No effect of hunger on attentional capture by food cues: two replication studies

Authors: Courtney Neal[1], Gillian V. Pepper[2], Caroline Allen[3], and Daniel Nettle*[1,4]

Author affiliations:

[1] Population Health Sciences Institute, Newcastle University, Newcastle, UK

[2] Psychology Department, Northumbria University at Newcastle, Newcastle, UK

[3] School of Psychology, Newcastle University, UK

[4] Institut Jean Nicod, Département d'études cognitives, École Normale Supérieure, Université PSL, EHESS, CNRS, Paris, France

***Correspondence:** Daniel Nettle, daniel.nettle@ens.psl.eu.

Abstract

Hunger is a powerful driver of eating behaviour. However, the relationship between hunger and food-related cognition remains poorly understood. Previous research found that hunger increased the ability of food cues to capture attention in a US student sample (*N*=23; Piech, Pastorino, & Zald, Appet., 54, p579-582, 2010). We conducted online (*N*=29) and in-person (*N*=28) replications of this study with British participants, using the same stimuli sets and protocols as the original study, with a Bayesian analytical approach. The studies use the Emotional Blink of Attention (EBA) task, in which participants must identify a rotated image in a Rapid Serial Visual Presentation. The targets are preceded by distractors – "neutral", "romantic", or "food" images. We predicted that food images would create a greater attentional blink when participants were hungry than when they were sated, but romantic and neutral images would not. Our participants completed the task twice, at the same time of day, on two different days, 6-11 days apart; once when hungry (overnight plus 6h fast) and once when sated (after eating a self-selected lunch in the preceding hour). Our results did not support the original finding that hunger increases attentional capture by food cues, despite both of our experiments passing manipulation and quality assurance checks. While the lack of replication of the original finding may result from differences in the sample, responses to stimuli, or other limitations, it is also possible that the original finding may not be generalisable. This may be explained by the sensitivity of the EBA paradigm to the physical distinctiveness of distractors from filler and target images, rather than the emotional valence of the distractors, as previously thought. Our studies were pre-registered on Open Science Framework (https://osf.io/w2a8f and https://osf.io/v4wpt).

1. Introduction

In this paper, we present two replications of an experiment that demonstrated an effect of hunger on attentional capture by food cues. The findings, by Piech *et al*. (2010) (henceforth PPZ), have been widely cited as evidence that hunger heightens perception of food cues through an involuntary attentional mechanism, with potential implications for eating behaviour. PPZ found that food images became more powerful distractors when participants were hungry, even when participants were rewarded for ignoring the food. Participants were worse at detecting targets following a food image when they were hungry compared to when they were sated. The same was not true for neutral or romantic images.

PPZ used the emotional blink of attention (EBA) task, in a sample of US undergraduate students. Participants completed the task twice, on two different days: once after fasting for six hours (hungry), and once after eating as usual (sated). Overall performance was worse when distractor images (neutral, romantic, or food) were placed two images before a target (lag2) than when they were placed eight images before a target (lag8), as is consistent with the presence of an attentional blink. PPZ’s key result was a significant interaction between state (hungry or sated) and image category (neutral, romantic, or food) in lag2 trials, but not lag8 trials. Participants had worse performance on lag2 trials with food distractors when they were hungry which was not true for lag2 trials with neutral or romantic distractors.

Davidson *et al*. (2018) used an adapted version of the PPZ EBA paradigm to assess the relationship between the ability of food stimuli to create an emotional blink of attention and the motivation to eat before and after eating. They found task performance in trials with food distractors was consistently worse than in trials with neutral distractors. Additionally, performance after food distractors became worse as appetite increased. Although their findings appear to support those reported by PPZ, the variations and extensions in their methods make it difficult to compare the results of the two studies directly.

Arumäe *et al*. (2019) used an EBA task and hunger manipulation more in line with that of PPZ. Each of their participants completed one session after a 6h fast, and one session after a breakfast meal provided by the researchers. Arumäe *et al*. (2019) found no evidence of a significant state X image category interaction effect and suggested this result may be because of differences in attentional biases in different subpopulations. However, while their EBA task followed the same procedure as PPZ, they used different images to PPZ as fillers, distractors, and targets, and they only used two categories of distractor images (neutral and food). They also presented their images on a white background, rather than black. Furthermore, the EBA task was one of three tasks that participants completed in each session. As the procedure and stimuli sets differed from PPZ, Arumäe *et al*. (2019) may not be a sufficiently "close replication" (as described in Brandt *et al*., 2014) to contest the findings of PPZ.

