Accepted Manuscript

Implicit evaluation of chocolate and motivational need states interact in predicting chocolate intake in everyday life

Anna Richard, Adrian Meule, Jens Blechert

Please cite this article as: A. Richard, A. Meule and J. Blechert, Implicit evaluation of chocolate and motivational need states interact in predicting chocolate intake in everyday life, Eating Behaviors, https://doi.org/10.1016/j.eatbeh.2019.01.006

Implicit evaluation of chocolate and motivational need states interact in predicting chocolate intake in everyday life

Anna Richard[1,2,*], Adrian Meule[1,2], & Jens Blechert[1,2]

[1]Department of Psychology, University of Salzburg, Salzburg, Austria

[2]Centre for Cognitive Neuroscience, University of Salzburg, Salzburg, Austria

*Correspondence:

Anna Richard, MSc.

University of Salzburg

Department of Psychology

Hellbrunner Straße 34

5020 Salzburg, Austria

Phone: +43 662 8044 5159

Email: anna.richard@sbg.ac.at

Abstract

Snack food consumption has a high relevance for health and is partially controlled by implicit, motivational processes that make self-control difficult at certain times. Specifically, research suggests that individuals with a more positive implicit food evaluation consume more snack foods in the laboratory under conditions of high motivational needs (e.g., hunger and food craving). Yet, no study investigated if and under which circumstances implicit evaluation of food predicts snack food intake in real life. In the present study, 60 female undergraduate students (mean age: 22.3 ± 2.34 years) at the University of Salzburg, Austria, completed a chocolate-related Single Category Implicit Association Test in the laboratory and then reported snack food intake during seven days of signal-contingent Ecological Momentary Assessment. Results showed that a more positive implicit evaluation of chocolate was associated with a higher likelihood of consuming chocolate in states of high hunger and high momentary chocolate craving, whereas no such modulatory pattern was found in states of low hunger or low chocolate craving. Therefore, interventions targeting daily chocolate craving and consumption may be particularly beneficial in specific situations (i.e., in states of high hunger and craving) and also in vulnerable populations (e.g., those with a more positive implicit food evaluation).

Keywords

1. Introduction

Most health-conscious individuals deliberately plan and control their food intake to some degree. However, also other motivational and partially implicit determinants are documented. For example, positively toned, reward-related responses towards palatable foods (e.g., approach tendencies) can be automatically activated by their mere presence (Berridge, Ho, Richard, & DiFeliceantonio, 2010) and may trigger consumption. It has been suggested that these food–approach associations are acquired through repeated pairing of positive affect with the food itself and/or food consumption (Chen & Bargh, 1999; Cohen & Farley, 2008; Ferguson, 2008) and, thus, may determine whether a food will (or will not) be eaten. However, palatable foods do not necessarily lead to food consumption in all instances (Hill, 2007; Weingarten & Elston, 1991). Rather there may be particular states that foster the impact of implicit, motivational processes on eating behavior (Friese, Hofmann, & Schmitt, 2009). Hunger, for example, makes food appear more rewarding (Siep et al., 2009) and promotes food seeking behavior in general. Relatedly, food craving—defined as an intensive urge to consume a specific type of food—is often a precursor of food consumption and can be partly distinguished from feelings of hunger (Hallam, Boswell, DeVito, & Kober, 2016). Therefore, both food craving and hunger are referred to as states that motivate food intake (Appelhans, French, Pagoto, & Sherwood, 2016); their relative impact on actual food intake, however, likely depends on the presence of underlying implicit, motivational processes.

One of such motivational processes is the implicit evaluation of food, which is the degree to which a stimulus is automatically evaluated as positive or negative (De Houwer, Teige-Mocigemba, Spruyt, & Moors, 2009). Implicit food evaluation is usually assessed with food-related implicit measures such as the Implicit Association Test (Greenwald, McGhee, & Schwartz, 1998). Although previous research findings suggest that outcomes of these measures reflect trait-like interindividual differences (e.g., Egloff & Schmukle, 2002), it was

also found that more positive implicit food evaluation was associated with higher hunger, food deprivation, and momentary craving for the given food (Kraus & Piqueras-Fiszman, 2016; Richard, Meule, & Blechert, 2018; Seibt, Häfner, & Deutsch, 2007; Stafford & Scheffler, 2008), suggesting that implicit food evaluations are sensitive to momentary motivational states as well.

