the other hand, mindfulness-based interventions hold promise in more effectively targeting maladaptive habitual eating (Warren, Smith, & Ashwell, 2017), as they have been proposed to influence addictive behaviors by altering the lower-level reinforcement learning mechanisms responsible for instilling these behaviors in the first place (Brewer, 2019).

Indeed, from the perspective of reinforcement learning (RL) theory (Skinner, 1963), eating behaviors can be reinforced by the consequences resulting from the experience: hedonic or rewarding experiential qualities, or relief from negative affective states (Yeomans, Blundell, & Leshem, 2004). As a result of this reinforcement learning process, exposure to various triggers, ranging from internal (e.g., emotions) to external cues (e.g., situational context), can elicit cravings for food— independently of the organism's physiological need states (Papies & Barsalou, 2015). While there is still some debate as to craving's conceptual definition (White, Whisenhunt, Williamson, Greenway, & Netemeyer, 2002), a proposed definition (Weingarten & Elston, 1990) is that of "an intense desire to consume a particular food or food type that is difficult to resist". In addition, because habitual behaviors resulting from reinforcement learning cycles are typically executed unconsciously (Graybiel, 2008), they can paradoxically continue to be performed despite having the potential to carry *decreased* reward value compared to when they were initially instilled, a process described as reward *de*valuation (Miller, Shenhav, & Ludvig, 2019). In other words, a person may persist in carrying out a maladaptive eating behavior out of habit, simply because this is what has been done previously – but the person may no longer *like* this behavior or the consequences it produces.

The process of learning the reward value of specific behaviors, and making decisions based on those values, may be the key mechanistic aspect through which mindfulness operates to influence maladaptive eating habits (Brewer et al., 2018). For example, learning to purposefully pay attention to present-moment experiences through mindfulness training (Kabat-Zinn, 1994), has been proposed to foster the recognition of a maladaptive eating habit behavior's reward value (Brewer et al., 2018). This approach fosters the development of skills for the individual to become aware of and attuned to the reinforced relationships between cues, food cravings, and maladaptive eating behaviors. Importantly, mindfulness may promote awareness of the persistence of an eating habit which has *lost* its reward value, by promoting the identification of the negative consequences resulting from the behavior (e.g., *discontentment* from having eaten, such as that induced by gastrointestinal discomfort, or guilt/self-blame). In this sense, mindfulness has been proposed to *re-calibrate* reward values assigned to habitual eating behaviors by intentionally directing attention towards, and becoming aware of, the full range of the consequences of those behaviors (Brewer, 2019; Brewer et al., 2018; Ludwig, Brown, & Brewer, 2020).

In support of the effectiveness of mindfulness-based approaches for maladaptive eating behaviors, Mason, Jhaveri, Cohn, and Brewer (2018) found that app-based mindfulness training attenuated cravings for food and induced a 40.21% reduction in craving-related eating behaviors after one month in overweight or obese women. Moreover, mindfulness training was shown to attenuate the relationship between cravings and unhealthy habitual behavior after 4 weeks, an effect observed with respect to cigarette cravings and smoking (Elwafi, Witkiewitz, Mallik, Thornhill, & Brewer, 2013). Such decoupling between appetitive urges to consume craved items and the engagement in consummatory behaviors is indicative that mindfulness plays a role in dismantling key automated links involved in reinforced habit-driven behavior patterns. However, the hypothesis that mindfulness training targets the critical aspect of reward value reduction assigned to maladaptive eating has not been empirically addressed.

One commonly used and well-established reinforcement learning model, the Rescorla-Wagner model (1972), posits that learned expectations of reward are updated as a function of a prediction error term, or the discrepancy between the rewarding properties *actually* experienced from an outcome and those which were *expected* to be experienced. For example, if an individual has previously encoded a high reward value from eating a piece of cake at a bakery, encountering the smell of freshly baked pastries from this bakery would likely activate the past learned associative memory. Thereby, upon encountering the triggering cue (the smell of pastries), the individual may expect high levels of reward from performing this behavior (i.e., eating) and automatically carry it out (i.e., walking inside the bakery, purchasing and eating the cake). However, if the actual consequence experienced from eating is highly discrepant from what had been expected – for example, if the individual notices feeling strongly discontent from having eaten due to sluggishness and gastrointestinal discomfort – the reward value assigned to eating the cake will be updated as lower than the previously stored (and expected) value.

In addition to expected values of rewards reflecting learned predictions concerning the reward signal a behavior is expected to produce (Barto, 1998), another aspect directly motivating behavior involves the motivational impetus or urge to perform a behavior that is elicited by a conditioned cue (Berridge, 2012). This urge or 'wanting' aspect not only reflects the expected reward value acquired from past learning experiences, but additionally encompasses motivational factors specific to the present moment (hunger signals, stress, etc.) (Berridge, 2012). This dimension can be conceptualized as 'present-moment reward values', reflective of the expected rewarding properties a behavior will produce in conjunction with the experience of one's current motivational state (Berridge, 2012). For example, the smell of a bakery may trigger an especially potent urge to eat one's favorite piece of cake if this cue were to be encountered on an empty stomach. However, this cue may not trigger the urge to eat to such an extent if encountered just after having eaten a copious meal.

Here, the overarching goal of this research project was to determine whether an app-delivered mindfulness training intervention would improve maladaptive eating behaviors by specifically altering reinforcement learning processes. To address this, two studies were conducted. In Study 1, 64 females (average body mass index >25) were administered our app-based mindful eating intervention over a period of 8 weeks. Participants were instructed to 1) complete the app's core mindfulness training modules (brief video session trainings aimed at providing insight into habitual eating mechanisms, becoming attuned to the reasons motivating habitual eating, and developing mindful eating skills) (Mason et al., 2018), and 2) use our novel mindful eating craving tool whenever they experienced a food craving. The advantage of this novel craving tool is that it can be available to participants at the exact moment that cravings are experienced. In addition, it offers the advantage of being used in the individual's naturalistic setting and context in which cravings are triggered. Specifically, the following aims were addressed for each study. First, Study 1's objective was to examine the effectiveness of our app-based mHealth intervention on self-reported maladaptive eating behaviors, which we expected to be attenuated following our intervention given our previous observations of mindfulness training on this type of outcome (Mason et al., 2018). Second, the objective of Study 1 was to investigate whether reinforcement learning processes operated as mechanisms of eating behavior change underlying our intervention. To address this, we examined the trajectory of reward values (expected values of reward, and present-moment reward values) as well as maladaptive eating behavioral outcomes (frequency/magnitude of food intake) across uses of our mindful eating craving tool embedded in our intervention. We also determined whether changes in reward valuation predicted the extent of changes in eating behavioral outcomes. Based on the notion that mindfulness may influence habitual behaviors by inducing the re-calibration of reward values due to the allocation of attention to the behavior's consequences (Brewer et al., 2018), we hypothesized that reward values and eating behaviors (frequency and food intake magnitude) would significantly decrease across the number of mindful craving tool uses. We also hypothesized that the extent of changes in reward valuation would predict corresponding changes in maladaptive habitual eating behaviors. Finally, the objective of Study 2 was to prospectively examine whether the effectiveness of our novel craving tool on reward valuation and corresponding changes in eating behaviors would be replicated in a larger independent sample within the general community using our mHealth intervention outside the context of a clinical study.

Table 1. Participant characteristics

Characteristics	*M*	SD	Range
Age (yrs)	53.42	10.57	21–68
Weight (lbs)	190.18	41.27	105–280
BMI	33.00	7.16	19.88–50.74
		N	%
Craved food type			
Sweet		45	70.31
Salty		19	29.69
Ethnicity			
White/Caucasian		59	92.19
Hispanic		1	1.56
Pacific Islander		1	1.56
Asian		1	1.56
Black		1	1.56
Multiracial		1	1.56
Meditation experience			
Prior meditation experience		38	59.38
Daily meditation practice		32	50

STUDY 1: METHODS

Participants

A total of 64 female participants were included in this study, who were, on average, overweight as defined by having a body mass index (BMI) above 25 (Williams, Mesidor, Winters, Dubbert, & Wyatt, 2015)). Participant characteristics at baseline are displayed in Table 1 and explicitly listed in Supplementary Materials.