To our knowledge, there have been no close replications of the experiment reported in PPZ. In this paper, we report the results of two replications using British samples. The first replication was online, due to the COVID-19 pandemic, and the second took place in person like PPZ. Our central aim was to replicate the effect that demonstrates the influence of hunger attentional capture by food cues – a state X image category interaction effect in lag2, but not lag8, trials.

2. Methods

We carried out two pre-registered experiments that replicated the experiment reported in PPZ. The pre-registered protocols and predictions are available online at https://osf.io/w2a8f and https://osf.io/v4wpt. The Newcastle University Faculty of Medical Science Research Ethics Committee (reference 8999/2020) granted ethical approval for both studies. All aspects of the experiments were presented on PsyToolKit (Stoet 2010, 2017).

2.1 Participants

For both experiments, we recruited 30 participants, the same number as PPZ (though, PPZ analysed data from only 23 participants after exclusions). We used a flexible stopping rule for sample size, requiring a minimum sample size of 30, and Bayes Factor of $<\frac{1}{10}$ or >10 for the critical state X image category interaction in lag2 trials (see '2.4 Data Analysis') to stop participant recruitment. Both experiments met the Bayes Factor criterion at the first point of inspection, after 30 participants.

For Experiment 1 (E1; online), we recruited 30 individuals using opportunity sampling (ages 21–34 years, *M* = 28.43, *SD* = 3.69; women = 17, men = 13). We informed participants that they would need access to Google Chrome on a PC or laptop with a physical keyboard, and a quiet place where they would not be disturbed during the study. Recruitment and data collection for E1 took place from June 14th, 2021–July 23rd, 2021.

For Experiment 2 (E2; laboratory), we recruited 30 individuals from a research volunteer pool maintained by Newcastle University (ages 20–79 years, *M* = 42.9, *SD* = 20.2; women = 18, men = 11, non-binary = 1). We informed participants that they would need to attend Newcastle University on two occasions, approximately one week apart. Recruitment and data collection for E2 took place from November 16th, 2021–February 16th, 2022.

We informed participants in both experiments that, to take part, they should have normal or corrected-to-normal vision and should not have a medical condition requiring them to eat regularly that would exclude them from safely completing a fast.

Participants received a 10 GBP retail gift card for each session they completed. If their average accuracy across both sessions was over 80% or 90% (on trials with a target), they received an additional 5 GBP or 10 GBP gift card, respectively. The participant with the highest average accuracy score in each experiment also received a prize of a 50 GBP gift card. We informed participants of these monetary incentives during recruitment.

2.2 Procedure

Both experiments had a within-subjects design. Participants completed two sessions on different days, six to 11 days apart; one in the hungry condition and one in the sated condition. The order of hungry and sated sessions was counterbalanced.

All sessions started six hours after participants had woken up. Waking time and session times were agreed with each participant during recruitment and were the same for both sessions. PPZ did not indicate what time of day their sessions took place. By personalising and standardising session timing for each participant, we minimised potential impacts of circadian rhythm or fatigue on cognitive performance (Schmidt *et al*. 2007; Valdez *et al*. 2007) and other unidentified confounding factors related to timing.

In the hungry condition of both experiments, we instructed participants to refrain from eating from waking until after their session that day. This resulted in a minimum of six hours without eating prior to the experiment, the same as PPZ. We instructed participants to drink water and caffeinated drinks as usual in the hungry condition, but to avoid satiating drinks (such as those with high milk, sugar, or calorie content). PPZ instructed participants to “continue drinking as usual” in the hungry condition. We excluded consumption of potentially satiating drinks to create a robust hunger manipulation (an approach used in more recent research with hungry and sated conditions; Redlich *et al*. 2022). We specified that participants could consume caffeinated drinks in the hungry condition to limit potential impacts of caffeine withdrawal on the cognitive performance of habitual caffeine users (James & Rogers, 2005).

In the sated condition of both experiments, we instructed participants to eat and drink as usual from waking, as PPZ did. We asked participants to eat lunch in the hour before their session started, which PPZ did not specify. We implemented this requirement to minimise the level of hunger participants experienced in the sated condition, and hence to maximise the difference between conditions.

E1 participants were asked to complete the study in a quiet place where they would not be disturbed. E2 participants completed their sessions onsite in a controlled, laboratory environment and were tested alone. The display in E2 was a 61.13 cm, 1920 x 1200 resolution monitor which participants viewed from approximately 70 cm away.