Numerous attempts have been made to determine relationships between implicit food evaluations and eating-related outcomes. However, whether a more positive implicit food evaluation leads to higher subsequent snack consumption has received mixed support: the majority of studies did not find conclusive evidence for direct relations between implicit measures and consumption (for an overview, see Dimofte, 2010 and Friese, Hofmann, & Wänke, 2009). Therefore, moderating variables have been investigated to explore when and under which circumstances implicit measures of food evaluation influence eating behavior. It is assumed that the impact of implicit evaluations on consumption is stronger when the capacity for impulse control is reduced (e.g., Friese, Hofmann, & Schmitt, 2009). For example, it has been found that implicit food evaluation mostly predicted behavior in states of high motivational needs, such as hunger or craving (for an overview see Roefs et al., 2011).

While most of past research on when and how implicit measures predict food consumption has been conducted in the laboratory, it is still unclear whether these measures also predict consumption in "real life". In fact, laboratory studies often fail to map the dynamic fluctuations of hunger and craving and participants restrict their food intake when they feel observed (Robinson, Hardman, Halford, & Jones, 2015). In contrast, smartphone-based Ecological Momentary Assessment (EMA) more validly captures fluctuations in hunger and food craving (Berkman, Giuliani, & Pruitt, 2014; Reichenberger et al., 2018; Richard, Meule, Reichenberger, & Blechert, 2017). Therefore, in the current study, participants first completed a measure of implicit food evaluation—the Single Category Implicit Association

Test (Karpinski & Steinman, 2006) for measuring the strength of association between a target (here: chocolate) and an attribute (here: pleasant vs. unpleasant)—in the laboratory and then reported snack food intake during seven days of EMA.

Previous research suggests that implicit measures of food evaluation predict eating behavior in conditions of high motivational needs. The aim of the current study was to examine predictors of daily chocolate consumption probability by means of state chocolate craving, hunger, and implicit evaluation of chocolate. Therefore, we expected that individuals with a more positive implicit evaluation of chocolate would consume chocolate more likely only when they were hungry and/or experienced a current craving for chocolate. Furthermore, it has been suggested that implicit food evaluation may no longer predict eating-related outcomes when controlling for the explanatory power of explicit measures of palatability (e.g., Ayres, Conner, Prestwich, & Smith, 2012). Thus, we further examined whether the pattern of results would remain the same after controlling for participants' self-reported palatability ratings for chocolate.

2. Methods

2.1 Participants

Parts of the current study have been published previously, where we reported predictors of implicit evaluation of chocolate (Study 2; Richard, Meule, & Blechert, 2018). Participants were 66 female undergraduate students from the University of Salzburg, Austria, and they reported no current or past eating disorders (assessed on written self-report). Datasets from 6 participants were discarded due to technical problems ($n = 3$), due to compliance lower than 50% during EMA ($n = 2$), and because they did not follow the study protocol correctly ($n = 1$). Mean age was 20.3 years ($SD = 2.34$, Range: 18–30) and mean body mass index was 21.3 kg/m² ($SD = 2.79$, Range: 15.6–30.9).

2.2 Measures

2.2.1 Single Category Implicit Association Test (SC-IAT)

A SC-IAT (Karpinski & Steinman, 2006) was used for assessing implicit evaluation of chocolate. Participants first practiced the categorization of positive and negative words (20 trials), followed by two testing blocks (70 trials each). In the testing blocks, participants sorted stimuli into one of three categories labeled *pleasant, unpleasant*, and *chocolate*, with *chocolate* being paired with *pleasant* in the first block and with *unpleasant* in the second block. Category labels were displayed in the top left and right hand corners of the screen. Ten negative words (fear, sadness, hate, accident, pain, violence, enemy, evil, war, and loss) and ten positive words (vacation, celebration, freedom, joy, peace, gift, happiness, laugh, love, and summer) served as evaluative categories. Ten chocolate pictures (taken from the food-pics database; Blechert, Meule, Busch, & Ohla, 2014; picture numbers: 0056, 0159, 0189, 0289, 0290, 0291, 0293, 0441, 0501, and 0506) served as the target category.

In every trial, a stimulus appeared and remained on the screen until a response was made or a maximum of 1700 ms had elapsed. Errors were signaled by a red cross. Inter-trial interval was 150 ms. In the first block, *d* was the response key for negative words and *l* was the response key for positive words and chocolate pictures. In the second block, negative words and chocolate pictures shared the *d* key and positive words were sorted on the *l* key. Block order was the same across participants as has been previously recommended (Egloff & Schmukle, 2002; Gawronski, 2002).

