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Cue discriminability predicts instrumental conditioning

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ABSTRACT

Charting mental acts that succeed or fail under unconscious instances of cognition informs debates on the nature and potential functions of consciousness. A prominent method to exclude conscious contributions to cognition is to render visual stimuli unconscious by short and pattern-masked presentations. Here, we explore a combination of visual masking and pixel noise added to visual stimuli as a method to adapt discriminability in a fine-grained fashion to subject- and stimulus-specific estimates of perceptual thresholds. Estimates of the amount of pixel noise corresponding to perceptual thresholds are achieved by psychometric adaptive algorithms in an identification task. Afterwards, the feasibility of instrumental conditioning is tested at four levels of cue discriminability relative to previously acquired estimates of perceptual thresholds. In contrast to previous reports (Pessiglione et al., 2008), no evidence for the feasibility of instrumental condition was gathered when contributions of conscious cognition were excluded.

1. Introduction

The delineation of mental acts that depend on consciousness from the ones that do not has been instrumental to investigate potential functions of consciousness (Baars, 1997; Kouider & Dehaene, 2007). Knowledge about the limits of unconscious cognition not only informs debates on the nature of consciousness in general (Dehaene & Changeux, 2011; Dehaene, Charles, King, & Marti, 2014; Mudrik, Faivre, & Koch, 2014) but also has an impact on further topics in cognitive science such as cognitive control (van Gaal, De Lange, & Cohen, 2012), language processing (Rastle & Brysbaert, 2006), or learning & memory (Greene, 2007; Hannula & Greene, 2012; Henke, 2010).

It seems undisputed that unconscious processing can go beyond the integration of low-level visual features such as size, shape, color and motion (e.g., Blake & Fox, 1974; Watanabe, Náñez, & Sasaki, 2001). Consciousness may be the crucial ingredient for cognition to succeed at higher levels of complexity, such as the learning of dependencies between temporally discontiguous events (e.g., Clark & Squire, 1998). However, conflicting evidence exists on whether, to what extent, and under which circumstances e.g. unconscious numerical cognition (Bahrami et al., 2010; Hesselmann, Darcy, Sterzer, & Knops, 2015), unconscious response inhibition (Chiu & Aron, 2014; Lin & Murray, 2015; van Gaal et al., 2012; van Gaal, Ridderinkhof, Scholte, & Lamme, 2010), or unconscious long-term memory (Clark & Squire, 1998; Duss et al., 2014; Greene, Spellman, Levy, Dusek, & Eichenbaum, 2001; Hannula, Ryan, Tranel, & Cohen, 2007; Konstantinidis & Shanks, 2014; Pessiglione et al., 2008; Reber, Luechinger, Boesiger, & Henke, 2012; Ryan, Althoff, Whitlow, & Cohen, 2000; Smith & Squire, 2005) succeeds or fails.

Unconscious processing is often investigated by assessing effects of visual stimuli that are delivered such that they are not perceived consciously. Methods to hide visual stimuli from awareness include among others interfering with cognitive processes such as e.g. attention (e.g., Raymond, Shapiro, & Arnell, 1992; Reber et al., 2017) or perception by e.g., flash suppression (Hesselmann

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et al., 2015; Kreiman, Fried, & Koch, 2001) or backward masking (Greenwald, Klinger, & Schuh, 1995; Quian Quiroga, Mukamel, Isham, Malach, & Fried, 2008). Masking has been a prominent method to reliably render stimuli unconscious (reviewed in Kouider & Dehaene, 2007). Masked presentations are considered to elicit unconscious processing when two conditions are met. First, participants either report complete unawareness or perform at chance on tasks that require them to directly discriminate or identify the masked stimulus, i.e., direct tests or awareness tests (Greenwald et al., 1995). Second, stimulus presentations nevertheless affect behavior indirectly. Such indirect or unconscious effects are usually obtained on tasks that are not directed at masked stimuli per se but at something else such as a clearly discriminable and detectable stimulus following the masked stimulus (Greenwald et al., 1995).

A challenge is to stimulate weakly enough to reliably obtain chance performance on direct tests but nevertheless strongly enough to obtain significant effects on indirect tests. Often, presentation duration of the stimulus is the parameter of choice to adjust stimulation intensity. However, presentation duration can only be adjusted with limited precision using standard computer hardware (Elze, 2010). Duration can only be varied in discrete steps corresponding to the display's refresh-rate (approximately 16.6 ms at 60 Hz). Thus, a participant may be aware of most of the stimuli at 3 refresh-cycles (50 ms) while stimulation is very weak or even too weak at 2 refresh-cycles (33 ms) to elicit even unconscious processing. Furthermore, researchers tend to choose conservative values of presentation duration that are also fixed across participants. Together, coarse-grained resolution of presentation duration and the choice of a fixed presentation duration across subjects may result in high inter-individual variability. In the current work, we propose a method of individual adjustments of stimulus intensity using a more fine-grained method than presentation duration to render stimuli indiscriminable. Random pixel noise added to brief and masked visual stimuli can be varied in a virtually continuous fashion and is efficient to render stimuli indiscriminable when applied in combination with brief presentation duration and pattern masking.

Assessing effects of various kinds of noise has a long tradition in psychophysics (Lu & Dosher, 2008) but only few studies we are aware of have used noise as a tool to investigate unconscious processing (e.g., Seitz & Watanabe, 2003). Both masking and pixel noise can be seen as forms of noise added to a perceptual signal. Regarding perception as a process that accumulates sensory evidence over time (Parker & Newsome, 1998), a pattern mask acts as noise in the temporal domain while pixel noise added to an image acts as noise in the spatial domain. Numerous previous masking studies have made efforts to keep noise in the spatial domain constant e.g. by matching visual features between stimuli and using the same or highly similar masking images throughout the experiment (Greenwald et al., 1995; Mastropasqua & Turatto, 2015; Pessiglione et al., 2008). Rather than in the spatial domain, they adjusted the signal to noise level in the temporal domain by varying the presentation duration of the stimuli, i.e., the signal, and the masks (i.e., the noise; see e.g., Pessiglione et al., 2008). We here propose to fix the timing aspects of the masking procedure but adjust the amount of spatial noise added to the visual signal. As we combine pixel noise with backward masking and short presentation duration, the amount of pixel noise required to render stimuli unconscious is rather low such that the image information is well preserved.

