Value-modulated attentional capture depends on explicit awareness

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Abstract

Value-modulated attentional capture (VMAC) reflects a process by which a priori neutral stimuli gain attentional priority when associated with reward, independently of goal or stimulus-driven attentional control. Although VMAC has been classically considered an automatic and implicit process, the nature of the underlying learning process remains unclear. For instance, VMAC could be driven by the stimulus predictive value alone (Pavlovian learning) or, alternatively, by the automatization of an instrumental response to the associated stimulus (an attentional habit). Although recent research has demonstrated that it is possible to observe VMAC when the associated stimulus is response-irrelevant, to our knowledge, the role of the informational value of the associated stimulus during learning remains unexplored. In a well-powered replication of a previous study, we found that VMAC disappears when participants are not explicitly informed about the stimulus-reward contingency in the pre-task instructions. In a second experiment, we show that when instructions are manipulated between groups, only the instructed group shows VMAC. Interestingly, although the no-instruction group did not show VMAC at the group level, participants who became aware of the stimulus-reward contingencies did show robust VMAC at the end of the task. Meta-analytic evidence further supports our conclusion by showing that when stimulus-reward contingencies are included in the instructions the effect size of reward-driven distraction increases. Taken collectively, these findings suggest that the learning process behind VMAC may not be entirely implicit.

Keywords: reward, explicit awareness, learning, attention, capture

Introduction

When a stimulus feature is predictive of reward it can bias attention irrespective of our current goals or the physical properties of stimuli (Anderson et al., 2011b; Awh et al., 2012; Della Libera & Chelazzi, 2009; Theeuwes, 2018). In one of the first demonstrations of this phenomenon, Anderson et al. (2011a) adapted the additional singleton task (Theeuwes, 1992) to manipulate the value of two singleton distractors presented in a visual search task. Participants underwent a training stage where they had to search for two colors that predicted rewards of different magnitudes. In a test stage, the relevant feature changed and participants were asked to search for a diamond-shaped stimulus, while the previous target colors acted as singleton distractors. Anderson et al. (2011a) found that when a high-value singleton distractor was presented in the search display, reaction times (RTs) increased compared to low-value singleton trials, an effect called "Value-Modulated Attentional Capture" (VMAC)[1].

Some authors have suggested that VMAC relies on Pavlovian learning (Colaizzi et al., 2020; Le Pelley et al., 2016), and thus, in the predictive value of the feature associated with the magnitude of reward. Nevertheless, in 'two-stage' experimental paradigms, like the one introduced in the previous paragraph, these features are both predictive and response-relevant during the training stage. Thus, any attentional capture subsequently elicited by these features could be explained by the automatization of an instrumental response (Failing & Theeuwes, 2018). In other words, actively selecting the stimulus associated with reward could give rise to some sort of "attentional habit" (Anderson, 2016). To discard this possibility, Le Pelley et al. (2015) adapted the Anderson et al. (2011a) paradigm to make the reward-predictive feature

[1] Reward-driven distraction often receives different names depending on whether the singletons associated with reward are the most salient item in the display (i.e., value "modulates" the attentional capture of an already salient item) or whether all items in the display are equally salient (i.e., value "drives" attentional capture; Anderson et al., 2011b). For the sake of simplicity, we will use the term VMAC when referring to both cases.

task-irrelevant. They removed the training stage and modified the testing stage of Anderson et al. (2011a) so that the color of the singleton was predictive of reward, but always acted as a distractor, rendering color irrelevant during the whole task. With this setting, Le Pelley et al. (2015) found that VMAC is not dependent on task relevance. It can be observed even when attending to the high-value singleton results in the omission of reward (see also Pearson et al., 2016).