Mean reaction time differences between the two testing blocks were divided by the standard deviation of all correct response times within both blocks and—according to the D600 algorithm (Glashouwer, Smulders, de Jong, Roefs, & Wiers, 2013; Greenwald, Nosek, & Banaji, 2003)—a 600 ms addition was used as penalty for errors. Higher D600 scores indicate a more positive implicit evaluation of chocolate. Non-responses (i.e., latencies > 1700 ms; 0.90% of trials) and responses < 400 ms (2.30% of trials) were excluded from analyses (Greenwald et al., 2003; Karpinski & Steinman, 2006). For determining the internal reliability, D600 scores were calculated for four mutually exclusive subsets. Internal reliability was $\alpha = .753$ for these subsets. Furthermore, bootstrapped Spearman–Brown corrected split-half reliability estimates for reaction time differences between the first and second block (which were used for calculating the D600 algorithm) were obtained using the R package splithalf (Parsons, 2018) performing 5000 random splits (Spearman–Brown-corrected $r_{sb} = .72$, 95% CI = [.59, .82]).

2.2.2 Palatability ratings

Chocolate picture ratings were used for assessing explicit evaluation of chocolate. Participants were presented with the same 10 chocolate pictures used in the SC-IAT and were asked to indicate their perceived palatability of the depicted chocolate on a 10-point scale

ranging from 1 (*not at all*) to 10 (*very palatable*). Responses were averaged across all pictures and internal reliability was $\alpha = .802$ in the current study.

2.2.3 Food Cravings Questionnaire–Trait–reduced (FCQ–T–r)

The chocolate version of the FCQ–T–r (Meule & Hormes, 2015) was used for assessing the frequency and intensity of chocolate cravings in general (i.e., trait chocolate craving). Items are scored on a six-point scale ranging from *never/not applicable* to *always*. Total scores can range between 15 and 90 and higher scores indicate higher trait chocolate craving. Internal reliability was $\alpha = .936$ in the current study.

2.2.5 EMA measures

Participants first rated their average hunger since the last prompt on a continuous slider (from 0 [not at all] to 100 [very hungry]). Participants then indicated how often they had thought about snack foods since the last prompt and—if so—they were asked to report them separately in a text box. In addition, they rated their desire to eat (i.e., craving intensity) for the specific snacks they had thought about on a continuous slider (from 0 [not at all intense] to 100 [very intense]). Finally, participants reported the number of consumed snacks since the last prompt and were also asked to indicate the type of snack they had consumed in a text box. Snack foods were defined as foods that were not consumed as part of principal meals (e.g., chocolate-containing foods, sweets, fruits and vegetables, chips, pastries; Richard et al., 2017). We explicitly did not constrain EMA measures to chocolate-containing snack foods as we did not want to trigger chocolate craving or consumption artificially. All responses were entered into the smartphone application PsyDiary, which was programed in collaboration with the Smart Health Check research group at the department of MultiMediaTechnology of the Salzburg University of Applied Sciences, Austria (https://www.smarthealth.at/project/psydiary-2). Supported platforms are Android and iOS

with EMA questions being accessed and defined via the online-platform LimeSurvey

(www.limesurvey.org).

2.3 Procedure

The study was approved by the ethics committee of the University of Salzburg and

participants signed informed consent before commencing the study. Participants were tested

in the laboratory individually. They filled in the FCQ–T–r online at home. In the laboratory,

they completed the chocolate version of the Food Cravings Questionnaire–State (Meule &

Hormes, 2015; data not analyzed here) and then rated the perceived palatability of the

chocolate pictures before performing the SC-IAT. Afterwards they were trained on the EMA

protocol and usage of the smartphone application. Participants were explicitly asked to report

any snack food craving and consumption and not only to report their chocolate craving and

consumption. They completed seven days of EMA and were prompted with 5 daily signals at

10 a.m., 1 p.m., 4 p.m., 7 p.m., and 10 p.m. At the end of the study, participants answered

questions on reactivity and were then fully debriefed and compensated with course credits.