Recruitment procedure

Participants were recruited through social media advertising (e.g., Facebook), following a procedure and inclusion criteria fully described in Supplementary Materials. A Consolidated Standards of Reporting Trials (CONSORT) diagram (Fig. 1) illustrates the participant flow process for the study: of the 136 participants who were assessed for eligibility, 41 did not meet all inclusion criteria and 9 declined to participate. Of the 86 participants deemed eligible for the study, 64 participants enrolled (22 participants canceled or did not attend baseline assessment appointments). Of the 64 participants who enrolled in the study, 46 (71.9%) completed post-intervention assessments (N = 18 did not respond to post-

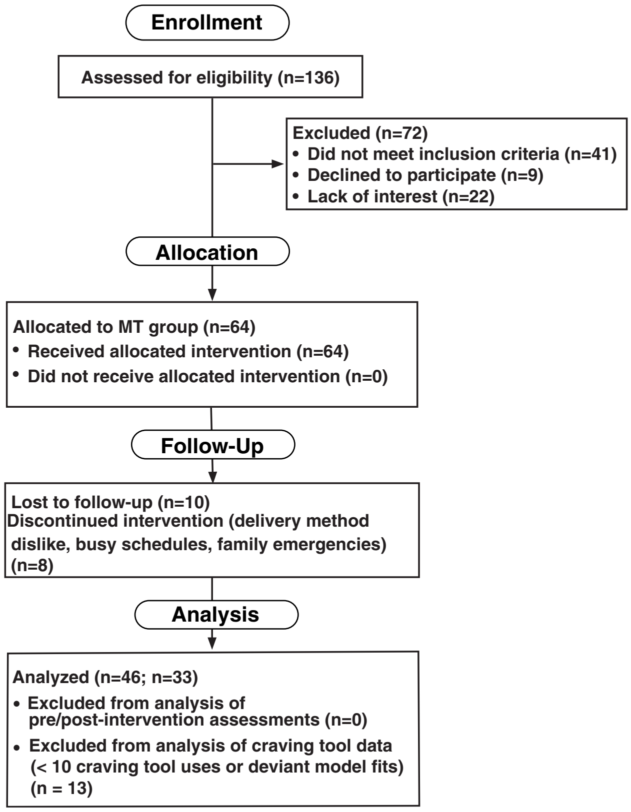

Fig. 1. Participant flow CONSORT diagram for Study 1

intervention completion invitations). These retention rates are comparable to those reported in other studies using mHealth interventions (Brindal et al., 2013; Carter, Burley, Nykjaer, & Cade, 2013; Thomas & Wing, 2013).

Experimental procedure

Participants were screened during a telephone interview for eligibility. Eligible individuals were invited to the laboratory (Mindfulness Center, Brown University, Providence RI) for a baseline assessment, during which they provided informed consent for participating in the study. Participants' height and weight were recorded, and they filled out a battery of baseline questionnaires using Qualtrics Survey Tool (see *Baseline and Post-Intervention Assessments of emotional and habitual eating*). Finally, a study coordinator instructed participants on how to use the app-based mindful eating intervention and encouraged to use it over the following eight weeks by 1) completing the app's core mindfulness training modules, and 2) using the mindful eating craving tool when they experienced food cravings. Eight weeks after having completed baseline assessments, participants were invited to complete the same questionnaires administered at baseline using Qualtrics Survey Tool. Mindful eating craving tool data were assessed each time the tool was used and were recorded via the app's electronic database. Participants received a $10 Amazon gift card upon the completion of baseline assessments, and a $20 Amazon gift card following the completion of post-intervention assessments.

MHealth mindfulness intervention

Delivered in the form of an app compatible with common smartphone device platforms (iOS and Android), the app-based mindfulness training intervention (Eat Right Now®) emphasizes the development of mindfulness training skills to help individuals improve their eating habits. The core of the app's program is comprised of over 28 daily modules intended to help individuals become attuned to the reasons motivating their unhealthy eating habits (e.g., emotional triggers rather than hunger), as well as the types of foods they tend to habitually overeat. The training modules also introduce participants to mindful eating skills. Each module teaches a new mindfulness technique through a brief video lecture (typically 6–8 minutes) (Mason et al., 2018). Participants were instructed to engage in the completion of these training modules at a self-paced rate (sequential modules were "locked" such that only one module could be completed per day to prevent "content binging") during the 8-week intervention period. Participants had the opportunity to repeat training modules previously completed as many times as desired. The effectiveness of these mindfulness training modules was previously demonstrated (Mason et al., 2018): completion of the app's module-based intervention was shown to be effective in reducing craving-related eating (40.21% reduction) in women with overweight and obesity. In addition to completing the mHealth intervention's core training modules, participants were instructed to use the mindful eating craving tool whenever they experienced a food craving over the course of the 8-week period as part of the intervention.

Mindful eating craving tool

The app's mindful eating craving tool consisted in a mindful eating exercise that was to be practiced when participants experienced a food craving. This involved: the simulation of an experience eating the craved food (Fig. 2A, Screenshot1), indicating the strength of their food craving relative to their baseline craving level (Fig. 2A, Screenshot2), and an option to eat or refrain from eating the craved food (Fig. 2A, Screenshot2). If participants refrained from eating, the exercise resumed, but if they chose to eat, they were invited to rate the magnitude of their intake (Fig. 2A, Screenshot3) and to direct mindful awareness towards the present-moment experience (bodily sensations, emotions, thoughts) induced by eating as well as provide a rating of their contentment levels from having eaten (Fig. 2A, Screenshot4). A conceptual model of the sequence of events, learning or behavioral processes occurring while using the craving tool is depicted in Fig. 2B. The full description of the app's use is included in the Supplementary Materials.

Measures

Baseline assessments: demographic variables and body mass index. Age, sex, meditation experience (whether participants had any prior experience in meditation, and whether they practiced meditation daily), as well as the types of foods craved, were recorded via self-report assessments during baseline testing sessions. Body mass index (BMI) was

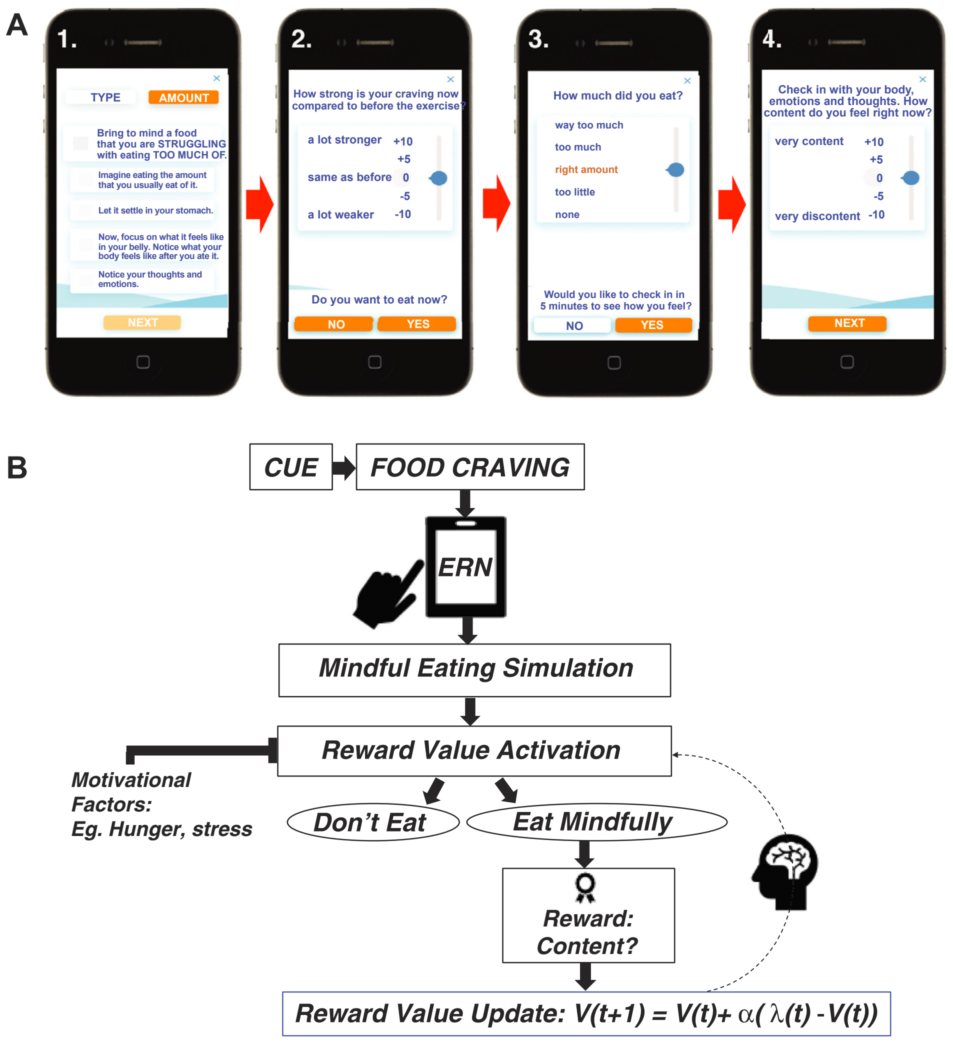

Fig. 2. A) Screenshots illustrating a prototypical craving tool use. Upon the experience of a food craving, participants initiated the use of the craving tool by mentally simulating the experience of eating the craved food (Screenshot1), after which they indicated the intensity of their food craving with respect to their baseline craving level (Screenshot2). If participants chose to eat the craved food by answering "Yes" to the question "Do you want to eat now?" (Screenshot2), they were prompted to rate the amount of food eaten (Screenshot3) as well as the contentment level they experienced after having eaten (Screenshot4). B) Diagram illustrating the theoretical model depicting the involvement of reinforcement learning mechanisms underlying the impact of mindfulness on maladaptive eating habits. The equation depicts the Rescorla-Wagner reinforcement learning model used to compute expected reward values (V) at each craving tool use or trial (t), as a function of the prediction error which is weighed by a fixed learning rate parameter (α). The prediction error is defined as the discrepancy between the outcome of the behavior (λ), i.e. contentment level experienced from eating, and the expected reward value of eating acquired from the previous encounter with the behavior. ERN: Eat Right Now app-based mindfulness training program.

obtained by dividing participants' weight (kg) by the squared value of their height (m^2). Participants' weight was recorded using a digital scale and their height was assessed using a calibrated stadiometer.