In E1 and E2, each session lasted approximately 35 minutes. Participants provided informed consent, then gave their age and gender. They then completed the EBA task ('2.3.1 Emotional blink of attention (EBA) task') and were asked if they had been interrupted during the task upon its completion. They provided a self-reported hunger rating ('2.3.2 Self-reported hunger rating'), answered additional questions ('2.3.3 Additional measures'), and, only in their second session, completed a dietary restraint scale ('2.3.4 Dietary restraint'). At the end of their second session, we debriefed participants and reminded them of how and when they would receive their rewards.

2.3 Measures

2.3.1 Emotional blink of attention (EBA) task

The EBA task used in both experiments was designed to be a replication of the version used by PPZ (Figure 1). The task itself consisted of one block of 16 practice trials and six blocks of 32 real trials. There were one-minute breaks between blocks. Trial order was randomised within each block. Each trial was a rapid stream visual presentation (RSVP) of 17 images shown for 100ms each. Images were shown on a full-screen black background. Each trial started with a fixation cross, and participants pressed the spacebar to start the trial. A target was present in 75% of the real trials. This was an image that had been rotated by 90º, clockwise or anticlockwise. Both RSVP filler images and target images were photos of landscapes, some of which contained buildings.

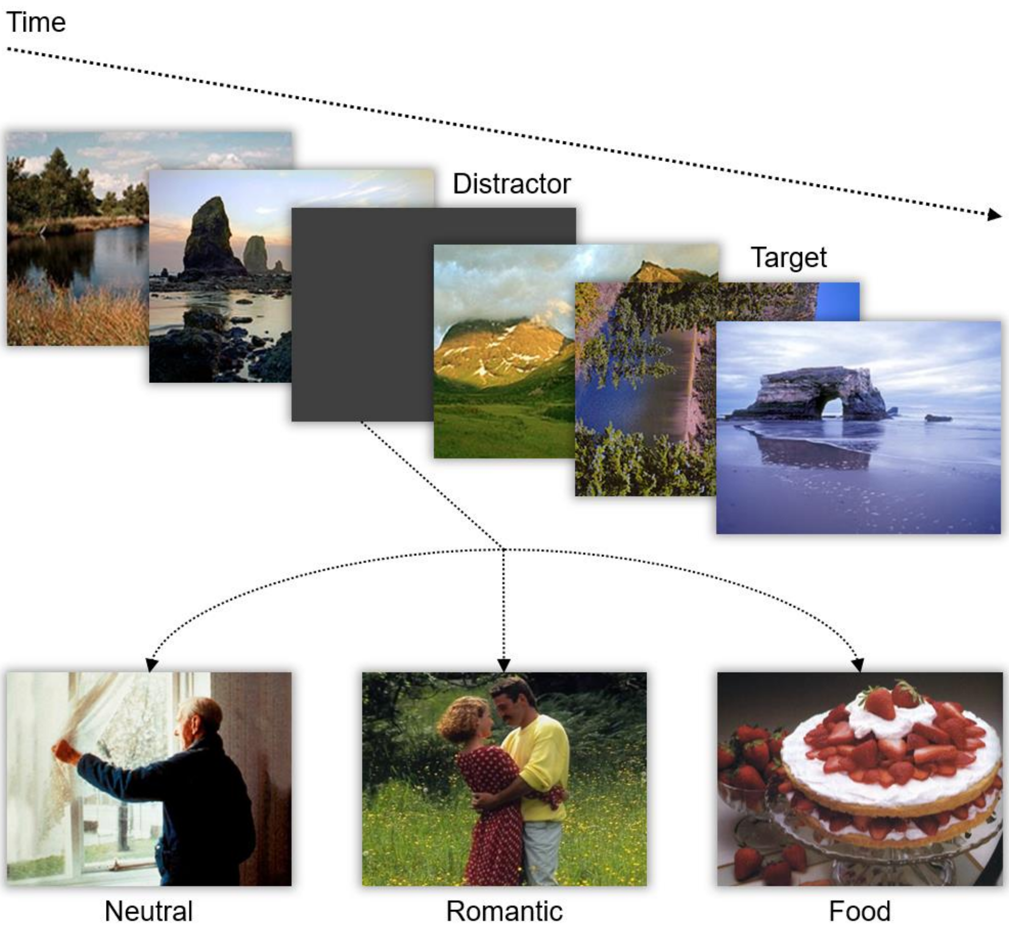
A single distractor image was present in all trials with a target. Distractors were categorised as either food, romantic, or neutral images. They were only in position four, six, or eight in the RSVP sequence, and either two positions (lag2) or eight positions (lag8) before a target.