2.4 Data Analyses

Hunger and craving intensity were used as predictors for chocolate consumption and

implicit evaluation of chocolate served as moderator of these relationships. We additionally

modeled palatability ratings, time of day, and trait chocolate craving as covariates for the

relationships of hunger, craving intensity, and chocolate consumption. To analyze the nested,

longitudinal structure of the data, we applied generalized linear mixed models using R (R

Core Team, 2017) and the R package lme4 (Bates, Maechler, Bolker, & Walker, 2015). The

five signals per day (Level 1) were nested within participants at Level 2. Time of day (coded

as 0 [Signal 1] to 4 [Signal 5]) was entered uncentered into the model. Hunger and craving

intensity (Level 1) were person-mean centered and SC-IAT scores, palatability ratings, and

trait chocolate craving (Level 2) were grand-mean centered. Chocolate consumption was

rescaled into a binary outcome (0 = no chocolate consumption [which includes either no snack food consumption or snack food consumption other than chocolate], 1 = chocolate consumption), as only 0.30% of all signals (n = 1904) contained more than one chocolate consumption episode (n = 23 signals with 2 episodes, n = 3 signals with 4 episodes and n = 1 signal with 5 episodes). Specifically, data were analyzed using mixed effects logistic regression models to estimate the odds of consuming chocolate during the signal preceding epoch as a function of hunger and craving during that epoch as well as an individual's implicit evaluation of chocolate. Palatability ratings, time of day, and trait chocolate craving served as covariates to explore whether pattern of results would be stable irrespective of the effects of palatability ratings, time of day, and trait chocolate craving (see Tables S1 to S3 in the online supplementary material, respectively). Palatability ratings of the chocolate images were used as a measure of explicit evaluation of chocolate in addition to the implicit evaluation of chocolate (reflected by reaction times and errors in the SC-IAT).

Using a top-down data analytic strategy (c.f. Zuur, Ieno, Walker, Saveliev, & Smith, 2009), we first entered all main effects (i.e., craving intensity, hunger, and implicit evaluation of chocolate), two-way interactions (i.e., craving intensity × hunger, craving intensity × implicit evaluation of chocolate, and hunger × implicit evaluation of chocolate), and three-way interactions (i.e., craving intensity × hunger × implicit evaluation of chocolate) as fixed effects into our full model. Relative model fit statistics—Akaike information criterion (AIC) and Bayesian information criterion (BIC)—were used for model comparisons to test if including a random part (i.e., random intercept or slopes) would improve the overall model fit. The best random model for our analyses was a random intercept model (cf. random model; left intersection of Table 1). We then removed predictors from the random model that did not lead to a significant improvement in model fit by calculating χ^2 difference tests (cf. winning model; right intersection of Table 1). A non-significant χ^2 difference test indicates that the two

models are comparable in terms of overall model fit, in which case the more parsimonious model is preferred. A significant χ^2 difference test indicates that dropping the parameter significantly worsens the fit of the model. Odds ratios (*OR*; probability of consuming chocolate vs. not consuming chocolate) and their 95% confidence intervals were calculated for the intercept and predictor variables. Plots and tables were generated with the R package sjPlot (Lüdecke, 2017).

3. Results

Participants responded to 1904 EMA prompts out of a possible 2100, reflecting a mean response rate of 90.7% (*SD* = 8.05, Range: 66–100). Chocolate-containing foods were consumed at 182 signals during EMA, accounting for 23.7% of all reported snack foods (*n* = 655). Mean hunger ratings were 34.5 (*SD* = 21.2, Range: 0–100) and mean craving intensity was 26.2 (*SD* = 30.0, Range: 0–100) for all snack foods and 54.9 (*SD* = 22.3, Range: 3–100) for chocolate-containing foods in particular.

Higher craving intensity and lower hunger were associated with a higher likelihood of consuming chocolate, whereas implicit evaluation of chocolate did not increase the likelihood of consuming chocolate (Table 1). The two-way interactions of implicit evaluation of chocolate with craving intensity and hunger were not significant, but there was a significant three-way interaction of craving intensity × hunger × implicit evaluation of chocolate (Table 1). A more positive implicit evaluation of chocolate was associated with a higher likelihood of consuming chocolate, but only when both hunger and craving intensity were high, whereas no such modulatory pattern was found when hunger or craving intensity was low (Figure 1). Including palatability ratings (*OR* = 1.18, *p* = .351; Table S1), time of day (*OR* > 1.55, *p* < .200; Table S2), or trait chocolate craving (*OR* = 1.32, *p* = .092; Table S3) as covariates did

not change the pattern of results (all tables can be found in the online supplementary

material).

4. Discussion

The current study investigated whether—and under which motivational need states—

everyday chocolate consumption is driven by an implicit evaluation of chocolate. Although

implicit evaluation of chocolate was not directly related to chocolate consumption, an

interactive pattern with hunger and craving was found: a more positive implicit evaluation of

chocolate was associated with a higher likelihood of consuming chocolate in states of high

hunger and high momentary chocolate craving, whereas no such modulatory pattern was

found in states of low hunger or low chocolate craving.