Baseline and post-intervention assessments of emotional and habitual eating. The self-report questionnaires Salzburg Stress Eating Scale (SSES), Reward Based Eating Drive (RED) Scale, and Food Craving Questionnaire-Trait, Reduced (FCQ-T-r) were administered at baseline and post-intervention assessments to assess the impact of the mindfulness intervention on participants' emotional and habitual eating patterns. Each scale is more thoroughly described in the Supplementary Materials.

Intervention completion. The number of mindful training modules completed by participants (M = 26.68, SD = 18.68) were recorded via the app's electronic database.

In-the-moment experience sampling assessments using the mindful eating craving tool app

Present-moment reward values. Immediately after completing the mindful eating simulation implemented in the tool's exercise, participants rated the intensity of their craving (relative to their baseline craving level, i.e. before the initiation of the mindful eating simulation exercise). (Fig. 2A. Screenshot2). To do this, they answered the question 'How strong is your craving now compared to before the exercise?' using a sliding Likert scale ranging from – 10 to +10 (−10 = *a lot weaker*, 0 = *same as before*, +10 = *a lot stronger*). A score equal to or greater than zero indicated that the behavior's reward value was experienced as elevated relative to when they started the simulation exercise, whereas a negative score indicated that the behavior's reward value was experienced as lower than when they started the exercise. Scores were divided by 10 in order to be rescaled between −1 and 1 for data analysis.

Eating behaviors. When prompted by the question 'Do you want to eat right now?' following the mindful eating simulation, participants' decisions to eat or not were recorded as 1 ('Yes') or 0 ('No'), which determined the frequency of eating behaviors following each craving tool use (Fig. 2A. Screenshot2). Participants' amount of food eaten was also recorded on a Likert scale ranging from 1 to 5 (*1 = none, 2 = too little, 3 = right amount, 4 = too much, 5 = way too much*, Fig. 2A. Screenshot3).

Contentment experienced from eating. If participants chose to eat the craved food after having completed the mindful eating simulation exercise, they were asked to pay mindful attention towards the present-moment phenomenological qualities experienced after having eaten (bodily sensations, thoughts, emotions), and rate the extent to which they felt content from having eaten (Fig. 2A. Screenshot4). To do this, participants received the prompt 'Check in with your body, thoughts, and emotions. How content do you feel right now?' after having eaten, and entered their contentment rating using a Likert Scale (−10: very discontent, +10: very content). Scores were divided by 10 in order to be rescaled between −1 and 1 for data analysis.

Data analysis

A total of $N = 46$ participants were included in the analysis of pre/post-intervention self-report assessments of maladaptive eating behavior data. For analyses of craving tool data, deviant values of Aikake Index Criterion fit indices obtained from the learning models were found for a participant with an extreme value for number of craving tool uses (> 4 SD from the mean). This participant was therefore excluded, and to ensure the inclusion of sufficient datapoints per participant to depict learning and behavioral trajectories across time, a cutoff of 10 craving tool uses was applied as a criterion for inclusion in the analyses, yielding a remaining total of $N = 33$ subjects in the analyses. On average, participants used the craving tool 27.53 times (SD = 12.15). Significance levels were set at a threshold of $P < 0.05$.

Computational reinforcement learning model descriptions. A Rescorla-Wagner model of reinforcement learning (Rescorla and Wagner, 1972) was used (Supplementary Materials: Equation 1) to estimate participants' expected reward values assigned to their eating behaviors as a function of the rewarding consequences of the behavior – i.e., the contentment experienced from eating. Next, in order to compare the goodness of fit of our learning model to our data with that of alternative types of RL models, we also estimated expected values using a learning model (Rescorla-Wagner/Pearce-Hall Hybrid Model) in which learning rates were dynamically updated at each trial (Supplementary Materials: Equations 3–4). The softmax function was used to compute the expected likelihood of selecting an action (eating or not eating) at each trial (Supplementary Materials: Equation 2). Full model description is included in the Supplementary Materials.

Learning model selection. Model fit indices (Akaike Information Criterion or AIC) were computed for each participant and compared between models to determine the model which best fit the data. Paired-samples t-tests on AIC fit indices revealed that model fits were superior for the Rescorla-Wagner model relative to the Rescorla-Wagner Pearce-Hall Hybrid model ($P < 0.001$). The fact that the RW model fit our data best indicates that reward value learning in the context of craving-related eating was more accurately modeled using a static learning rate, rather than using learning rates which dynamically fluctuate based on prediction error magnitude. Average probability that the observed action was selected was of 0.69.

Finally, to explore whether free parameters estimated from the model were associated with any behavioral outcome assessed in this study, pairwise correlation analyses were conducted between learning model parameters (learning rate, inverse temperature, v0_eat, v0_no_eat) and behavioral outcome variables (baseline SSES, FCQ-t, and RED scores, as well as difference scores between post-intervention and baseline assessment scores on each of these measures).

Multi-level regression analyses. Multi-level regression analyses were conducted using SPSS statistical analysis software package (SPSS, Inc.) to examine trajectories of reward values (expected reward values and present-moment reward values), expected likelihood of eating (as estimated from our RL model) and eating behaviors across craving tool uses, as well as the relationship between reward valuation processes and eating behaviors. To do this, TIME (craving tool use number) was entered as a first-level predictor of the following outcome variables: expected reward values, present-moment reward values, expected likelihood of eating, decisions to eat or not, and magnitude (amount) of eating intake. Separate models were run using each targeted outcome as the dependent variable.

Next, to evaluate the relationship between reward valuation processes and eating behaviors, multi-level regression models were conducted using expected reward values as a first-level predictor of eating behavior outcomes. Separate models were run on decisions to eat or not and eating intake amounts as dependent variables. Similarly, multi-level regression models were also conducted using present-moment reward values as a first-level predictor of each eating behavior outcome variable (frequency of eating intake, amount of food eaten), as well as using the expected likelihood of eating at each trial as a first-level predictor of each eating behavior outcome variable. Finally, to determine the correspondence between expected and present-moment reward values, multi-level regression analysis was used to determine the predictive relationship between expected reward values (1st-level predictor) and present-moment reward values (outcome variable). For all multi-level regression analyses described and reported here, logistic regression model was used for models conducted on the categorical outcome variable (trial-by-trial decisions to eat or not), whereas linear regression was used for models including continuous outcome variables (present-moment reward values, expected reward values, amount of food eaten, and expected likelihood of eating at each trial).

Effects of the intervention on self-reported eating behaviors. Paired t-tests using time (pre-, post-intervention) as a within-subjects factor were conducted on each outcome variable assessing self-reported eating behavior patterns (SSES, RED, FCQ-T-r scale scores). Effect sizes were also computed in Cohen's d units as well as their corresponding 95% confidence interval (0.20, small; 0.50, medium; 0.80, large) (Cohen, 1988).

Ethics

This study was approved by the Brown University Institutional Review Board. Each participant signed the study consent form and provided informed consent prior to study participation.

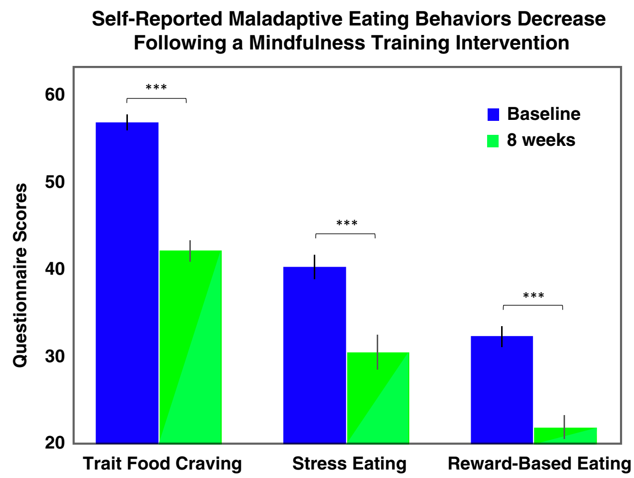

Fig. 3. Scores on the Salzburg Stress Eating Scale (SSES), reward eating drive scale (RED), and trait food craving questionnaire (FCQ-T-r) as assessed at baseline and at 8 weeks following the start of the app-based mindfulness training intervention. Means (error bars represent standard errors of the mean) are displayed for each scale by time of assessment. ***$P < 0.001$ obtained from paired-samples t-tests

STUDY1: RESULTS

Effects of the mindfulness intervention on self-reported eating behaviors

To assess changes in self-reported maladaptive eating behaviors induced by our intervention, we compared self-report assessments of each of these outcome variables at the eight-week follow-up to those obtained at baseline. We found significant pre/post-intervention reductions on all three self-report assessments of self-reported eating outcomes. First, paired t-tests revealed significant reductions from baseline at post-intervention assessments in stress eating ($t_{(45)} = 6.83$, $P < 0.001$, M = 40.39 and $SE = 0.80$ at baseline, $M = 30.59$ and $SE = 1.28$ post-intervention). This reduction corresponded to a large effect size of change, as reflected by Cohen's $d = 1.35$. The same pattern of results were obtained with respect to reward eating drive ($t_{(45)} = 8.16$, $P < 0.001$, M = 32.44 and SE = 1.18 at baseline, M = 21.89 and SE = 1.41 post-intervention), and trait food craving ($t_{(45)} = 8.11$, $P < 0.001$, M = 56.93 and SE = 1.40 at baseline, M = 42.24 and SE = 2.01 post-intervention). These effects also corresponded to large effect sizes of change, as reflected by Cohen's d measures of effect sizes ($d = 1.19$, $d = 1.25$ for RED and FCQ-T-r respectively). Means and standard errors of the mean are illustrated in Fig. 3.