Participants had to identify whether a target image was present in each trial by using key presses. They had five seconds to respond after every trial. If they correctly identified the presence of a target, they had to indicate the direction of its rotation by using the arrow keys within five seconds.

Accuracy was calculated by dividing the number of target trials in which they correctly identified the direction of the target rotation by the total number of trials with targets, then multiplying by 100. Participants were shown their cumulative accuracy for that session after each block, and their total accuracy for that session at the end of the task. The displayed accuracies were based only on trials with targets.

We used the same image sets as PPZ, as the original authors shared these with us. Most of these images had been acquired from the International Affective Picture System (IAPS) database (Lang *et al*., 2008), with additional supplementation from the internet for romantic and food distractors. As there were more images than required in each category, the subset we used may have differed slightly from the subset PPZ used. In total, 168 different distractor images were used (56 from each category), alongside 84 landscape images as fillers. An additional 84 landscape images were used as target images; these were duplicated, with one copy rotated 90° clockwise and one copy rotated 90° anticlockwise.

Figure 1. Representation of part of a single EBA task trial.



Note. In half of the trials with targets, the distractor image was shown eight places before the target (lag8), rather than two (lag2) as shown.

2.3.2 Self-reported hunger rating

After completing the EBA task in all sessions, in E1 and E2, participants answered the question 'How hungry are you?' using a scale anchored at 0 (not at all hungry) and 7 (extremely hungry). We used their responses as a manipulation check.

2.3.3 Additional measures

For all sessions, in E1 and E2, we asked participants when they last had something to eat. This came after the self-reported hunger rating. It provided a condition compliance check and an alternative measure of hunger for exploratory analyses. We also asked if they regularly skipped breakfast, for the purpose of exploratory analyses.

2.3.4 Dietary restraint

Participants completed the dietary restraint scale (Herman & Polivy, 1975; Herman, Polivy, Pliner, Threlkeld & Munic, 1978) after the EBA task in their second session, in E1 and E2. We scored participants using the methods of Herman & Polivy (1975). PPZ used this scale to explore the relationship between dietary restraint and attentional capture of food cues in lag2 trials in the hungry condition. While they did not find evidence of a significant relationship, we retain it here for comparability (Table S1).

2.4 Data Analysis

Data were analysed and visualised in R (R Core Development Team, 2020) using the tidyverse (Wickham *et al*., 2019), brms (Bürkner, 2017, 2018), BayesFactor (Morey & Rouder, 2018), bayestestR (Makowski *et al*. 2019b), parameters (Lüdecke *et al.*, 2020), cowplot (Wilke, 2020), patchwork (Pedersen, 2022), ggpattern (FC *et al*., 2022) and extrafonts (Chang, 2022) packages. Our data and code are available at https://osf.io/w5en6/.

PPZ excluded participants who reported a lower hunger rating in the hungry condition than in the sated condition. Using these criteria, we excluded no participants in E1, and one participant in E2. PPZ also excluded participants with accuracy more than two standard deviations below the mean for the respective hunger condition. We excluded one participant from E1 and one from E2 based on these criteria.

While PPZ used frequentist analyses, we analysed E1 and E2 data using Bayesian methods to allow us to implement a flexible stopping rule during data collection and provide evidence in support of null findings. To allow easier comparison with the original study, we also present frequentist analyses equivalent to those used by PPZ (Table S2) – these results support the Bayesian outcomes of our main predictions for replication.

We fitted Bayesian linear mixed models, which followed the structure of the ANOVAs used in PPZ (Table S3), allowing for repeated measures of the same participant. We used weakly informative priors of *N*(1, 10) (McElreath, 2020). We initially fitted models analysing all trials together, before fitting separate models for lag2 and lag8 trials.

We used paired Bayesian *t*-tests to assess differences in hunger rating between states and to test accuracy differences between lags within each category, each category (in lag2 and lag8 trials, separately), and states for each category in lag2 trials.

We pre-registered conditional requirements for successful replication of the main findings of PPZ. Our conditions were based on the strength of evidence for two key predictions:

P1. There will be a state X image category interaction effect on accuracy in lag2 trials – participant's accuracy will only be reduced after food distractors in their hungry session.

P2. There will not be a state X image category interaction effect on accuracy in lag8 trials.