Individual adjustments of discriminability are achieved by psychometric adaptive algorithms of noise-level. Individual estimates are obtained before the main experiment using a psychometric adaptive algorithm (QUEST; Watson & Pelli, 1983). These procedures enable to investigate effects of masked stimuli at several degrees of discriminability within-subject. As we use procedures from psychophysics, we use the term 'threshold' as is common in psychophysics. We refer to the 'threshold' as the stimulus intensity at which subjects report having seen the stimulus 50% of the time (Kingdom & Prins, 2009). Thus, such a threshold intensity, as well as some intensities below this threshold, i.e., sub-threshold or subliminal intensities, can result in significantly above chance performance in a direct discrimination or detection test (i.e., $d' > 0$). In unconscious processing research, in contrast, the term 'threshold' is defined as the maximal stimulus intensity at which direct detection or discrimination test performance does not exceed chance (i.e., $d' = 0$: Greenwald et al., 1995). Thus, 'sub-threshold' or 'subliminal' stimulus intensities are defined as intensities at which, ideally, the participants report never having seen or being able to discriminate masked stimuli at all.

It is therefore important to keep in mind that significant effects on indirect tests at stimulus intensities corresponding to below-threshold stimulus intensities on direct tests do not per se index purely unconscious processing according to the terminology we use. To make claims of truly unconscious processing, one can either require a d' that is insignificantly different from zero on a direct test in combination with a d' significantly above zero on the indirect test, or use the regression method introduced by Greenwald, et al. (1995). Here, we assess claims of unconscious processing by the regression method as it makes more efficient use of all the data gathered, especially in the design we use here. To this aim, a regression model ($y = ax + b$) is fitted to the data taking the direct measure as predictor (x) and the indirect measure as criterion (y). Claims of unconscious processing can be made if the regression line is above zero at $x = 0$, i.e. if the intercept (b) is significantly larger than zero.

Here, we test the proposed procedures by adapting a paradigm to assess the feasibility of unconscious instrumental conditioning (Pessiglione et al., 2008), that has also been replicated in different contexts by others (Atas, Faivre, Timmermans, Cleeremans, & Kouider, 2013; Mastropasqua & Turatto, 2015).

2. Methods

2.1. Design

The study consisted of three parts. In the first part, subject- and stimulus- specific thresholds were estimated in an identification task in which the noise level was varied continuously according to an adaptive psychometric algorithm (QUEST; Watson & Pelli, 1983). Note that we refer to the noise level at which participants report having been able to identify the image in 50% of the trials as 'the threshold of perception' as is common in psychophysics. In studies of unconscious perception, in contrast, the threshold often denotes stimulus intensity at which participants perform at chance level in a direct discrimination or identification test. The second part tested for instrumental conditioning (Pessiglione et al., 2008). This test was conducted at four levels of discriminability that were set relative to the estimates obtained in the first part. Stimuli were presented either at a clearly discriminable level (> th), at the level of the previously estimated threshold of conscious perception (@th), and at two levels below this threshold (< th, ≪th). Instrumental conditioning performance is taken as the indirect measure since participants were instructed to rely on their 'gut feeling' in case they could not perceive the stimuli (Pessiglione et al., 2008). The third part consisted of an awareness test (direct test). Here, identification performance was measured at the four levels of discriminability also used in the conditioning test (> th, @th, < th, ≪th).

2.2. Participants

Thirty-one students and employees from the University of Bonn, Germany participated in the study. Data from two participants was lost due to computer malfunction. The remaining 29 participants (13 female) had a mean age of M = 26.2 years (SD = 3.6 years), had normal or corrected-to-normal vision, and gave written informed consent. Subjective measures of awareness (see below) were lost in two further participants such that analyses involving these measures were performed with data from the remaining 27 participants. Participants were paid for participation with a minimum of 10 €. Depending on their performance on the conditioning task (see below), participants could earn up to 30 €. The mean amount paid was M = 21.41 € (SD = 8.25 €).

2.3. Stimuli

Ten images of objects with a white background (320x320 pixels) were used as stimuli. Two images were used in the practice run of the conditioning experiment only. The remaining eight stimuli (Fig. 3) were randomly assigned in pairs of two to one of the four levels of discriminability (> th, @th, < th, ≪th) for each participant. The six images assigned to reduced discriminability levels (@ th, < th, ≪th) were subjected to the initial threshold estimation and the final awareness test. Six masking images were created by assigning random color-values to a 10 × 10 grid of tiles and applying various random image filters.

2.4. Apparatus

The experiment was conducted in a room with no windows and constant lighting conditions. We used octave (www.gnu.org/software/octave), the psychophysics toolbox 3 (www.psychtoolbox.org), and the implementation of the QUEST algorithm from the Palamedes toolbox (www.palamedestoolbox.org; Kingdom & Prins, 2009) on a Sony Vaio laptop computer running a Linux operating system (Debian 7.2, www.debian.org). The resolution of the LCD-Screen was 1024 × 768 pixels, and the refresh-rate of the display was 60 Hz.

2.5. Procedure

2.5.1. Threshold estimation

The initial threshold estimation consisted of 192 trials, i.e., 32 trials for each of the six stimuli. A trial comprised the presentation of fixation cross for 300–800 ms (randomly jittered), followed by a forward-mask for 167 ms, the presentation of one of the six stimuli for 67 ms, a backward-mask for 167 ms, and a blank screen for 1000 ms (Fig. 1). The participants' task was to identify the stimulus presented between the masks. Following the blank screen, all six stimuli were presented side by side until the participant chose one stimulus by key-press (keys 1–6 on the number-pad). On trials where the participants were unable to make a reasonable guess as they did not perceive even a slight hint about the masked stimulus, they were instructed to respond by repeatedly going through each of the six response-buttons from 1 to 6. These instructions were necessary because we observed that subjects in pilot studies adopted the behavior to always respond with the same button on such trials with very low stimulus intensity. Such behavior would have introduced biases in the estimates of noise levels corresponding to perceptual thresholds estimated by adaptive algorithms. Following their choice, participants were additionally prompted to indicate whether they saw the masked stimulus or not by key press (1: seen, 0: unseen).