Effects of the mindful eating craving tool use on reward valuation and eating behaviors

Modulation of reward valuation processes and eating behavior across time. To determine whether reward values, expected likelihood of eating (estimated from our RL model), as well as eating behaviors (frequency/intake amount) exhibited significantly decreasing slope trajectories across craving tool uses, we conducted multi-level regression analyses on reward values (expected and present-moment reward values) and expected likelihood of eating using TIME (number of craving tool uses) as a first-level predictor, and individual subject as the 2nd-level predictor. Results revealed that expected reward values estimated from the Rescorla-Wagner computational reinforcement learning model exhibited significantly decreasing slopes across number of craving tool uses ($B = -0.006$, SE = 0.002, $t = -4.15$, $P < 0.001$, Fig. 4A). No significant effect of time was found with respect to present-moment reward values ($B = -0.002$, SE = 0.002, $t = -0.79$, $P = 0.437$). Expected likelihood of eating estimated from our RL model also significantly decreased across TIME ($B = -0.013$, SE = 0.003, $t = -4.19$, $P < 0.001$, Fig. 4B). In other words, we observed a significant decrease in expected reward values (but not present-moment reward values) as well as a significant decrease in the expected likelihood that participants opted to eat across number of craving tool uses.

Eating intake frequency and eating amounts also exhibited decreasing slopes across number of craving tool uses ($B = -0.007$, SE = 0.002, $t = -4.45$, $P = 0.005$, for decisions to eat or not, $B = -0.013$, SE = 0.003, $t = -4.25$, $P = 0.001$, for eating amount). In other words, participants ate significantly less (opted fewer times to eat and reported reduced eating intake) across number of craving tool uses.

Predictive impact of reward valuation processes on eating behaviors. To examine whether changes in reward valuation processes predicted participants' eating behavior, we conducted multi-level regressions on eating behavior (frequency/intake amount) using reward values and expected

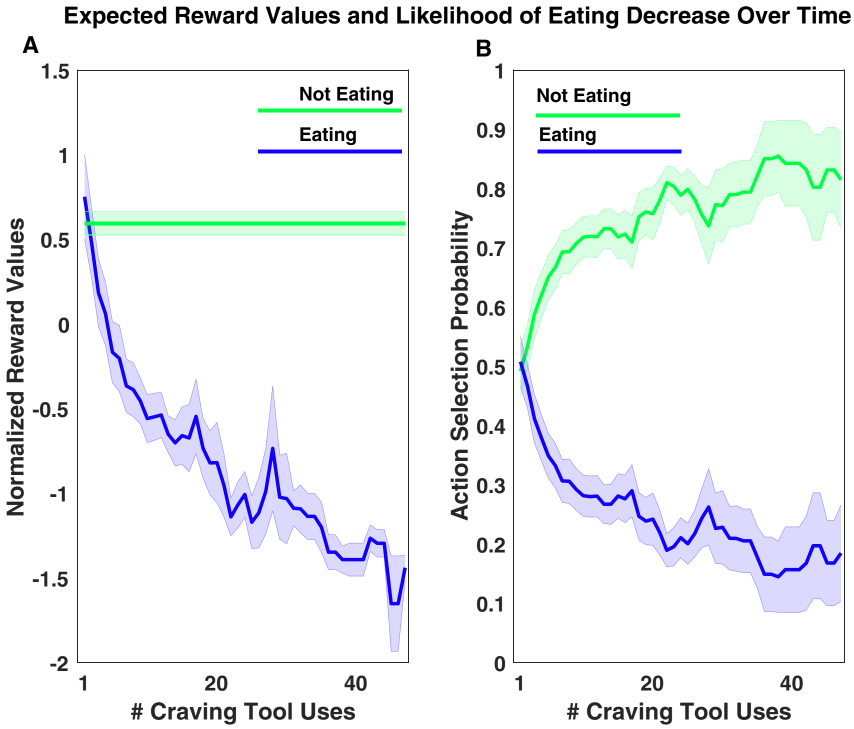

Fig. 4. A) Mean expected reward values for participants in Study1 (n = 33, shaded areas represent standard errors of the mean) by number of mindful eating craving tool uses. B) Mean expected likelihood of selecting each action for participants in Study1 (eating or not eating) across craving tool uses, with shaded areas representing standard errors of the mean

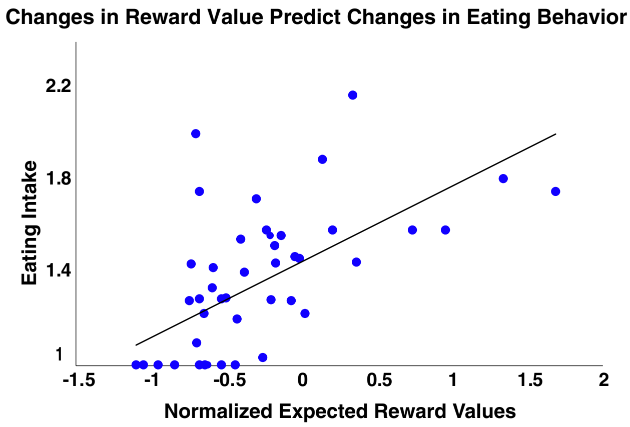

Fig. 5. Amount of food intake by normalized expected reward values for participants in Study1 (averaged across participants) at each craving tool use

likelihood of eating as first-level predictors, and individual subject as the 2nd-level predictor. These analyses revealed that expected reward values significantly predicted eating frequency (B = 0.162, SE = 0.060, t = 2.72, P = 0.007) as well as the amount of food intake at each craving tool use (B = 0.324, SE = 0.131, t = 2.48, P = 0.020, for eating amount, Fig. 5). In addition, multi-level regression model analyses revealed a significant predictive effect of present-moment reward values on frequency of eating intake (B = 0.473, SE = 0.052, t = 9.19, P < 0.001) as well as eating amount reported at each craving tool use (B = 0.985, SE = 0.114, t = 8.65, P < 0.001).

Finally, multi-level regression analysis revealed that the expected likelihood of eating (estimated from our RL model) predicted decisions to eat or not (B = 0.100, SE = 0.062, t = 16.083, P < 0.001). In other words, both expected and present-moment reward values, as well as expected likelihood of eating predicted eating behaviors (frequency/intake amount): higher reward values and higher expected likelihood of eating predicted increased eating, whereas lower reward values/expected likelihood of eating predicted reduced eating behavior across craving tool uses.

Correspondence between present-moment and expected reward values. In order to assess the correspondence between both variables, we assessed the predictive relationship between expected reward values (1st level predictor) over present-moment reward values using multi-level regression analyses. These revealed a significant positive predictive effect of expected reward values over present-moment reward values (B = 0.137, SE = 0.070, t = 1.96, P = 0.051). In other words, higher expected reward values for eating predicted higher present-moment reward values for eating, whereas vice versa, lower expected reward values for eating predicted lower present-moment reward values.

RL model parameters and emotional/habitual eating outcomes. To explore whether parameters estimated from our RL model reflected individual participant characteristics related to emotional or habitual eating, we conducted pairwise correlations between subjects' individual parameter estimates (learning rate, inverse temperature, v0eating, v0no_eating) and habitual/emotional eating questionnaire outcomes (baseline scores on SSES, FCQ-t, RED, as well as pre-post difference scores on each of these scales). These analyses revealed no significant relationship between individual parameter estimates and participant characteristics related to emotional/habitual eating.

STUDY2: METHODS

Study 2's aim was to examine whether the effects related to the use of our novel embedded mindful eating craving tool on eating reward valuation and eating behaviors would be prospectively replicated in a larger independent sample of individuals using the app-based mindful eating intervention outside the confines of a clinical research setting.

Participants

Inclusion criteria for this study were determined as participants having initiated the start of the app-based mindful eating intervention between July 1st 2019 to April 29th 2020. For data analysis purposes, the sample was divided into two subsets based on frequency of craving tool usage: 76 had used the tool 10 or more times, though one participant with a deviant number of trials (6 SD from the mean) was excluded yielding a remaining of 75 participants having used the tool more than 10 times for data analysis ($M = 15.29 \pm 6.97$ app uses, sex: 59 Females, 16 Males, $M = 49 \pm 14$ years of age). In addition, a total of 1,044 individuals had used the tool less than 10 times (3.22 ± 1.67 uses on average, sex: 810 Females, 228 Males, 6 Other, $M = 45 \pm 13$ years of age). For clarity, these distinct subsamples are further referred to as the high-use sample, and low-use sample, respectively. The aggregated sample size for this study (both high- and low-use samples combined) included in data analysis was of 1,119 participants.