Previous research suggests that specific motivational need states (i.e., hunger or

craving) increase the attractiveness of a given food and the likelihood of its consumption

(Appelhans et al., 2016). Indeed, higher momentary craving was associated with a higher

probability of chocolate consumption, confirming that craved foods are likely to be consumed

(Martin, O'Neil, Tollefson, Greenway, & White, 2008). Interestingly, when looking at the

significant main effects, hunger was negatively related to chocolate consumption, that is,

when participants were hungry they were less likely to eat chocolate. One could speculate that

individuals may rather consume a main meal when being hungry, thus reducing the likelihood

of consuming chocolate. In addition, sweet foods, such as chocolate, are often consumed as a

desert, when hunger is already low. Thus, in line with previous research, our findings

demonstrate that hunger does not necessarily trigger chocolate consumption (Cheval, Audrin,

Sarrazin, & Pelletier, 2017; Cleobury & Tapper, 2014; Meule & Hormes, 2015). This pattern

also adds to the growing literature on the partial independence of craving and hunger

experiences (e.g., Reichenberger et al., 2018).

Also in line with previous research, we observed no direct relationship of implicit food

evaluation (here: regarding chocolate stimuli) and snack food consumption (Dimofte, 2010;

Friese, Hofmann, & Wänke, 2009). Despite the lack of this direct relationship, an interactive

pattern was found: in states of high hunger and craving, implicit evaluation of chocolate

predicted chocolate consumption, which is in line with previous research showing that the

effect of implicit food evaluation on eating behavior is greater when the capacity of impulse

control is reduced (Roefs et al., 2011). Importantly, to the best of our knowledge, the current

study is the first that extended previous results from laboratory studies into real life using

smartphone-based EMA, affording high external validity and generalizability. Such

converging evidence from both lines of research (i.e., laboratory- and smartphone-based)

may, therefore, more robustly inform theorizing about determinants of chocolate intake as a

function of hunger, craving, and implicit evaluation of chocolate as well as respective

interventions.

The current study also needs to highlight some limitations and associated future

directions. First, the current study targeted chocolate and, thus, findings cannot be generalized

to other snack foods in a straightforward manner or to food in general. Although chocolate is

a typically craved and frequently consumed food in Western societies (Richard et al., 2017;

Rozin, Levine, & Stoess, 1991; Weingarten & Elston, 1991), a promising future direction

would be to extend this approach to other cultures and other snack food categories. Second,

we implemented only a probability measure of chocolate and no amount measure. This leaves

open the question whether chocolate cravings necessarily lead to overconsumption of

chocolate or whether consumption of small quantities would potentially prevent it. Therefore,

future studies could investigate whether implicit evaluation, craving intensity, and hunger also

predict consumption frequency or amount. For this, a more continuous sampling of snack consumption—for instance, electromyogram-based chewing detection (Blechert, Liedlgruber, Lender, Reichenberger, & Wilhelm, 2017) or swallowing sound detection measurements (Sazonov et al., 2010)—may be used in combination with the signal-contingent EMA sampling used in our study. Third, interpretation of results is based on a sample of young female students with a predominantly normal weight, which limits generalizability to men, individuals with a higher age, lower education, under- or overweight, and clinical samples (e.g., individuals with eating disorders). Finally, implicit measures have been criticized for their proneness to measurement error (due to low reliability indices), faking, or context dependency (for an overview of some common caveats, see Gawronski & De Houwer, 2014; Hahn & Gawronski, 2018), questioning the conclusions derived from such measures. Therefore, an examination of potential context effects awaits further study (e.g., through repeated, mobile assessment of IATs; Waters, Miller, & Li, 2010).

The finding that the probability of consuming chocolate is higher in individuals with a more positive implicit evaluation of chocolate during times of hunger and craving can guide interventional efforts by specifying the *who* and the *when* of chocolate (over-)consumption. As individuals were particularly prone to consume chocolate when they experienced strong state chocolate cravings in the current study, gaining control over these state cravings may be of particular importance when addressing chocolate consumption and its reduction. Particularly, individuals most frequently report the experience of food cravings as the main cause for their non-adherence to a diet (Hall & Most, 2005) and food cravings have been associated with a lower self-reported dieting success (Meule, Richard, & Platte, 2017). Therefore, a new line of research moves away from a weight loss and dietary restriction-oriented approach towards an acceptance-based, mindful eating approach. Thereby, individuals learn to accept their upcoming cravings, to eat according to their internal signs of hunger, or to distance themselves from their thoughts of food (for an overview, see Brewer et

al., 2018; Tapper, 2018). The question of whether these interventions work for certain individuals (i.e., with a higher implicit evaluation of chocolate) or for anyone in certain motivational need states (i.e., in states of hunger and craving) is an open and certainly fruitful future direction. Importantly, as hunger and chocolate craving experiences underlie temporal and dynamic fluctuations, these interventions may be more beneficial—and, thus, should be applied—in the individuals' everyday lives.