The discriminability of the six images was varied by adding pixel noise to the images. A noisy image was generated by adding a random number from a Gaussian distribution to each pixel value of the original image. The noise level corresponds to the variance of this Gaussian distribution. To this aim, images are loaded into a 320 × 320 × 3 array of floating point values ranging from 0 to 1. The first two dimensions are x and y coordinates and the last dimension corresponds to intensities in red, green and blue (RGB). To add noise, we created an array of the same size (320 × 320 × 3) with random values from a normal distribution with a mean of zero and variable variance (ranging from 0 to 2.5). Values in the noise array were then added elementwise to image array. Resulting values below 0 or above 1 were set to 0 or 1, respectively.

An adaptive Bayesian psychometric algorithm (QUEST; Watson & Pelli, 1983) was used to estimate the noise level corresponding to the threshold of conscious perception on each upcoming trial based on previous attempts of the participant to identify the stimuli. An instance of the QUEST algorithm was initialized for each of the six stimuli with the parameters $\gamma = \frac{1}{6}$ (guess-rate), $\lambda = 0.005$ (lapse-rate), $\beta = 0.5$ (slope of psychometric function). The variance of the Gaussian noise distribution ranged between zero, i.e., no noise, clearly discriminable and 2.5, i.e., indiscriminable (arbitrary units, see above). As initial prior distribution for the threshold estimates, we chose a uniform distribution ranging from zero to 2.5. The mean of the posterior distribution was taken as the estimate of the noise level corresponding to the threshold of conscious perception. The initial threshold estimates were thus 1.25 for each of the six stimuli and started to diverge on ensuing trials when the QUEST algorithm was updated with responses provided by the participants (Fig. 1, top left).

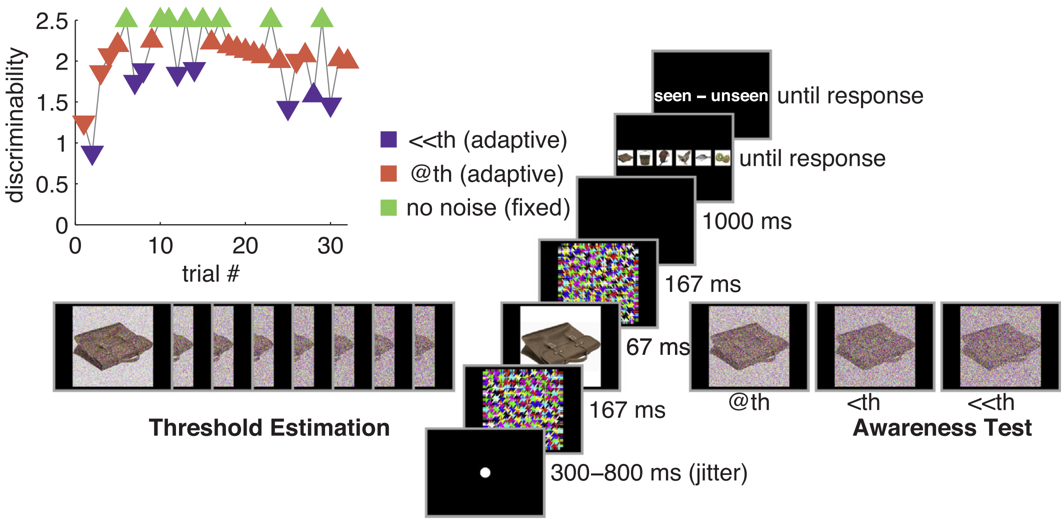

Fig. 1. Threshold estimation and awareness test. The figure depicts the sequence of events from bottom to top. The level of noise added to the stimulus shown between the masks was guided by the QUEST algorithm during the initial threshold estimation. The noise level in the awareness test was set to the levels of discriminability according to the final estimate of the threshold resulting from the threshold estimation (> th, @th, < th, ≪th). The diagram in the top left denotes an exemplary time course of noise added to a stimulus in the initial threshold estimation procedure. Discriminability is expressed as 2.5 minus noise variance for display purposes. Note that high noise level reflects low discriminability and vice versa. For convenience and display purposes we therefore numerically express discriminability as 2.5, i.e., maximal noise variance, minus the noise variance used. This way, high versus low discriminability is reflected in high versus low numbers ranging from 0 (indiscriminable) to 2.5 (clearly discriminable).

For each stimulus, 16 trials were presented at the noise level corresponding to the running estimate. On 8 trials the noise level was set to the running estimate multiplied by 2 (below threshold, ≪th), and on the remaining 8 trials the noise was set to zero (clearly discriminable, > th). Clearly discriminable stimuli were introduced so that the participants were occasionally reminded of what to look for, and below threshold stimuli (≪th) were introduced to achieve better coverage of the range of noise levels.

2.5.2. Instrumental conditioning test

Following the initial threshold test, the feasibility of instrumental conditioning was assessed at the four levels of discriminability (> th, @th, < th, ≪th). The noise level corresponding to the four levels of discriminability was set according to the final estimate of the threshold noise level derived from the initial threshold test (see above). Discriminability was either set to the maximum (run 1, clearly discriminable, no pixel noise, > th), to the threshold of conscious perception (run 2, @th), to 1.5 times (run 3, < th), or to 2 times the noise level corresponding to the threshold (run 4, ≪th).

Of the two stimuli assigned to a run, one was randomly chosen to be rewarding and the other to be punishing (see Fig. 2; Pessiglione et al., 2008). In each run, the number of rewarding versus punishing stimulus presentations was equal. A trial entailed the presentation of a fixation cross for 300–800 ms (jittered), a forward-mask for 167 ms, either the rewarding or the punishing stimulus for 67 ms, a backward-mask for 167 ms, a blank screen for 1000 ms, and a question mark for a maximum of 2000 ms. Here, the subject chose to either push the space bar (GO response) or not (no-GO response), i.e., wait for 2000 ms. The presentation of the question mark was followed by a feedback screen, which informed the participant about the monetary gain or loss resulting from the current trial and the total amount of money earned during the experiment so far. The feedback screen displayed an image of an one-euro coin surrounded by a red circle in case of positive reward, an one-euro coin with a red[1] cross on top in case a negative reward, and empty white rectangle in case of a no-GO response (i.e., no reward or punishment, see Fig. 2). Furthermore, the total amount of money earned so far was depicted in the middle on the top of the screen. In case of a GO response, a feedback screen was shown immediately following the GO response. If the subjects pressed the GO response following the rewarding or punishing trial, the outcome was monetary gain or loss, respectively. If subjects chose the no-GO response, no gain or loss resulted.