Our statistical conditions required a Bayes factor of greater than 10 or less than 0.1 to support the prediction or the null, respectively. For successful replication, a Bayes Factor greater than 10 was required for both P1 and P2. Alongside Bayes Factors, we present 89% credible intervals (CI) and the probability of direction (*pd*). The latter indicates "the probability that a parameter is strictly positive or negative" (Makowski *et al*., 2019a).

3. Results

First, we report hunger manipulation, paradigm, and practice effect checks. We then present results related to the two predictions required for successful replication (P1 and P2). We report E1 and E2 results together. Ancillary results, produced by conducting other analyses reported by PPZ, can be found in Tables S4-9.

3.1 Hunger manipulation check

There was evidence that participants had higher hunger ratings in their hungry session than in their sated session (BFs > 1000; Table 1), in E1 (median difference = 5.43 , 89% CI [5.76, 5.06], pd = 100%) and E2 (median difference = 5.01 , 89% CI [5.48, 4.52], pd = 100%).

3.2 Blink of attention check

PPZ reported higher accuracy in lag8 trials, compared to lag2 trials (Table 1; Figure 2), across all distractors, suggesting all distractors produced a blink of attention at lag2. This was supported in E1 (BF > 1000, median difference = 6.91, 89% CI [5.61, 8.12], pd = 100%) and E2 (BF > 1000, median difference = 7.18, 89% CI [5.79, 8.43], pd = 100%). Planned paired Bayesian *t*-tests (Table S4) provided evidence for accuracy differences in lag2 and lag8 trials for all distractors, in line with PPZ (Figure 2).

3.3 Practice effect check

PPZ reported a practice effect; participants had higher accuracy in their second session. This was also true in E1 and E2 (Table 1). While the Bayes factors did not reach our strict threshold (BF > 10) for supporting this prediction, the evidence for a practice effect was substantial as per the Bayes factor thresholds of Wetzels et al. (2011), in E1 (BF = 7.60, median difference = 2.62, 89% CI [1.15, 4.09], pd = 99.92%) and E2 (BF = 9.85, median difference = 2.87, 89% CI [1.27, 4.31], pd = 99.88%). The pd values also suggest a significant practice effect (Makowski *et al*., 2019a).

3.4 Replication of main findings (P1 and P2)

PPZ found a significant state X image category interaction in lag2 trials (P1), but not in lag8 trials (P2). In our experiments, there was evidence to support an absence of a state X image category interaction effect in lag2 trials in E1 and in E2 (Table 2; Figure 2). Thus, P1 was not supported. In E2, there was no evidence of state X image category interaction effect in lag8 trials (Table 2). In E1, the Bayes factors did not reach our strict threshold (BF < 1/10) to support the absence of a state X image category interaction at lag8 (Table 2). However, the evidence was substantial as per the Bayes factor thresholds of Wetzels *et al*. (2011). Overall, given the lack of support for P1, we did not replicate the key finding of interest in PPZ.

Table 1. Descriptive statistics of self-reported hunger rating in each state, and of accuracy on the EBA task in lag2, lag8, session 1, and session 2 trials.

Study	Mean hunger rating (SD)		Mean accuracy (SD)			
	Sated	Hungry	Lag2	Lag8	Session 1	Session 2
PPZ	2.4 (1.2)	5.4 (1.4)	-	-	75.50 (7.30)	80.20 (6.70)
E1	0.5 (0.7)	6.0 (0.9)	84.03 (11.07)	90.97 (8.35)	86.18 (7.73)	88.82 (5.79)
E2	0.4 (0.9)	5.4 (1.4)	82.27 (12.23)	89.48 (9.84)	84.42 (8.70)	87.33 (7.96)