Intervention

Participants had access to the same 28 core training modules and mindful craving tool described in Study 1. Subjects were not invited to the laboratory for assessment sessions or given any explicit instructions concerning the completion of the intervention.

Measures

Data related to the mindful eating craving tool were directly recorded in the app's database. The same measures specific to the use of the craving tool described in Study 1 (present-moment reward values, contentment experienced from eating, decisions to eat or not and amounts of food eaten at each craving tool use) were used to examine modulations of reward valuation and eating behaviors across craving tool uses, as well as the predictive relationship between the two. For the subset of participants having used the craving tool more than the cutoff value of 10 times, average craving tool use was 19 times (SD = 26.58) for the high-use sample, and average number of mindfulness training modules completed was of 55.95 (SD = 61.62), whereas average craving tool use was of 3.22 ± 1.67 times with an average of 38.25 ± 49 modules completed for the low-use sample.

Data analysis

Computational modeling. As in Study 1, a computational Rescorla-Wagner reinforcement learning model was used (Supplementary Materials: Equation 1) in participants with >10 craving tool uses (the high-use sample) to estimate eating behavior reward values for each action (eating/not eating) at every craving tool use. Expected likelihood of selecting each action at every trial was also computed as in Study 1 using the softmax function (Supplementary Materials: Equation 2).

Similar to Study 1, in order to compare the fit of our model with an alternative type of RL model, a RW/Pearce-Hall Hybrid RL model was also conducted (Supplementary Materials: Equations 3–4). As in Study 1, a paired t-test comparing AIC fit indices between models (RW and RW/Pearce-Hall) revealed that the RW model had a superior fit to our data compared to the RW/Pearce-Hall ($ps < 0.001$).

This indicates that data from this independent sample was also better modeled by a learning rule including a static learning rate, as opposed to learning rates which dynamically shift across trials. The RW model's average likelihood of selecting the observed action was of 0.72.

Next, for participants in the low-use sample ($N = 1{,}044$) that had fewer data time points available for reliable model parameter estimation, reward values were computed using the same Rescorla-Wagner model as for the high-use sample (Equation 1), and used as variables in multi-level regression models. However, parameters for these subjects (learning rate, V0_no_eat, V0_eat, inverse temperature) were estimated using empirical priors obtained from the high-use sample dataset, a method described in previous work (Gershman, 2016). The average probability that the observed action was selected for this low-use subsample was of 0.78. The details for the implementation of this approach are listed in the Supplementary Materials.

Multi-level regression analyses. Reward values (expected and present-moment reward values) as well as expected likelihood of eating were used as first-level predictors in multi-level regression analyses to examine trajectories across craving tool uses of reward value modulations, as well as eating behaviors (decisions to eat or not, and eating intake amount). Multi-level regression analysis was also used to determine the trial-by-trial predictive impact of reward valuation processes (expected reward values, present-moment reward values, expected likelihood of eating) on eating behavior (food intake frequency and amount). Finally, to determine the correspondence between expected reward values and present-moment reward values, multi-level regression analysis was also used to assess the predictive relationship between expected reward values (1st-level predictor) and present-moment reward values (outcome variable). As in Study 1, logistic regression was used in models conducted on the categorical dependent variable (decisions to eat or not), and linear regression was used in models conducted on all of the other continuous variables (expected reward values, present-moment reward values, expected likelihood of eating, and amount of food intake). These analyses were first conducted in the high-use sample. Next, using empirical priors from these participants to compute expected reward values in the low-use sample, we examined whether the same pattern of results would be found in the low use sample. Having confirmed similar general results patterns in each sample, unless otherwise specified we now report additional results for the full combined sample for clarity and brevity. Results reported below are listed, however, in Supplementary Materials, for both the high- and low-use sample separately. In addition, because participants in Study 2 included other sexes than the female-only sample of Study 1, sex was included as an interaction term with 1st level predictors for all multi-level models specified. Because all interaction terms yielded non-significant effects over the outcome variables of the models, analyses were conducted without interaction terms, and these are not discussed further.

Ethics

As the data included in this study were de-identified app-based observations, after review, this study was deemed exempt from oversight by the Brown University Institutional Review Boards as per United States' federal regulations (45 CFR 46.104).

STUDY2: RESULTS

Modulation of reward valuation processes and eating behavior across time

To examine whether reward values and expected likelihood of eating (estimated from our RL model) significantly decreased across TIME, we conducted multi-level regression analyses on these outcome variables using TIME (number of craving tool uses) as a first-level predictor, and individual subject as the 2nd-level predictor. As in Study 1, results revealed a significantly decreasing slope of expected reward values ($B = -0.03$, SE $= 0.002$, $t = -15.02$, $P < 0.001$, Fig. 6A and C) but not present-moment reward values ($B = -0.001$, SE $= 0.002$, $t = -0.67$, $P = 0.507$) across number of craving tool uses. Also in line with results from Study 1, expected likelihood of eating exhibited significantly negative slopes across number of craving tools uses ($B = -0.05$, SE $= 0.003$, $t = -17.58$, $P < 0.001$, Fig. 6B and D). In other words, we replicated results from Study 1, such that participants in Study 2 also exhibited significant reductions in expected reward values and expected likelihood of eating, but not in present-moment reward values, across time.

Next, to determine whether eating behaviors (frequency/intake amount) significantly decreased across time, we conducted multi-level regression analyses on eating behavior outcome variables (frequency/intake amount) using TIME as a first-level predictor, and individual subject as a 2nd-level predictor. In contrast to results obtained from Study 1, eating intake frequency ($B = -0.004$, SE $= 0.003$, $t = -1.48$, $P = 0.153$) and eating intake ($B = -0.01$, SE $= 0.006$, $t = -1.80$, $P = 0.117$) did not exhibit a significant negative slope trajectory across number of craving tool uses in the high-use subsample. The low-use sample of participants exhibited an increase in eating decisions across time ($B = 0.011$, SE $= 0.006$, $t = 2.06$, $P = 0.040$), but no significant difference in food intake across number of craving tool uses ($B = 0.020$, SE $= 0.013$, $t = 1.50$, $P = 0.135$). In other words, the reduction in eating frequency and intake across number of craving tool uses observed in Study 1 was not replicated in participants from Study 2: eating intake did not show significant changes across time in these participants, and participants having used the tool less than 10 times opted to eat more often across trials.

As the increased eating frequency across TIME in Study 2's low-use sample was in the opposite direction as that found in Study 1's participants who showed decreased eating frequency and intake across TIME, post-hoc follow-up analyses were conducted to examine the presence of non-linear trajectory changes in eating frequency across TIME in these participants (Study 2's low-use sample). Thus, we examined changes in eating frequency by modeling a U-shape trajectory across TIME as first-level predictor (quadratic term for the effect of TIME), revealing a significant inverted U-shaped pattern in eating frequency across time ($B = -0.013$, SE $= 0.002$, $t = -5.75$, $P < 0.001$). To determine trial number peaks for this inverted U-shaped pattern, linear effects of TIME were examined separately in participants with varying numbers of app uses. These analyses revealed that participants with 2 ($B = 0.10$, SE $= 0.029$, $t = 3.64$, $P < 0.001$) and 3 craving tool uses ($B = 0.06$, SE $= 0.02$, $t = 3.15$, $P = 0.002$) exhibited increased eating frequency across trials. While participants with 4 trials showed a trend for significance in increased eating frequency ($B = 0.035$, SE $= 0.018$, $t = 1.91$, $P = 0.058$), those with 5 or more showed no change (all $ps > 0.143$) or a decrease (participants with 7 app-uses: $B = -0.032$, SE $= 0.015$, $t = -2.16$, $P = 0.032$) in eating frequency. In other words, in the low-use sample, eating frequency follows an inverted U-shaped function depicting increased frequency over the first 2 to 3 trials, followed by a drop over the remaining trials.