We assumed that successful learning could be achieved faster when stimulus- discriminability was high. Therefore, the number of trials in a run increased with decreasing discriminability (> th: 16 trials, @th: 32 trials, < th and ≪th: 72 trials). Furthermore, we increased the reward and punishment magnitudes with decreasing discriminability (> th: ± 0.2 €, @th: ± 0.4 €, < th: ± 0.6 €, ≪th: ± 1 €). We increased reward magnitudes because we assumed that participants would more likely stay engaged in the task at lower discriminability levels where they might feel that they were unable to discern the stimuli at all. Covarying reward magnitude with discriminability was expected to make it more likely to find evidence for unconscious conditioning. If there is no evidence for unconscious conditioning, low incentives should not explain the absence of an effect.

[1] For interpretation of color in Figs. 1–7, the reader is referred to the web version of this article.

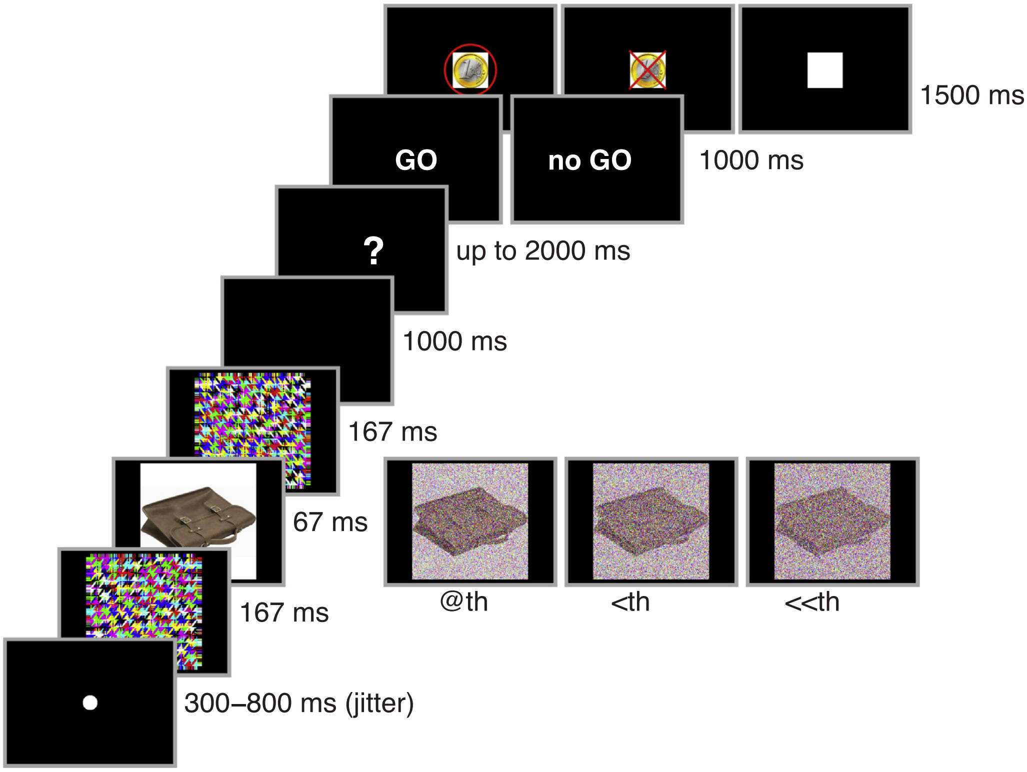

Fig. 2. Conditioning Test. Events in a trial are depicted from bottom to top. Participants viewed a masked presentation of a cue and were instructed to either push the space-bar (GO-response) as long as the question mark was on screen or not (no-GO responses). Choice of the GO response resulted in either monetary gain or loss depending on the masked cue's identity. Choice of the no-GO response was neither rewarded nor punished. Instrumental Conditioning is indicated if participants more frequently choose the GO-response versus the no-GO response following rewarding cues. The image of a briefcase is one of eight possible cues and is depicted without noise (> th), at a noise level corresponding to the mean of the threshold estimates across all participants (@th), and at two levels below this threshold (< th, ≪th). Noise levels varied in stimulus- and subject-specific manner and the average across participants is taken here solely for display purposes.

Participants were instructed that a GO response was the risky choice as it could result in gain or loss of money whereas the no GO responses was safe as neither gain or loss could result from this choice. Furthermore, participants were told that they would be able to easily distinguish the cues in the beginning, but that this would become increasingly difficult and ultimately impossible later on. Thus, participants were instructed to rely on their 'gut feeling' if they were unable to discern the stimuli (Pessiglione et al., 2008).

Conditioning performance is either expressed as a contrast of the proportion of GO responses following rewarding ($p_{GO|r}$) versus punishing ($p_{GO|p}$) cues or as a single d′ index, i.e., $d' = Z(p_{GO|r}) - Z(p_{GO|p})$. In case $p_{GO|r/p}$ were exactly zero or one, these values were replaced by 0.01 or 0.99, respectively, to obtain finite d′.

After each of the four runs, subjects were asked how often they could discern the stimulus on a scale from 0 to 10 (0: never, 5: 50%, 10: always). This number was taken as a subjective measure of awareness for the given discriminability level.

2.5.3. Awareness test

Finally, the identification performance of each of the images was assessed at the noise levels used in the conditioning part. This awareness test was identical to the initial threshold test, except for the fact that the noise level corresponding to the threshold was not adapted by the QUEST algorithm. Instead, stimuli were presented at the noise levels of discriminability (> th, @th, < th, ≪th) used in the instrumental conditioning test. Identification performance at each of the four discriminability levels in the awareness test was taken as the objective measure of awareness (direct test). To this aim, we computed d′ for each stimulus in the final threshold test, i.e., d′ = Z(hit-rate) − Z(false-alarm-rate), and averaged these stimulus-specific d′s across stimuli for each participant at each of the four levels of discriminability. Again, in case of the hit- or false-alarm rates being exactly zero or one, these values were replaced by 0.01 or 0.99, respectively, to obtain finite d′s.

2.6. Code, data and software availability

Data, the code to analyze the data, and the code to run the paradigm along with the stimuli can be downloaded from www.github.com/rebrowski/conditioning.git. Code to run analyses and produce the figures is documented in jupyter notebooks (www.jupyter.org) running either MATLAB or R.