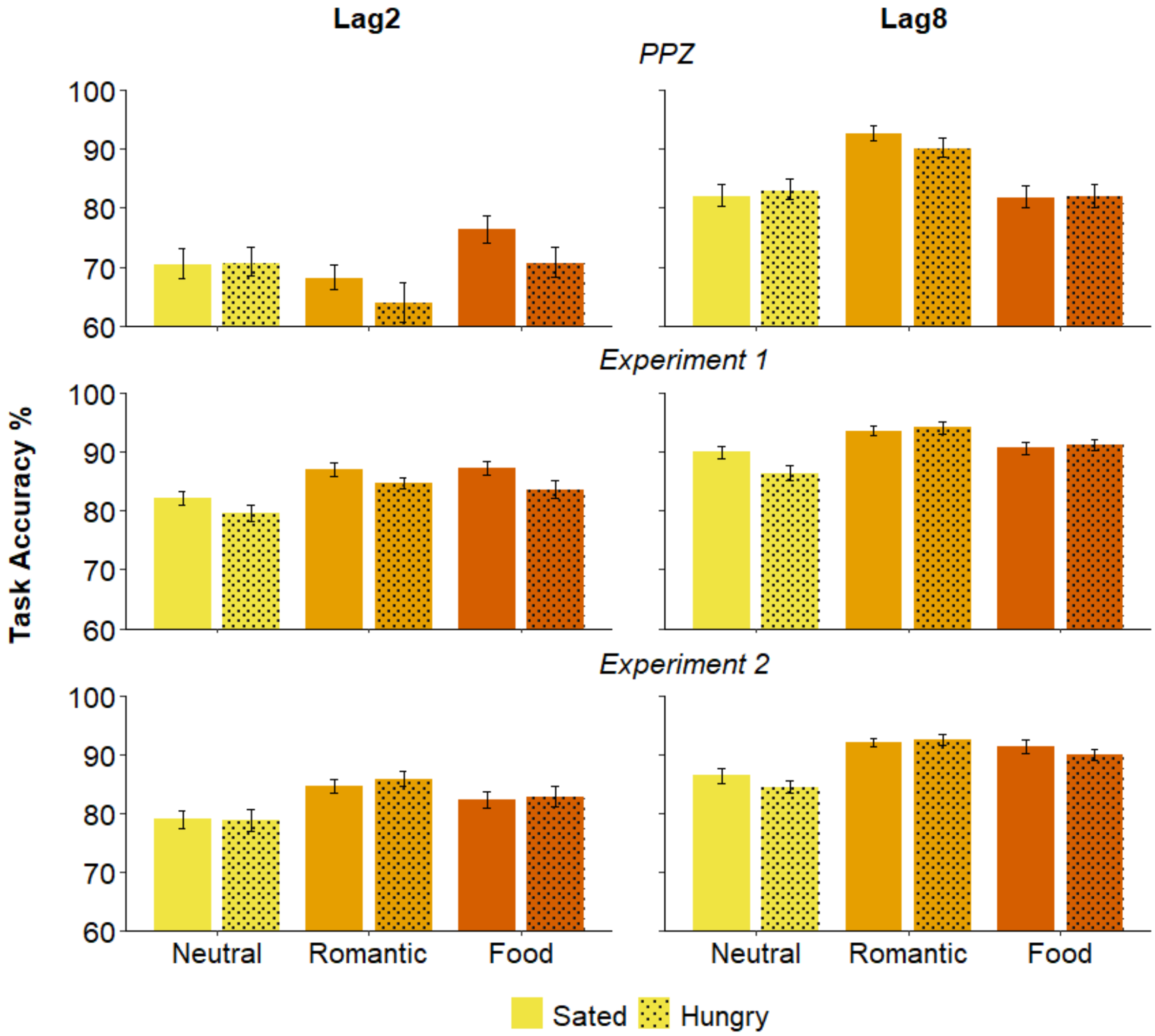
Note. PPZ values are missing for lag2 and lag8 columns as they were not reported.

Table 2. Model output for P1 and P2 in E1 and E2, and corresponding findings of PPZ

PPZ	E1	E2
P1: Interaction effect of image category and state in lag2 trials		
Significant	Evidence for null	Evidence for null
p = .03	BF = 0.06	BF = 0.09
F(2, 21) = 3.8	sated:romantic: median diff. = 0.02, 89% CI [-3.58, 4.11], pd = 50.28%	sated:romantic: median diff. = -0.79, 89% CI [-5.26, 4.15], pd = 60.27%
	sated:food: median diff. = 1.34, 89% CI [-2.39, 5.24], pd = 71.33%	sated:food: median diff. = -0.29, 89% CI [-4.70, 4.76], pd = 53.73%
P2: Interaction effect of image category and state in lag8 trials		
Not significant	Inconclusive	Evidence for null
Not reported	BF = 0.26	BF = 0.06
	sated:romantic: median diff. = -3.55, 89% CI [-6.94, -0.11],pd = 94.97%	sated:romantic: median diff. = -1.92, 89% CI [-5.12, 1.36], pd = 82.10%
	sated:food: median diff. = -3.57, 89% CI [-6.67, 0.07], pd = 95.50%	sated:food: median diff. = -0.35, 89% CI [-3.81, 2.85], pd = 56.33%

Note. The dependent variable is accuracy (%). "*Median diff.*" is the median difference.

Figure 2. Accuracy in PPZ, and E1 and E2, separated by lag, image category, and state.