Predictive impact of reward valuation processes on eating behaviors

Finally, to determine whether changes in reward valuation predicted eating behavior across time, we conducted multi-level regression analyses on eating behavior (frequency/intake amount) using reward values and expected likelihood of eating (estimated from our RL model) as first-level predictors, and individual subject as a 2nd-level predictor. As found in Study 1, expected reward values significantly predicted eating behaviors ($B = 0.788$, SE $= 0.040$, $t = 19.70$, $P < 0.001$; $B = 1.676$, SE $= 0.100$, $t = 16.68$, $P < 0.001$ for decisions to eat or not and eating intake amount

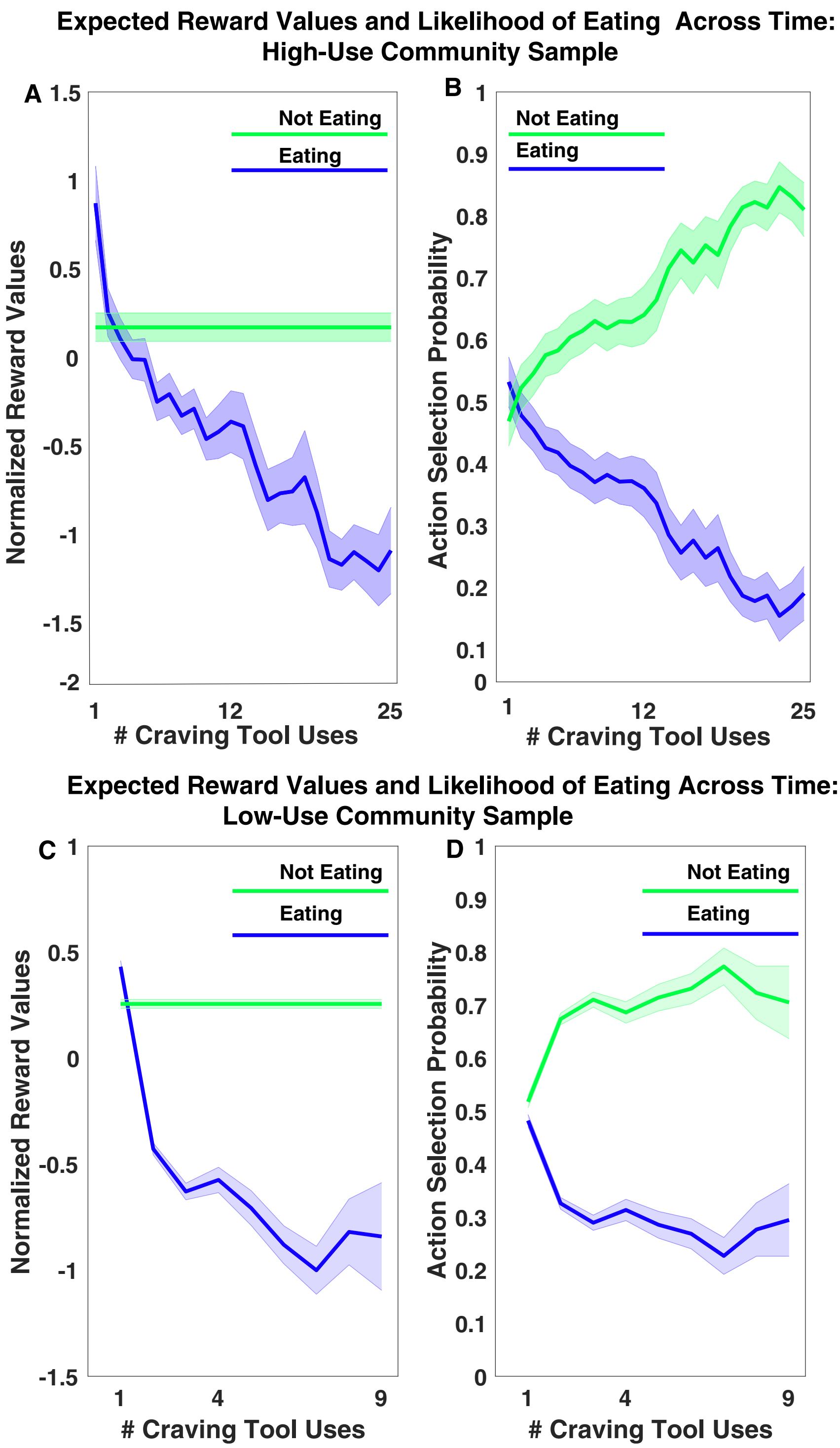

Fig. 6. A–B) Mean expected reward values (panel A) and mean expected likelihood of selecting each action (eating or not eating, panel B) by number of mindful eating craving tool uses for Study 2's independent community high-use sample (n = 75). Shaded areas represent standard errors of the mean. C-D) Mean expected reward values (panel C) and mean expected likelihood of selecting each action (eating or not eating, panel D) across craving tool uses, with shaded areas representing standard errors of the mean for Study 2's independent community low-use sample (n = 1,044).

respectively). The same pattern of results was obtained using present-moment reward values as a predictor of eating behavior (B = 0.474, SE = 0.018, t = 25.85, P < 0.001; B = 1.05, SE = 0.042, t = 24.98, P < 0.001, for decisions to eat or not and eating intake amount respectively). Also in line with the results obtained in Study 1, expected likelihood of opting to eat at each craving tool use estimated from our RW model significantly predicted whether participants chose to eat or not at each trial (B = 1.05, SE = 0.016, t = 65.11, P < 0.001). In other words, results from Study 1 were replicated, such that higher trial-by-trial reward values and expected likelihood of eating predicted enhanced eating, and conversely, lower trial-by-trial reward values and expected likelihood of eating predicted reduced eating.

Correspondence between present-moment and expected reward values

As in Study 1, to examine the correspondence between expected and present-moment reward values, we assessed the predictive relationship between expected reward values (1st level predictor) over present-moment reward values using multi-level regression analyses. These analyses revealed a significant positive predictive effect of expected reward values on present-moment reward values ($B = 0.20$, $SE = 0.03$, $t = 6.66$, $P < 0.001$). In other words, higher expected reward values for eating predicted higher present-moment reward values for eating, and conversely, lower expected reward values for eating predicted lower present-moment reward values.

DISCUSSION

In sum, the results of these studies can be summarized as follows. First, in Study 1, participants exhibited reductions in self-reported maladaptive eating following mindfulness training for 8 weeks. Study 1's results also revealed that expected reward values and eating behaviors exhibited a significant negative slope across number of mindful eating craving tool uses. Finally, results of Study 1 revealed that reward values (expected and present-moment) predicted eating behavior across craving tool uses. The majority of results obtained in Study 1 with respect to our mindful eating craving tool were replicated in a naturalistic independent sample of participants within the general population (Study 2). These results are discussed in light of their implications with respect to the mechanistic framework underlying the impact of mindfulness on maladaptive eating as well as treatment for health-detrimental behaviors or obesity risk factors. It is important to note, however, that effects presented and discussed in this report cannot causally be attributed to our intervention due to the single-arm nature of the study and lack of control group. Nonetheless, this research project constituted a first step in determining a mechanistic framework for mindfulness training's impact on behavioral change involving reinforcement learning, setting the stage for prospective randomized controlled trials investigating this mechanistically supported framework.

First, the effects of our mHealth intervention on reductions in self-reported maladaptive eating habitual behaviors (stress eating, reward-based eating, trait food craving) are consistent with our hypothesis. These results are directly in line with those from studies having examined the effects of mindfulness-based interventions on eating in response to emotions (for review, see (Katterman, Kleinman, Hood, Nackers, & Corsica, 2014)) and consistent with those from a previous study having administered our mHealth intervention in overweight or obese women (Mason et al., 2018). Here, the findings of Study 1 replicate the findings from Mason et al. (2018), and additionally reveal that our mindfulness intervention reduces stress eating, another outcome of maladaptive eating habits associated with overweight and obesity (Torres & Nowson, 2007).

The results observed with respect to the impact of our intervention on self-report assessments of maladaptive eating behaviors indicate that mindfulness training (1) attenuates eating behaviors in response to high levels of emotions and stress, (2) fosters a greater sense of control over eating, and (3) reduces preoccupations over food. This is potentially due to the fact that mindfulness enables participants to become aware of and recognize reinforced behavior patterns between emotional triggering cues, food cravings and eating behaviors (Brewer et al., 2018). Therefore, by becoming aware of eating behaviors triggered as automatic responses to either positive emotions or negative emotions, participants may gain greater behavioral flexibility over their eating behaviors and make more objective/intentional choices with respect to their habitual eating patterns. This enhanced behavioral flexibility over eating behaviors fostered by mindfulness training may in turn attenuate preoccupations over food and provide a greater sense of control over eating habits and cravings. Our findings revealing that our mHealth intervention significantly reduced maladaptive eating behaviors associated with obesity (Torres & Nowson, 2007) support the implementation of mindfulness-based interventions targeting these behaviors for the treatment of obesity and weight-related health outcomes. Nonetheless, further studies are needed to validate these results using a control group in order to control for factors non-specific to our intervention.

Importantly, the findings of these studies assessed whether the use of a novel mindful eating craving tool would target a specific aspect of reinforced maladaptive habitual eating behaviors: that of the expected reward value assigned to maladaptive eating. As hypothesized, our results revealed that the reward values assigned to habitual eating behaviors significantly decreased across number of craving tool uses. This observed reduction in reward values across craving tool uses supports our view that paying mindful attention to consequences from maladaptive eating (e.g. disgust, gastrointestinal discomfort that usually accompany over-eating) can successfully calibrate and decrease reward valuation processes assigned to the eating behavior (Brewer et al., 2018), and foster the development of an internally regulated motivation to disengage from the habitual behavior (Brewer, 2019; Ludwig et al., 2020).

Furthermore, Study 1's results revealed reductions in craving-related eating behaviors (eating frequency and intake amount) across number of craving tool uses, which were consistent with our hypotheses as well as findings demonstrating effects of mindfulness-based interventions on binge eating behaviors (for review, see (Katterman et al., 2014)). This finding may be due to the mindful allocation of attention to the actual consequences resulting from a maladaptive reinforced behavior, thereby fostering decreased motivation to engage in the habitual behavior itself (Brewer et al., 2018).