3. Results

3.1. Feasibility of pixel noise in masked stimuli to vary discriminability

Adding pixel noise to masked images was effective to render stimuli indiscriminable in varying degrees. First, we computed psychometric curves separately for each stimulus in the set (Fig. 3). A Weibull function was fitted for each stimulus separately to data from the threshold estimation test and awareness test (Kingdom & Prins, 2009). Stimulus discriminability ranged from chance performance in the identification test to nearly perfect performance with intermediate degrees in between.

Next, we assessed the effects of the factor discriminability (> th, @th, < th, ≪th) on discrimination performance in the final threshold-test (objective measure of awareness, d′), and on the awareness ratings obtained after each run in the conditioning test (subjective measure of awareness) using one-way repeated measures ANOVAs. The ANOVA with d′ of the awareness test as dependent variable revealed a significant effect of discriminability ($F_{2.26,88.11}$ = 465.762, $p < .001$, η_G^2 = 0.896; Hyunh-Feldt corrected; Mauchly's test for sphericity: W = 0.516, $p < .001$, ε = 0.752). Bonferroni-corrected post hoc *t*-tests were conducted between neighboring discriminability levels ($\alpha_{crit.} = \frac{0.05}{3} = 0.016$). Discrimination performance decreased with decreasing discriminability, and all pairwise comparisons were significant. Performance at the clearly discriminable level (M[SD] = 4.39[0.28]) was higher than at the threshold level (M[SD] = 2.51[0.64], t_{28} = 13.270, $p < .001$, d = 2.46). Performance at threshold was higher than below threshold (M[SD] = 1.19[0.60], t_{28} = 14.288, $p < .001$, d = 2.65), which, in turn, was higher than clearly below threshold (M[SD] = 0.56[0.42], t_{28} = 7.627, $p < .001$, d = 1.42).

The one-way repeated measures ANOVA with the subjective awareness ratings as dependent variable revealed a significant effect of discriminability ($F_{3,78}$ = 95.230, $p < .001$, η_G^2 = 0.667). Bonferroni-corrected post hoc *t*-tests between awareness ratings for neighboring discriminability levels ($\alpha_{crit.} = \frac{0.05}{3} = 0.016$) all rendered significant differences. Again, the awareness ratings decreased with decreasing levels of discriminability. Awareness ratings at the clearly discriminable level (M[SD] = 9.74[0.71]) were higher than at the level of the estimated threshold (M[SD] = 6.00[2.29], t_{26} **= 7.905, $p < .001$, d = 1.52). Awareness ratings at threshold were higher than ratings below threshold (M[SD] = 3.67[2.51], t_{26} = 4.608, $p < .001$, d = 0.89). Finally, below threshold awareness ratings were higher than clearly below threshold ratings (M[SD] = 1.93[2.38], t_{26} = 3.445, $p = .002$, d = 0.66).**

**Th0.053= 0.016) all rendered significant differences. Again, the awareness ratings decreased
inability. Awareness ratings at the clearly discriminable level (M[SD] = 9.74[0.71]) were higher
threshold (M[SD] = 6.00[2.29], t**

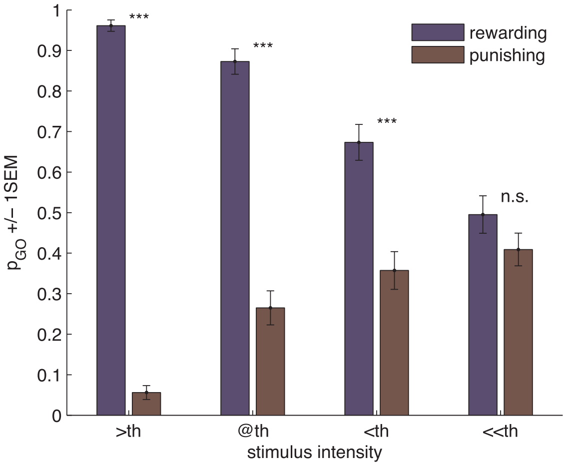

Fig. 4. Conditioning Results: Y-axis denotes the average proportions of GO responses separately for rewarding and punishing stimuli at the four levels of discriminability. ***: $p < .001$, n.s.: not significant.

= 0.06[0.09]); t_{28} = 38.114, $p < .001$, d = 7.08. At the threshold of perception, the proportion of GO responses following rewarding cues (M[SD] = 0.87[0.17]) was higher than following punishing cues (M[SD] = 0.27[0.23]); t_{28} = 9.823, $p < .001$, d = 1.82. At a discriminability of 1.5 × the noise level of the threshold, again, the proportion of GO responses following rewarding cues (M[SD] = 0.67[0.24]) was higher than following punishing cues (M[SD] = 0.36[0.25]); t_{28} = 4.498, $p < .001$, d = 0.84. At the clearly indiscriminable level, however, no significant difference between the proportion of GO responses following rewarding (M[SD] = 0.50[0.25]) versus punishing cues (M[SD] = 0.41[0.22]) was indicated; t_{28} = 1.518, p = .140, d = 0.28.

3.3. Relationship between measures of awareness and conditioning performance

To investigate the feasibility of unconscious conditioning, we computed regressions of objective and subjective measures of awareness on conditioning performance. We expressed conditioning performance as d′ to rewarding stimuli (see Section 2.5.2). As objective measure of awareness, we used the identification d′ for the stimuli in the final threshold test (see Section 2.5.3). As subjective measure of awareness, we used the raw values of the awareness ratings obtained after each run in the conditioning test. An intercept significantly larger than zero of regressions of measures of awareness on conditioning performance would be taken as evidence for unconscious contributions to conditioning (Greenwald et al., 1995). To get an overview, we made scatter plots of direct and indirect measures across participants. These results show a strong linear relationship between indirect and direct measures (Fig. 5).