Note. Trials are grouped by image distractor category, lag, and state. Lower task performance was hypothesised to indicate a greater attentional blink effect. The PPZ plots have been reproduced using Graph Data Extractor (2010) to extract data from the original published plots. Error bars indicate one standard error of the mean. For E1 and E2, error bars are within-subjects centred. This was not possible for PPZ because raw data were not available.

4. Discussion

We have reported two attempts to replicate the main finding of PPZ – an interaction effect of hunger condition and image category on accuracy in lag2 trials of an EBA paradigm (P1), but not in lag8 trials (P2). Evidence to support both P1 and P2 were required to successfully replicate the main finding of PPZ. We did not find evidence for P1 in E1 or E2, instead finding evidence in support of the null. Whilst we found evidence to support P2 in both replications, the lack of evidence to support P1 in either replication means that we did not successfully replicate the main finding of PPZ. These findings were despite efforts to ensure our pre-registered replication studies were as close to PPZ as possible. We liaised with the original authors (Piech *et al*., 2010), who supplied the original stimuli sets for our use and additional detail about their experiment and procedure.

It is unlikely that our unsuccessful replications were due to insufficient sample sizes. In both experiments, we employed a pre-registered Bayesian stopping rule during data collection to ensure we achieved the sample size required to provide conclusive evidence for the main finding of PPZ or the null. Our use of Bayesian analyses strengthened our experimental design by allowing us to evaluate evidence in support of the null as well as the alternative hypothesis. The most obvious differences in the samples in E1 and E2 compared to PPZ were the geographical location and age of the participants, as E1 and E2 had samples from the British population, whereas PPZ used a sample of US undergraduates. We were not able to definitively determine how the ages of the samples differed, as descriptive statistics of age were not reported in PPZ. It is unclear how age differences could have led to unsuccessful replication, especially given that the sample of Arumäe *et al*. (2019) were relatively close in age (M = 25.51, SD = 5.99) to our participants in E1 (M = 28.43, SD = 3.69).

Furthermore, it is also unlikely that differences in participant hunger can explain our null results. In both E1 and E2, our manipulation of hunger was successful and produced a larger difference in mean hunger rating between sessions than in PPZ. The latter may result from the additional controls we implemented on the timing of sessions and eating, as such details could not be provided by PPZ. This meant, in E1 and E2, participants completed their first and second sessions at the same time of day, their sessions were six hours after they had woken up, and they followed clear eating and drinking instructions to ensure they were appropriately fasted or sated for their sessions. However, there were procedural differences worth noting. E1 was hosted online due to Covid-19 restrictions, and we could not control display conditions during the experiment for each participant. Yet, given our within-subjects design, and that participants likely completed both sessions in the same setting on the same device, display conditions are unlikely to have had a significant impact on data quality. We were aware of this limitation before we conducted E1, hence, we pre-registered our commitment to run a second replication (E2) in a controlled laboratory setting if the first was not successful. As the outcomes of E2 supported those of E1, experimental settings are unlikely to be a significant cause of the unsuccessful replications.

We also ran several experimental checks that agreed with PPZ and, thus, such differences are unlikely to explain our differences in results. In E1 and E2, as in PPZ, there was substantial evidence for a practice effect across sessions and no correlation between dietary restraint and accuracy in lag2 trials with food distractors in the hungry condition (see Table S1). Furthermore, evidence from E1 and E2 indicated that the paradigm successfully created a blink of attention at lag2 for all distractors, as accuracy in lag2 trials was lower than in lag8 trials.

Despite our efforts to minimise deviations from the original study, overall accuracy was higher in E1 and E2 than in PPZ. This may suggest that our distractors were less effective at capturing the attention of our participants than in PPZ or that our participants were more able to suppress stimulus-driven attentional capture. We found notable differences in the main effects of image category on accuracy (see Tables S4-8) between PPZ and our replications. For example, PPZ found that romantic trials had the lowest accuracy at lag2, but at lag2 in E1 and E2, romantic trials had the highest accuracy. This means that of all the distractors at lag2, romantic distractors were the most likely to create an attentional blink in PPZ, but the least likely to create an attentional blink in E1 and E2. These differences may be because of the image sets used in our replications; it is probable that the exact image sets used in E1 and E2 were different to the original study, as the original authors were unable to identify the exact image subsets used from the larger image sets shared with us. This could account for the lack of state X image category interactions in our replications, and in those of Arumäe *et al*. (2019), as even subtle differences in image sets may alter whether an EBA occurs. Santacroce *et al.* (2023) highlight this. They showed that it is not the emotional valence of the distractor that leads to an attentional blink in an EBA task, but its physical distinctiveness from filler and target images. They surmised that such distinctiveness creates a 'pop-out' effect so the distractor can capture attention, which is not achieved by the emotional content of the distractor alone. This 'pop-out' effect then results in a blink that is subsequently magnified by the emotional content of the distractor. It is also worth noting that Arumäe *et al*. (2019) categorised their food distractor images based on their fat content (high or low) and whether they were sweet or savoury. They found that food type did not impact task performance. Furthermore, Hardman *et al*., (2021) found no relationship between hunger and attentional bias for high- or low-calorie food stimuli. Thus, it is unlikely that the foods represented in the food distractor images impacted participants' task performance on trials with food distractors.