With respect to the predictive relationship between reward valuation processes and eating intake, the observation that eating intake was predicted by reward values (expected and present-moment reward values) supports the view that consummatory behavior is regulated based on the experience of reward value in conjunction with motivational factors occurring in the present-moment, rather than solely by reward values learned and stored following past consequences resulting from the behavior (Berridge, 2012). However, though our results indicate a positive predictive relationship between expected and present-moment reward values (in both Studies 1 and 2), the observation that present-moment reward values did not decrease across time is consistent with the notion that the motivational impetus for engaging in appetitive behavior may 'lag behind' in being updated with a devalued outcome (Berridge, 2012). Nonetheless, the predictive impact of reward values as well as the expected likelihood of opting to eat following the craving tool exercise on eating behavior indicate that the change in behavior observed during the intervention (linear decrease in eating frequency/intake) is, at least in part, driven by changes in reinforcement learning processes. Moreover, the predictive impact of the expected likelihood of eating on participants' observed eating frequency indicates that our RL model exhibits significant predictive power over behavioral change induced by our mindful eating tool.

Finally, as in Study 1, Study 2's results reveal that the effects of the mindful eating craving tool use on reward valuation and eating behaviors, as well as the predictive relationship between the two variables, were replicated in a larger sample using the app within a community-based context. One observation which differed from Study 1's results was with respect to eating behaviors, which showed no change across time, or an increase in eating frequency for the subsample with under 10 craving tool uses. This may be due to the fact that participants used the craving tool less, on average, in the second study as compared to the first study. It is therefore possible that a change in behavior could occur only after having used the tool a sufficient number of times, and that recommendations for clinical implementations of this tool may be to emphasize its use on repeated occasions to derive beneficial behavioral change. More specifically, however, in subjects with low-usage of the app in Study 2's community sample (<10 trials), follow-up post-hoc analyses revealed that eating intake followed an inverted U-shaped function, with peak intake occurring at around 2–3 trials of use. It is also possible that low experience-sampling of the craving tool involves other factors, and that participants' learning patterns are contingent upon experiencing first-hand the consequences of engaging in eating behaviors at initial stages of the learning process for reward values and eating behavior on subsequent trials to modulate. Future studies systematically varying the number of craving tool uses between different groups of participants, as well as designs combining qualitative self-report assessments to quantitative behavioral measures from participants at different stages of the tool's use are needed to validate these conclusions.

For both Studies 1 and 2, it is also important to highlight the correspondence between self-reported present-moment reward values and the expected reward values estimated from behavior using the RL model. Because self-reported present-moment reward values are an independent measure that did not contribute to reward value estimation, this supports the validity of our modeling approach and its ability to capture meaningful patterns of change in both behavior and subjective experience in an ecologically valid setting.

Nevertheless, the present research is not without its limitations. First, our modeling was based on a relatively small number of trials in the majority of subjects when compared to more typical modeling studies using behavior in lab-based RL tasks. In part, this represents a trade-off with the added ecological validity (and resulting reduction in control) associated with our approach. However, the relationships we see with self-reported behavior (present-moment reward values) that were independent from reward value estimation suggest that, despite this small number of trials, the model was capable of capturing meaningful patterns of change. However, future studies will be necessary to confirm these effects before they are afforded high confidence. Next, the single-arm nature of our experimental design warrants the replication of the present findings by randomized-control trials using a wait-listed and/or active control group (assigned to a control intervention) to support our conclusions. In addition, future studies are needed to support whether the effects observed with respect to behavioral change, reward valuation, and the predictive relationship between the two, correspond to improvements in obesity-related health outcomes or biomarkers (e.g. BMI, cardiovascular health). In addition, the application of our paradigm in a randomized clinical trial involving clinical populations with disordered eating (e.g. binge eating disorder) and a control group to test the effectiveness of mindfulness training on unhealthy eating in a clinical context is an important future direction to this study. As has been examined in a previous neuroimaging study comparing brain responses to food cues in four different groups of participants (Schienle, Schafer, Hermann, & Vaitl, 2009), future studies of our craving tool would prove particularly useful in contrasting healthy control participants who are either at a normal (BMI <25) or overweight/obese (BMI >25) weight range, a group of binge eating disorder patients, and a group of patients suffering from bulimia nervosa. These comparisons would greatly aid in verifying whether our intervention and craving tool have reproducible effects on unhealthy eating habits that can be translated to a range of BMIs and clinical populations.

Future neuroimaging studies should also be conducted in order to investigate the neurobiological mechanisms underlying these effects, as potential brain region candidates mediating the present results can be hypothesized from previous work, and might be expected to involve the orbitofrontal cortex, which has been associated with reward value encoding (Shott et al., 2015), as well as reward-related subcortical regions (e.g. striatum) (Li, Schiller, Schoenbaum, Phelps, & Daw, 2011). Finally, future prospective studies should be conducted to determine whether changes in eating behaviors and reward valuation yield longer-lasting success outcome rates than traditional behavioral treatment interventions for maladaptive eating and obesity.

In conclusion, the results of these studies demonstrate that a mindfulness training intervention for maladaptive habitual eating successfully reduces self-reported maladaptive eating behaviors, and that the use of a novel mindful eating craving tool induces a down-regulation of eating behavior reward values and eating intake. Moreover, our results indicate that changes in reward values occurring from the use of our craving tool predicted changes in eating behavior. Results related to the use of our craving tool were further validated and replicated in a larger sample using our app-based intervention within the general population, and not having been recruited specifically for an experimental study. These results support the implementation of mindfulness training in health interventions for addictive behaviors. Future studies incorporating control groups/ interventions, weight loss outcomes, long-term behavioral success maintenance, as well as neural function assessments are needed to further support these results and determine their neurobiological mediators.

Funding sources: This study was funded by an institutional (Brown University Research Fund-Brewer) research grant allocated to Dr J. Brewer, and a Summer Research Assistantship (SRA) 2019 grant as part of the Brown University Program in Liberal Medical Education (PLME) awarded to I. Moseley.

Conflict of interest: Dr. Brewer is paid advisor to Sharecare, the company that owns the mindfulness app used in this study. This financial interest has been disclosed to and is being managed by Brown University, in accordance with its Conflict of Interest and Conflict of Commitment policies, including: (1) being restricted from recruitment, (2) being blinded to study group until after analysis, (3) not having access to data or performing analyses. All other authors report no biomedical financial interests or potential conflicts of interest.

Author contributions: V.T. performed the data analysis and wrote the first draft of the manuscript. I.M. performed the experiments and data collection, was involved in the study design and contributed to this research's funding. A.R. was involved in the study design and supervision of data collection execution. S.S. was involved in formal data analysis, contributed to writing the first draft, as well as revised and edited the manuscript. V.U.L. was involved in the conceptualization of the study design, participated in data execution collection, and manuscript revision and editing. R.S. had a supervisory role with respect to data analysis execution, and revised and edited this manuscript. J.A.B. revised and edited this manuscript, provided research funding and supervised the conduction of this research.

Acknowledgments: This study was supported by an institutional research grant (Brown University Research Fund - Brewer) allocated to Dr J. Brewer. I.M. was supported by a Summer Research Assistantship (SRA) 2019 grant as part of Brown University's Program in Liberal Medical Education. We would like to thank Dr Peter Hitchcock (Brown University) for valuable insight concerning analysis methods included in this manuscript, as well as Dr Carlos Vargas-Irwin (Brown University) for his time and involvement in software code script development related to data analyses and figure production. In addition, we would like to thank Dr Luke Chang (Dartmouth College) for his help as well as data analysis script configuration specific to computational learning models included in this article.

SUPPLEMENTARY MATERIAL

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2021.00020.

REFERENCES

Barte, J. C., ter Bogt, N. C., Bogers, R. P., Teixeira, P. J., Blissmer, B., Mori, T. A., et al. (2010). Maintenance of weight loss after lifestyle interventions for overweight and obesity, a systematic review. *Obesity Reviews*, *11*(12), 899–906. https://doi.org/10.1111/j.1467-789X.2010.00740.x.

Barto, A. G. (1998). Intrinsic motivation and reinforcement learning. In *Intrinsically mortivated learning in natural and artificial systems* (pp. 17–48). New York, NY: Springer.

Berridge, K. C. (2012). From prediction error to incentive salience: Mesolimbic computation of reward motivation. *The European Journal of Neuroscience*, *35*(7), 1124–1143. https://doi.org/10.1111/j.1460-9568.2012.07990.

Brewer, J. A. (2019). Mindfulness training for addictions: Has neuroscience revealed a brain hack by which awareness subverts the addictive process? *Current Opinion in Psychology*, *28*, 198–203. https://doi.org/10.1016/j.copsyc.2019.01.014.

Brewer, J. A., Ruf, A., Beccia, A. L., Essien, G. I., Finn, L. M., van Lutterveld, R., et al. (2018). Can mindfulness address maladaptive eating behaviors? Why traditional diet plans fail and how new mechanistic insights may lead to novel interventions. *Frontiers in Psychology*, *9*, 1418. https://doi.org/10.3389/fpsyg.2018.01418.

Brindal, E., Hendrie, G., Freyne, J., Coombe, M., Berkovsky, S., & Noakes, M. (2013). Design and pilot results of a mobile phone weight-loss application for women starting a meal replacement programme. *Journal of Telemedicine and Telecare*, *19*(3), 166–174. https://doi.org/10.1177/1357633X13479702.