As each participant was tested at each level of discriminability, these measures are dependent within participant. We therefore computed regressions separately for each participant and tested whether the mean of the resulting distributions of regression parameters deviated from zero. No evidence for the feasibility of subliminal conditioning was found. The slopes resulting from single-subject regression of threshold-test d′ on conditioning d′ were significantly different form zero (M[SD] = 0.92[0.33]; t_{28} = 14.914,

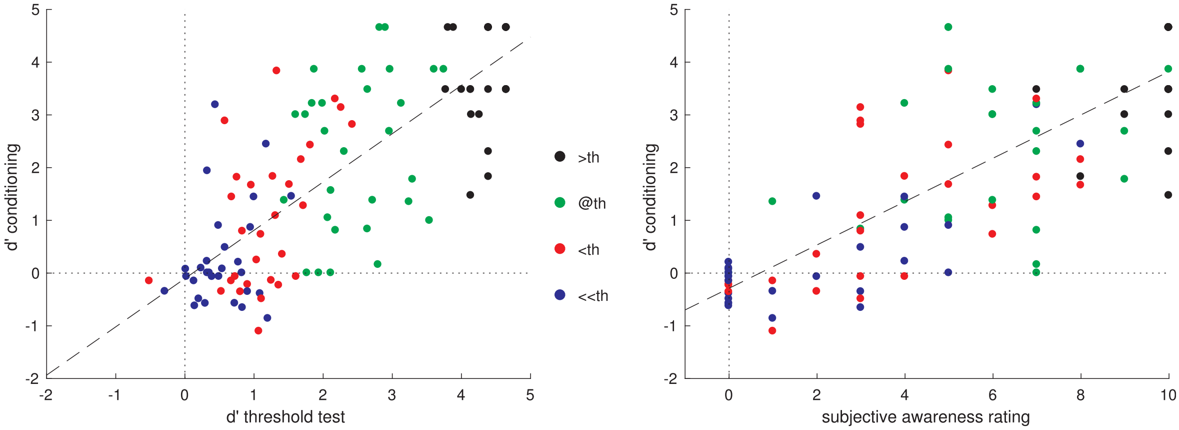

Fig. 5. Regressions of measures of awareness on conditioning performance. Left panel shows regression of performance on the awareness test (threshold test d′) on conditioning performance (d′). Right panel depicts the regression of subjective awareness (% seen images during conditioning) on conditioning performance (d′).

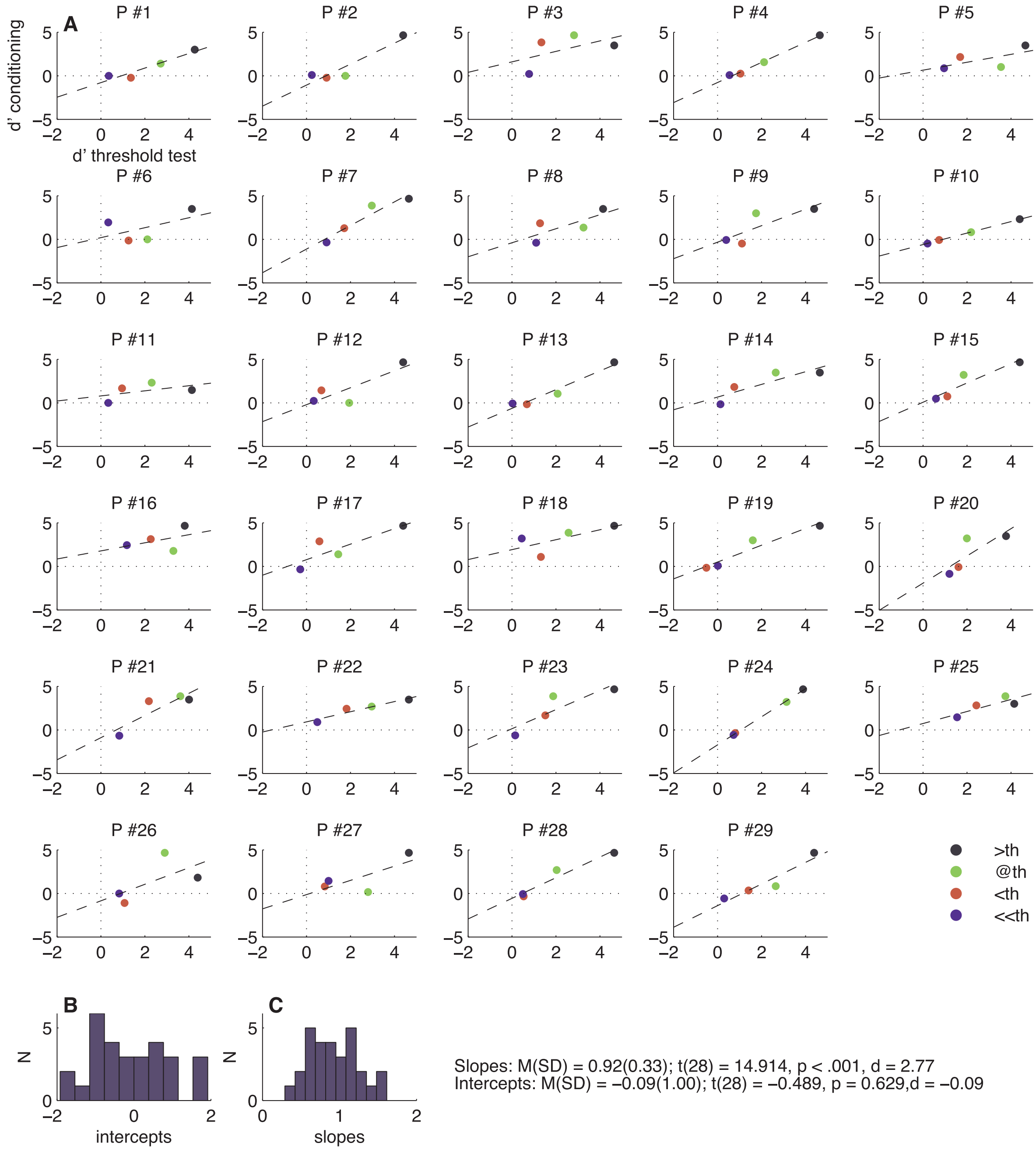

Fig. 6. Single subject regressions of awareness test performance on conditioning performance: (A) Y-axes denote performance on the conditioning test (d′) and x-axes denote performance on the awareness test (threshold test d′). A plot for each participant is depicted showing regression lines and individual data points. (B) Distribution of slopes resulting from single-participant regressions. (C) Distribution of intercepts resulting from single-participant regressions.

$p < .001$, $d = 2.77$; Fig. 6). The intercepts, however, were not significantly higher than zero ($M[SD] = -0.09[1.00]$, $t_{28} = -0.489$, $p = .629$, $d = -0.09$). The slope of the single-subject regressions of subjective awareness ratings on conditioning d′ were significantly different from zero ($M[SD] = 0.46[0.18]$); $t_{26} = 12.901$, $p < .001$, $d = 2.48$). Surprisingly, the intercepts were significantly smaller than zero ($M[SD] = -0.55[1.38]$); $t_{26} = -2.048$, $p = .047$, $d = -0.40$; Fig. 7). These results suggest that participants performed at chance level in the conditioning test even if they reported having seen the stimulus a few times. Thus, consciously perceiving the cue a critical amount of times seemed to be necessary to learn associations between cue, response and outcome in the current study.