References

Appelhans, B. M., French, S. A., Pagoto, S. L., & Sherwood, N. E. (2016). Managing temptation in obesity treatment: A neurobehavioral model of intervention strategies. *Appetite, 96*, 268–279.

Ayres, K., Conner, M. T., Prestwich, A., & Smith, P. (2012). Do implicit measures of attitudes incrementally predict snacking behaviour over explicit affect-related measures? *Appetite, 58*(3), 835–841.

Bates, D., Maechler, M., Bolker, B., & Walker, B. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software, 67*, 1–48.

Berkman, E. T., Giuliani, N. R., & Pruitt, A. K. (2014). Comparison of text messaging and paper-and-pencil for ecological momentary assessment of food craving and intake. *Appetite, 81*, 131–137.

Berridge, K. C., Ho, C. Y., Richard, J. M., & DiFeliceantonio, A. G. (2010). The tempted brain eats: Pleasure and desire circuits in obesity and eating disorders. *Brain Research, 1350*, 43–64.

Blechert, J., Liedlgruber, M., Lender, A., Reichenberger, J., & Wilhelm, F. H. (2017). Unobtrusive electromyography-based eating detection in daily life: A new tool to address underreporting? *Appetite, 118*, 168–173.

Blechert, J., Meule, A., Busch, N. A., & Ohla, K. (2014). Food-pics: an image database for experimental research on eating and appetite. *Frontiers in Psychology, 5*(617), 1–10.

Brewer, J. A., Ruf, A., Beccia, A. L., Essien, G. I., Finn, L. M., van Lutterveld, R., & Mason, A. E. (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), 1–11. .

Chen, M., & Bargh, J. A. (1999). Consequences of automatic evaluation: Immediate behavioral predispositions to approach or avoid the stimulus. *Personality and Social Psychology Bulletin, 25*, 215–224.

Cheval, B., Audrin, C., Sarrazin, P., & Pelletier, L. (2017). When hunger does (or doesn't) increase unhealthy and healthy food consumption through food wanting: The distinctive role of impulsive approach tendencies toward healthy food. *Appetite, 116*, 99–107.

Cleobury, L., & Tapper, K. (2014). Reasons for eating 'unhealthy' snacks in overweight and obese males and females. *Journal of Human Nutrition and Dietetics, 27*(4), 333–341.

Cohen, D. A., & Farley, T. A. (2008). Eating as an automatic behavior. *Preventing Chronic Disease, 5*, 1–7.

De Houwer, J., Teige-Mocigemba, S., Spruyt, A., & Moors, A. (2009). Implicit measures: A normative analysis and review. *Psychological Bulletin, 135*(3), 347–368.

Dimofte, C. V. (2010). Implicit measures of consumer cognition: A review. *Psychology & Marketing, 27*(10), 921–937.

Egloff, B., & Schmukle, S. C. (2002). Predictive validity of an Implicit Association Test for assessing anxiety. *Journal of Personality and Social Psychology, 83*, 1441–1455.

Ferguson, M. J. (2008). On becoming ready to pursue a goal you don't know you have: Effects of nonconscious goals on evaluative readiness. *Journal of Personality and Social Psychology, 95*(6), 1268–1294.

Friese, M., Hofmann, W., & Schmitt, M. (2009). When and why do implicit measures predict behaviour? Empirical evidence for the moderating role of opportunity, motivation, and process reliance. *European Review of Social Psychology, 19*, 285–338.

Friese, M., Hofmann, W., & Wänke, M. (2009). The impulsive consumer: predicting consumer behavior with implicit reaction time measures. In M. Wänke (Ed.), *Social psychology of consumer behavior* (pp. 335–364). New York: Psychology Press.

Gawronski, B. (2002). What does the implicit association test measure? A test of the convergent and discriminant validity of prejudice-related IATs. *Experimental Psychology, 49*, 171–180.

Gawronski, B., & De Houwer, J. (2014). Implicit measures in social and personality psychology. In H. T. Reis & C. M. Judd (Eds.), *Handbook of research methods in social and personality psychology* (pp. 283–310). New York, NY: Cambridge University Press.