While these findings emphasise the importance of considering physical distinctiveness during image stimuli selection, they also highlight the limitations of the EBA paradigm for studying changes in attentional blinks following a shift in motivational state. The EBA appears less reliant on the emotional valence of the image than previously thought. Consequently, a change in the emotional salience of a distractor following a change in motivational state may not impact the attentional blink to an observable extent. This may be made more challenging by the relatively small effect size of an EBA; Santacroce *et al.* (2023) found that even when an

EBA occurs, it is weaker than the attentional blink produced in a conventional attentional blink paradigm, in which participants must identify two targets that appear in close succession in a RSVP. In the experiments presented here, the motivational state of interest is hunger. We assume that the emotional valence, and consequently attentional bias, of food cues will increase with increasing hunger, resulting in a more pronounced EBA. However, Redlich *et al.* (2022) suggested that hunger may not be an appropriate manipulation for increasing the value of food stimuli. Further, a meta-analysis of 98 effect sizes found only a very weak positive correlation between hunger and attentional bias to food cues (Hardman *et al*., 2021). Given this, it is unlikely that hunger alone is capable of dramatically increasing the emotional valence of food cues to increase the strength of an emotional blink of attention.

These limitations of the paradigm and of our assumptions may also elucidate the lack of state X image category interactions in Arumäe *et al*. (2019). Despite this, Arumäe *et al*. suggested their result may be due to differences in their sample to PPZ. They proposed that certain traits or conditions (e.g., impulsivity and drug-dependency, respectively) may bias the attentional processing of rewarding stimuli and that stricter control over such confounds may be required to produce the expected effect. They also suggested that attentional biases for food cues may only be present in specific subpopulations, such as individuals with obesity (Castellanos *et al*., 2009). We did not record participants' BMI in E1 or E2, nor did PPZ. However, in their meta-analysis, Hardman *et al*., (2021) found there to be no relationship between an individual's weight status and their attentional bias for food cues. Another meta-analysis found no difference in attentional bias to food stimuli, across several tasks, between people with obesity or overweight and people with healthy weight (Hagan *et al*., 2020). Thus, the BMI of our samples is unlikely to be a reasonable explanation for our differences in results to PPZ.

Methodological, demographic or cultural differences across the studies may account for our failure to replicate the original finding of interest from PPZ. However, the failure may also result from limitations of the EBA paradigm and/or a weak relationship between hunger and attentional bias for food cues. At the very least, this suggests that the key findings of PPZ have limited generalisability, and, at most, it may suggest their finding was a false positive. Maxwell *et al*. (2015) suggested that adopting a Bayesian approach in parallel with multiple replication attempts can help to elucidate the likelihood of the null hypothesis given the results of the replication data. We used both strategies in this present study in an attempt to conduct a rigorous replication and quantify the strength of evidence in favour of the findings of PPZ or the null hypothesis.

We did not find a relationship between hunger and the attentional capture of food cues in the present study. Our findings agree with those of Arumäe *et al*. (2019), but contest those of PPZ

(Piech *et al*., 2010). While the results of Davidson *et al.* (2018) are consistent with those reported by PPZ, they tested a related, but different hypothesis. As a result, their methodology differed significantly from PPZ, and their results cannot be considered a true replication. Therefore, the evidence that hunger affects attentional allocation to food stimuli may be weaker than previously thought. We suggest that further replications of this study are required and that the role of hunger as a motivational driver for shifting cognitive resources towards food stimuli needs better characterisation. One such avenue could be to assess whether hunger needs to be experienced over longer periods of time or more frequently (e.g., in populations experiencing food insecurity) to have measurable effects on food-related cognition, rather than the acute hunger manipulation used here.

5. Data available

All code and data are available at:

6. Acknowledgements

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8. References

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