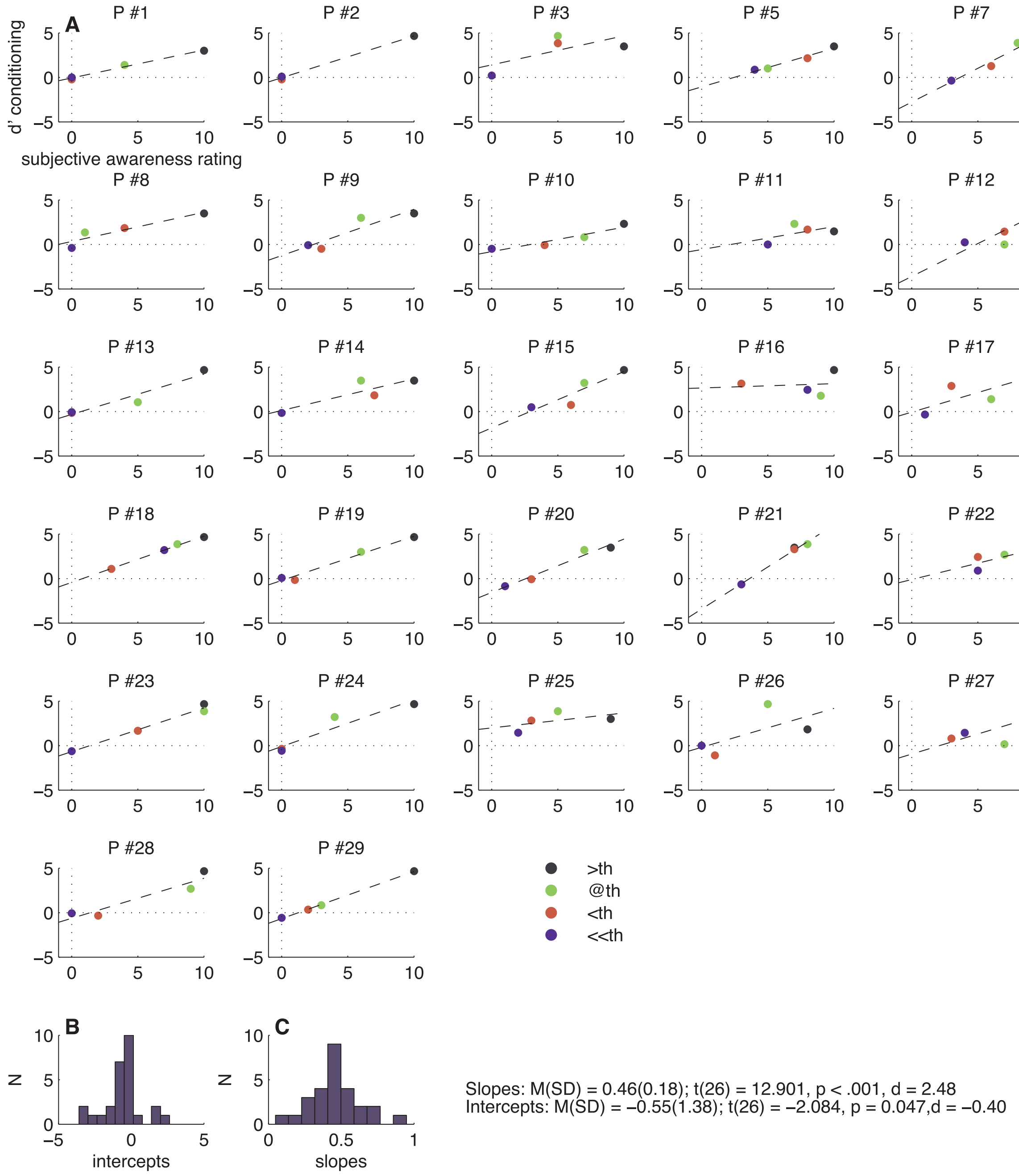

Fig. 7. Single subject regressions of subjective awareness reports on conditioning performance: (A) Y-axes denote self-reported awareness (% images seen during conditioning; subjective awareness measure) and x-axes denote performance on the conditioning task (d′). A plot for each participant is depicted showing regression-lines and individual data-points. (B) Distribution of slopes resulting from single-participant regressions. (C) Distribution of intercepts resulting from single-participant regressions.

4. Discussion

We investigated the feasibility of using pixel-noise added to masked visual stimuli as a means to render stimuli unconscious, and whether instrumental conditioning can occur under such unconscious conditions. The methods were feasible to achieve fine-grained adjustments of presentation conditions based on subject- and stimulus- specific thresholds of perception. Contrary to previous reports (Atas et al., 2013; Mastropasqua & Turatto, 2015; Pessiglione et al., 2008), no evidence for learning under subliminal conditions was found in an ensuing conditioning test.

We use the regression approach introduced by Greenwald et al. (1995) to assess the feasibility of unconscious learning. Advantages of the regression method are that it makes use of all the data collected, addresses the 'exhaustiveness' and 'exclusiveness' issues (Reingold & Merikle, 1988) of a classical dissociation approach, and avoids the necessity of post hoc exclusion of participants scoring above chance on the direct test (Shanks, 2017). However, the regression approach has also been criticized (Merikle & Reingold, 1998; Miller, 2000; Shanks, 2017). Issues specific to the method concerned the validity of a linear regression as statistical model in absence of a correlation between indirect and direct test performance (Merikle & Reingold, 1998). This criticism does not apply here as our data reveal a clear linear relationship between direct and indirect test. This relationship is very clear in our data because we varied discriminability of the stimuli in a parametric manner, relative to subject- and stimulus- specific estimates of threshold stimulus intensities. A further issue concerns a bias of the regression method towards finding positive intercepts, i.e., a bias towards finding (false) evidence in favor of unconscious effects (Miller, 2000; Shanks, 2017). Again, this criticism does not apply here for the simple reason that we do not find a significantly positive intercept in our data at all and make no claim of finding true unconscious effects.