Glashouwer, K. A., Smulders, F. T., de Jong, P. J., Roefs, A., & Wiers, R. W. (2013). Measuring automatic associations: validation of algorithms for the Implicit Association Test (IAT) in a laboratory setting. *Journal of Behavior Therapy and Experimental Psychiatry, 44*(1), 105–113.

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: the implicit association test. *Journal of Personality and Social Psychology, 74*, 1464–1480.

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology, 85*, 197–216.

Hahn, A., & Gawronski, B. (2018). Implicit social cognition. In J. T. Wixted (Ed.), *Stevens' Handbook of Experimental Psychology and Cognitive Neuroscience* (pp. 395–427). New York, NY: Wiley.

Hallam, J., Boswell, R. G., DeVito, E. E., & Kober, H. (2016). Gender-related Differences in Food Craving and Obesity. *Yale Journal of Biology and Medicine, 89*, 161–173.

Hall, D. M., & Most, M. M. (2005). Dietary adherence in well-controlled feeding studies. *Journal of the American Dietetic Association*, 105, 1285–1288.

Hill, A. J. (2007). The psychology of food craving. *Proceedings of the Nutrition Society, 66*, 277–285.

Houben, K., & Jansen, A. (2015). Chocolate equals stop. Chocolate-specific inhibition training reduces chocolate intake and go associations with chocolate. *Appetite, 87*, 318–323.

Kakoschke, N., Kemps, E., & Tiggemann, M. (2017). Approach bias modification training and consumption: A review of the literature. *Addictive Behaviors, 64*, 21–28.

Karpinski, A., & Steinman, R. B. (2006). The single category implicit association test as a measure of implicit social cognition. *Journal of Personality and Social Psychology, 91*, 16–32.

Kraus, A. A., & Piqueras-Fiszman, B. (2016). Sandwich or sweets? An assessment of two novel implicit association tasks to capture dynamic motivational tendencies and stable evaluations towards foods. *Food Quality and Preference, 49*, 11–19.

Lüdecke, D. (2017). sjPlot: Data Visualization for Statistics in Social Science. Retrieved from https://CRAN.R-project.org/package=sjPlot

Martin, C. K., O'Neil, P. M., Tollefson, G., Greenway, F. L., & White, M. A. (2008). The association between food cravings and consumption of specific foods in a laboratory taste test. *Appetite, 51*, 324–326.

Meule, A., & Hormes, J. M. (2015). Chocolate versions of the *Food Cravings Questionnaires*. Associations with chocolate exposure-induced salivary flow and ad libitum chocolate consumption. *Appetite, 91*, 256–265.

Meule, A., Richard, A., & Platte, P. (2017). Food cravings prospectively predict decreases in perceived self-regulatory success in dieting. *Eating Behaviors, 24*, 34–38.

Parsons, S. (2018). splithalf: robust estimates of split half reliability. *figshare*. doi:10.6084/m9.figshare.5559175.v4

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/

Reichenberger, J., Richard, A., Smyth, J. M., Fischer, D., Pollatos, O., & Blechert, J. (2018). It's craving time: time of day effects on momentary hunger and food craving in daily life. *Nutrition, 55-56*, 15–20.

Richard, A., Meule, A., & Blechert, J. (2018). When and how do explicit measures of food craving predict implicit food evaluation? A moderated mediation model. *Food Quality and Preference, 66*, 141–147.

Richard, A., Meule, A., Reichenberger, J., & Blechert, J. (2017). Food cravings in everyday life: An EMA study on snack-related thoughts, cravings, and consumption. *Appetite, 113*, 215–223.

Robinson, E., Hardman, C. A., Halford, J. C., & Jones, A. (2015). Eating under observation: a systematic review and meta-analysis of the effect that heightened awareness of observation has on laboratory measured energy intake. *American Journal of Clinical Nutrition, 102*(2), 324–337.

Roefs, A., Huijding, J., Smulders, F. T. Y., MacLeod, C. M., de Jong, P. J., Wiers, R. W., & Jansen, A. T. M. (2011). Implicit measures of association in psychopathology research. *Psychological Bulletin, 137*, 149–193.

Rozin, P., Levine, E., & Stoess, C. (1991). Chocolate craving and liking. *Appetite, 17*, 199–212.