Butryn, M. L., Webb, V., & Wadden, T. A. (2011). Behavioral treatment of obesity. *Psychiatric Clinics of North America*, *34*(4), 841–859. https://doi.org/10.1016/j.psc.2011.08.006.

Carter, M. C., Burley, V. J., Nykjaer, C., & Cade, J. E. (2013). Adherence to a smartphone application for weight loss compared to website and paper diary: Pilot randomized controlled trial. *Journal of Medical Internet Research*, *15*(4), e32. https://doi.org/10.2196/jmir.2283.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Laurence Erlbaum Associates.

Dietz, W. H., Jr. (1983). Childhood obesity: Susceptibility, cause, and management. *The Journal of Pediatrics*, *103*(5), 676–686. https://doi.org/10.1016/s0022-3476(83)80457-0.

Dingemans, A. E., Bruna, M. J., & van Furth, E. F. (2002). Binge eating disorder: A review. *International Journal of Obesity and Related Metabolic Disorders*, *26*(3), 299–307. https://doi.org/10.1038/sj.ijo.0801949.

Dombrowski, S. U., Knittle, K., Avenell, A., Araujo-Soares, V., & Sniehotta, F. F. (2014). Long term maintenance of weight loss with non-surgical interventions in obese adults: Systematic review and meta-analyses of randomised controlled trials. *BMJ*, *348*, g2646. https://doi.org/10.1136/bmj.g2646.

Elwafi, H. M., Witkiewitz, K., Mallik, S., Thornhill, T. A. T., & Brewer, J. A. (2013). Mindfulness training for smoking cessation: Moderation of the relationship between craving and cigarette use. *Drug and Alcohol Dependence*, *130*(1–3), 222–229. https://doi.org/10.1016/j.drugalcdep.2012.11.015.

Gershman, S. (2016). Empirical priors for reinforcement learning models. *Journal of Mathematical Psychology*, *71*, 1–6. http://doi.org/10.1016/j.jmp.2016.01.006.

Graybiel, A. M. (2008). Habits, rituals, and the evaluative brain. *Annual Review of Neuroscience*, *31*, 359–387. https://doi.org/10.1146/annurev.neuro.29.051605.112851.

Grilo, C. M., Masheb, R. M., Wilson, G. T., Gueorguieva, R., & White, M. A. (2011). Cognitive-behavioral therapy, behavioral weight loss, and sequential treatment for obese patients with binge-eating disorder: a randomized controlled trial. *Journal of Consulting and Clinical Psychology*, *79*(5), 675–685.

Kabat-Zinn, J. (1994). Wherever you go, there you are: Mindfulness meditation in everydaylife. New York, NY: Hyperion.

Katterman, S. N., Kleinman, B. M., Hood, M. M., Nackers, L. M., & Corsica, J. A. (2014). Mindfulness meditation as an intervention for binge eating, emotional eating, and weight loss: A systematic review. *Eating Behaviors*, *15*(2), 197–204. https://doi.org/10.1016/j.eatbeh.2014.01.005.

Li, J., Schiller, D., Schoenbaum, G., Phelps, E. A., & Daw, N. D. (2011). Differential roles of human striatum and amygdala in associative learning. *Nature Neuroscience*, *14*(10), 1250–1252. https://doi.org/10.1038/nn.2904.

Lowe, M. R. (2003). Self-regulation of energy intake in the prevention and treatment of obesity: Is it feasible? *Obesity Research*, *11*(Suppl), 44S–59S. https://doi.org/10.1038/oby.2003.223.

Ludwig, V. U., Brown, K. W., & Brewer, J. A. (2020). Self-regulation without force: Can awareness leverage reward to drive behavioral change? *Perspectives on Psychological Science*, *15*(6), 1382–1399. https://doi.org 10.1177/1745691620931460.

Maclean, P. S., Bergouignan, A., Cornier, M. A., & Jackman, M. R. (2011). Biology's response to dieting: The impetus for weight regain. *American Journal of Physiology – Regulatory, Integrative and Comparative Physiology*, *301*(3), R581–R600. https://doi.org/10.1152/ajpregu.00755.2010.

Mason, A. E., Jhaveri, K., Cohn, M., & Brewer, J. A. (2018). Testing a mobile mindful eating intervention targeting craving-related eating: Feasibility and proof of concept. *Journal of Behavioral Medicine*, *41*(2), 160–173. https://doi.org/10.1007/s10865-017-9884-5.

Miller, K. J., Shenhav, A., & Ludvig, E. A. (2019). Habits without values. *Psychology Review*, *126*(2), 292–311. https://doi.org/10.1037/rev0000120.

Papies, E. K., & Barsalou, L. W. (2015). Grounding desire and motivated behavior: A theoretical framework and review of empirical evidence. In *The psychology of desire* (pp. 36–60). New York, NY: Guilford Press.

Pi-Sunyer, F. X. (2002). The obesity epidemic: Pathophysiology and consequences of obesity. *Obesity Research*, *10*(Suppl. 2), 97S–104S. https://doi.org/10.1038/oby.2002.202.

Reilly, J. J., Methven, E., McDowell, Z. C., Hacking, B., Alexander, D., Stewart, L., et al. (2003). Health consequences of obesity. *Archives of Disease in Childhood*, *88*(9), 748–752. https://doi.org/10.1136/adc.88.9.748.

Rescorla, R. A., & Wagner, A. R. (1972). A theory of Pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. In A. H. Black & W. F. Prokasy (Eds.), *Classical conditioning II: Current research and theory* (pp. 64–99). New York, NY: Appleton-Century-Crofts.

Schienle, A., Schafer, A., Hermann, A., & Vaitl, D. (2009). Binge-eating disorder: Reward sensitivity and brain activation to images of food. *Biological Psychiatry*, *65*(8), 654–661. https://doi.org/10.1016/j.biopsych.2008.09.028.

Shott, M. E., Cornier, M. A., Mittal, V. A., Pryor, T. L., Orr, J. M., Brown, M. S., et al. (2015). Orbitofrontal cortex volume and brain reward response in obesity. *International Journal of Obesity (Lond)*, *39*(2), 214–221. https://doi.org/10.1038/ijo.2014.121.

Skinner, B. F. (1963). Operant behavior. *American Psychologist*, *18*(8), 503–515. https://doi.org/10.1037/h0045185.

Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction*. Cambridge, MA: MIT Press.

Thomas, J. G., & Wing, R. R. (2013). Health-e-call, a smartphone-assisted behavioral obesity treatment: Pilot study. *JMIR Mhealth Uhealth*, *1*(1), e3. https://doi.org/10.2196/mhealth.2164.

Thompson, D., Edelsberg, J., Colditz, G. A., Bird, A. P., & Oster, G. (1999). Lifetime health and economic consequences of obesity. *Archives of Internal Medicine*, *159*(18), 2177–2183. https://doi.org/10.1001/archinte.159.18.2177.

Torres, S. J., & Nowson, C. A. (2007). Relationship between stress, eating behavior, and obesity. *Nutrition*, *23*(11–12), 887–894. https://doi.org/10.1016/j.nut.2007.08.008.

Vocks, S., Tuschen-Caffier, B., Pietrowsky, R., Rustenbach, S. J., Kersting, A., & Herpertz, S. (2010). Meta-analysis of the effectiveness of psychological and pharmacological treatments for binge eating disorder. *International Journal of Eating Disorders*, *43*(3), 205–217. https://doi.org/10.1002/eat.20696.

Warren, J. M., Smith, N., & Ashwell, M. (2017). A structured literature review on the role of mindfulness, mindful eating and intuitive eating in changing eating behaviours: Effectiveness and associated potential mechanisms. *Nutrition Research Reviews*, *30*(2), 272–283. https://doi.org/10.1016/j.nut.2007.08.008.

Weingarten, H. P., & Elston, D. (1990). The phenomenology of food cravings. *Appetite*, *15*(3), 231–246. https://doi.org/10.1016/0195-6663(90)90023-2.

White, M. A., Whisenhunt, B. L., Williamson, D. A., Greenway, F. L., & Netemeyer, R. G. (2002). Development and validation of the food-craving inventory. *Obesity Research*, *10*(2), 107–114. https://doi.org/10.1038/oby.2002.17.

Williams, E. P., Mesidor, M., Winters, K., Dubbert, P. M., & Wyatt, S. B. (2015). Overweight and obesity: Prevalence, consequences, and causes of a growing public health problem. *Current Obesity Reports*, *4*(3), 363–370. https://doi.org/10.1007/s13679-015-0169-4.

Wu, T., Gao, X., Chen, M., & van Dam, R. M. (2009). Long-term effectiveness of diet-plus-exercise interventions vs. diet-only interventions for weight loss: A meta-analysis. *Obesity Reviews*, *10*(3), 313–323. https://doi.org/10.1111/j.1467-789X.2008.00547.x.

Yeomans, M. R., Blundell, J. E., & Leshem, M. (2004). Palatability: Response to nutritional need or need-free stimulation of appetite? *The British Journal of Nutrition*, *92*(Suppl. 1), S3–S14. https://doi.org/10.1079/bjn20041134.