We covaried both the number of trials and reward magnitude with discriminability in the conditioning experiment with the goal to increase the sensitivity to putative weak and slow unconscious learning effects. We therefore suggest that these design choices cannot account for the absence of evidence for unconscious instrumental learning in our study. First, the reward magnitude was increased with decreasing levels of discriminability to keep participants engaged and motivated as the task got harder. Here, one might argue that high incentives in runs with decreased cue discriminability kept participants from 'gambling' and they chose the 'no Go' response more often, making it harder for effects of unconscious conditioning to surface. However, this was not the case, and participants remained engaged in the task despite increasing difficulty and probability of getting punished for choosing the 'Go' response. This was indicated by a comparable average overall proportion of 'Go' responses across the four runs (> th: 51%, @th: 56% < th: 51% ≪th: 45%). Second, the number of trials was increased with decreasing levels of discriminability because we expected the rate of learning to decrease with decreasing levels of discriminability. Rather than introducing a bias towards absence of evidence, allotting more trials to runs with reduced detectability levels actually does the opposite, and increases sensitivity for putative weak and slowly emerging effects of unconscious conditioning.

Nevertheless, our data lacks convincing demonstrations of unconscious learning. Possible reasons for the absence of evidence for subliminal conditioning are numerous, and we restrict our discussion to the (in our opinion) most obvious candidates. First, one could argue that the use of pixel noise to prevent awareness is detrimental also for unconscious processing. Pixel noise actually degrades the stimulus itself, and degradation could in principle reach a level at which information of the stimulus identity is simply no longer present. However, we suggest that image degradation was too weak to be responsible for the absence of subliminal conditioning as the noise level required to render stimuli indiscriminable was low due to the additional pattern masking and short presentation duration. As a consequence, image information at noise levels corresponding to unconscious conditions was largely preserved as can be seen in Fig. 3. Thus, noise was but one contributing factor to achieve reduced stimulus discriminability, and was by itself too weak to induce the observed levels of discriminability. Furthermore, previous studies have demonstrated that unconscious processing of noise-masked stimuli can occur at higher noise levels than those applied in our current study (Seitz, Kim, & Watanabe, 2009).

Second, it is conceivable that participants failed to adopt an 'indirect' task instruction in unaware trials. Indirect or implicit strategies (e.g., 'rely on your gut feeling') are thought to be more sensitive to effects of unconscious stimuli than direct or explicit strategies (e.g., 'choose GO if the image of a hat appears'). Explicit learning was successful in the beginning when cue discriminability was high but became ineffective as discriminability decreased. Thus, participants might have continued to employ explicit strategies rather than relying on their 'gut feeling' as instructed. On the other hand, one could also argue that explicit experience with a task facilitates performance on an ensuing unconscious version of the task (Reber & Henke, 2011). We chose to decrease discriminability over the course of the experiment because it has been shown that explicit experience of a task set may direct attention to certain features of unconscious stimuli (Kunde, Kiesel, & Hoffmann, 2003), essentially suggesting top-down control over unconscious perception (Kiefer, Adams, & Zovko, 2012). In fact, a recent study reports evidence that attention is even a necessary requirement for unconscious instrumental conditioning to succeed (Mastropasqua & Turatto, 2015). However, none of these studies (Kiefer et al., 2012; Kunde et al., 2003; Reber & Henke, 2011) varied awareness decreasingly in intermediate degrees. Future studies might address interactions of explicit and implicit strategies and vary discriminability decreasingly as well as increasingly over the course of the experiment.

A third reason could simply be that awareness is required for instrumental conditioning. Assuming this possibility, it follows that previous studies may have overestimated the extent of unconscious cognition. While the numbers of participants in previous studies of unconscious conditioning seem appropriate according to standards in the field (55 in Atas et al., 2013; 28 and 27 in Exp. 1 and 2, respectively, in Mastropasqua & Turatto, 2015; 22 in Pessiglione et al., 2008), these standards have also been criticized as too low resulting in spurious findings and low reproducibility (Asendorpf et al., 2013; Vadillo, Konstantinidis, & Shanks, 2015). A further potential reason could be underpowered awareness tests resulting in false negatives for the hypothesis that residual conscious processing is responsible for putative unconscious processes (Vadillo et al., 2015; Wiens, 2006). Such a bias towards finding a significant indirect effect in absence of a direct effect is introduced when the number of observations in the indirect test are higher than in the direct test (Vadillo et al., 2015; Wiens, 2006), which is the case not only in the first report of unconscious instrumental conditioning (Pessiglione et al., 2008) but also in numerous further studies on unconscious processing (for a reveiw and meta-analyses see Vadillo et al., 2015). Such a bias could have been aggravated by the use of a two-tailed test resulting in lower power for the direct measure while a one-tailed test was used for the indirect measure (Pessiglione et al., 2008). As underpowered awareness tests have been part of established protocols and common practice, critique on these procedures has recently emerged (Vadillo et al., 2015). Here, we chose an equal number of trials (192) for both the awareness and the conditioning test. Of course, the question whether differences in statistical power of awareness tests alone may explain discrepancies between the current and previous findings is subject to further testing.

Either way, our data add to the debate on the role of consciousness in information integration (Mudrik et al., 2014). Instrumental conditioning requires the integration of information gathered in temporally distinct events, namely cue, response, and outcome. The temporal interval between cue and response was between one and two seconds, and a further second between response and outcome. While some research suggests that unconscious information can be integrated over much longer periods (up to a minute, e.g., Gaillard et al., 2007; or Reber et al., 2012, and even up to 25 minutes in Ruch, Züst, & Henke, 2016), studies of unconscious priming suggest much shorter integration intervals (hundreds of milliseconds, e.g., Dupoux, de Gardelle, & Kouider, 2008; Greenwald et al., 1995). A possible explanation for these disparate findings could be that longer integration intervals were found when the events to be integrated entail identical elements (Gaillard et al., 2007; Reber et al., 2012), while shorter integration intervals were reported when integration was also required on a semantic level (Dupoux et al., 2008; Greenwald et al., 1995; but see Ruch et al., 2016). Although there is agreement that spatial and temporal proximity as well as complexity or (semantic) abstraction of the information to be integrated together push and pull the boundaries of unconscious cognition (reviewed in Mudrik et al., 2014), the relationship between these dimensions remains unknown, and a large space especially along the temporal dimension remains uncharted. Our data thus add an instance of failed unconscious integration over the range of seconds of visually dissimilar stimuli (cue, feedback) with internally generated response choices.

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Conflict of interest

All authors declare no conflicts of interest.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.concog.2018.03.013.

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