Sazonov, E. S., Makeyev, O., Schuckers, S., Lopez-Meyer, P., Melanson, E. L., & Neuman, M. R. (2010). Automatic detection of swallowing events by acoustical means for applications of monitoring of ingestive behavior. *IEEE Transactions on Biomedical Engineering, 57*(3), 626–633.

Seibt, B., Häfner, M., & Deutsch, R. (2007). Prepared to eat: how immediate affective and motivational responses to food cues are influenced by food deprivation. *European Journal of Social Psychology, 37*, 359–379.

Siep, N., Roefs, A., Roebroeck, A., Havermans, R., Bonte, M. L., & Jansen, A. (2009). Hunger is the best spice: An fMRI study of the effects of attention, hunger and calorie content on food reward processing in the amygdala and orbitofrontal cortex. *Behavioural Brain Research, 198*, 149–158.

Stafford, L. D., & Scheffler, G. (2008). Hunger inhibits negative associations to food but not auditory biases in attention. *Appetite, 51*, 731–734.

Tapper, K. (2018). Mindfulness and craving: effects and mechanisms. *Clinical Psychology Review, 59*, 101–117.

Waters, A. J., Miller, E. K., & Li, Y. (2010). Administering the Implicit Association Test in an ecological momentary assessment study. *Psychological Reports, 106*(1), 31–43.

Weingarten, H. P., & Elston, D. (1991). Food cravings in a college population. *Appetite, 17*, 167–175.

Zuur, A., Ieno, E. N., Walker, N., Saveliev, A. A., & Smith, G. M. (2009). Mixed effects modelling for nested data. In A. Zuur, E. N. Ieno, N. Walker, A. A. Saveliev, & G. M. Smith (Eds.), *Mixed effects models and extensions in ecology with R* (pp. 101–142). New York: Springer.

Table 1

Odds ratios (OR), confidence intervals (CI), and standard errors (SE) for the mixed effects logistic regression model with the predictors craving intensity, hunger, implicit evaluation of chocolate, and their cross-level interactions to predict the odds of chocolate consumption at a signal.

	Random model				Winning model			
	OR	*CI*	*SE*	*p*	*OR*	*CI*	*SE*	*p*
Fixed parts								
(Intercept)	0.04	0.03 – 0.06	0.01	**<.001**	0.04	0.03 – 0.06	0.01	**<.001**
Craving intensity	3.30	2.69 – 4.04	0.34	**<.001**	3.31	2.72 – 4.04	0.34	**<.001**
Hunger	0.84	0.67 – 1.06	0.10	.150	0.78	0.65 – 0.94	0.07	**.009**
Implicit evaluation of chocolate	1.27	0.88 – 1.83	0.24	.206				
Craving intensity × hunger	0.90	0.74 – 1.10	0.09	.299				
Craving intensity × implicit evaluation of chocolate	1.10	0.90 – 1.35	0.11	.338	1.18	0.99 – 1.41	0.11	.066
Hunger × implicit evaluation of chocolate	0.84	0.68 – 1.04	0.09	.111	0.82	0.67 – 1.01	0.09	.064
Craving intensity × hunger × implicit evaluation of chocolate	1.23	1.01 – 1.50	0.13	**.039**	1.25	1.03 – 1.51	0.12	**.024**
Random parts								
$\tau_{00, participants}$		1.09				1.11		
$N_{participants}$		60				60		
Observations		1904				1904		
Akaike Information Criterion		972				971		
Deviance		848				849		
Hosmer-Lemeshow-χ^2		9.07; *p* = .336				7.38; *p* = .496		

Notes. *P*-values < .050 are printed in boldface. Observations refer to the number of all signals obtained during the 1-week Ecological Momentary Assessment. The Hosmer-Lemeshow-χ^2 analyzes whether the observed and expected values differ significantly and, therefore, a non-significant *p*-value indicates that the data fit the model.

Figure Caption

Figure 1. Interaction plot for the three-way interaction of craving, hunger, and implicit

evaluation of chocolate on the probability of chocolate consumption. A more positive implicit

evaluation of chocolate was associated with a higher probability of chocolate consumption in

states of high chocolate craving (+2 *SD*) and high hunger (+ 1 *SD*), but not in states of low

chocolate craving (−2 *SD*) or low hunger (−1 *SD*).

- A more positive implicit evaluation was not directly associated with chocolate consumption.

- Hunger and chocolate craving interact with implicit evaluation when predicting chocolate consumption.

- A higher likelihood of chocolate consumption was found when both hunger and chocolate craving were high.

- No such modulatory pattern was found in states of low hunger and/or low chocolate craving.

Figure 1