Although in “one-stage” paradigms the associated feature is always response irrelevant in the sense that participants do not need to pay attention to it to obtain reward, it nevertheless provides participants with information about the magnitude of reward. In other words, it could be the case that the expression of VMAC depends on participants paying attention to the distractor to gather information about the magnitude of reward in each trial. To test whether informational value could explain the results of Le Pelley et al. (2015), Watson et al. (2019) used the same paradigm as Le Pelley et al. (2015) but added a brief unrewarded phase at the end of the experiment, where participants were explicitly told that reward feedback would be omitted in the rest of the task (like the testing stage on Anderson et al., 2011). Watson et al. (2019) showed that the VMAC effect persisted even under these conditions, a result recently replicated by our lab with a substantially longer unrewarded stage (Garre-Frutos et al., 2024).

The evidence reviewed above suggests that the expression of VMAC occurs in conditions where the reward-associated feature is always irrelevant to the task, even after informing participants that the color of the distractor no longer holds informative value. However, although in Watson et al. (2019) color was task-irrelevant during the whole task, it provided participants with useful information during the learning stage, because explicit instructions about this contingency were provided beforehand. That is, even though VMAC was observed in conditions where the singleton distractors did not have informational value, learning always occurred in conditions where the reward-predictive feature had informational value.

The present study aims to test the role of informational value in the learning process underlying VMAC. One strategy to achieve this would be to remove the information value from an experimental paradigm otherwise similar to that of Watson et al. (2019) and Garre-Frutos et al. (2024)[2]. Following this strategy, we conducted two well-powered experiments based on the methodology used by Garre-Frutos et al. (2024) with the only exception that the instructions about color-reward contingencies were manipulated. If the informational value of distractors plays a role in VMAC, we would expect that VMAC during the learning stage would be modulated by both explicit instructions and spontaneous awareness of the color-reward association.

Experiment 1

In Experiment 1, we conducted a nearly exact replication of the learning stage in Garre-Frutos et al. (2024), with the only exception that participants did not receive any explicit instructions about stimulus-reward contingencies before conducting the task. At the end of the experiment, participants rated the number of points earned with each singleton color, to assess their explicit knowledge of the color-reward contingencies.

[2] Nota that in Le Pelley et al. (2015) participants did not receive instructions about stimulus-reward contingencies. However, in their study the learning stage was substantially longer than in Watson et al. (2019) and Garre-Frutos et al. (2024) and most of the participants became aware of the contingency (see Experiment 2 of Watson et al., 2015). In fact, in other studies where participants were explicitly informed of the contingency, the learning stage is substantially shorter than in the seminal study of Le Pelley et al. (2015). In the present work, we evaluated the learning process under typical conditions as a function of whether or not participants were instructed about the stimulus-reward contingency.

Method

Participants.

Based on a power analysis reported in supplementary material, we aimed to recruit at least 80 participants. Potential participants were contacted through the distribution lists of the University of Granada. From the group of undergraduate students who showed an interest in participating, 83 participants (65 self-identified as female; $M_{\text{age}} = 21.2$; $SD_{\text{age}} = 3.34$) were recruited in exchange for course credits. All of them had normal or corrected to normal vision and were naive as to the purpose of the experiment. Participants conducted the task in an online meeting with the investigator, where instructions regarding the calibration procedure were explained in detail (see below). We removed one participant for exceptionally low response accuracy (< 0.7) The study was approved by the Ethical Review Committee of the University of Granada (ref. 2442/CEIH/2021).

Stimuli, Design, and Procedure.

The materials and procedures of this experiment are based on Garre-Frutos et al. (2024). The study was conducted online, like a large body of research with this task (Albertella et al., 2019, 2020; Le Pelley et al., 2022; Liu et al., 2021; Watson et al., 2020). To control for differences in participants' distance to the screen, we scaled stimulus size to screen distance using the virtual chinrest developed by Li et al. (2020). Before starting the experiment, participants were asked to fit an object with a standard size (i.e., a credit card or a driver's license) to a rectangle on the computer screen, whose size they could change using two buttons from the keyboard. Second, participants performed a blind spot procedure to estimate screen distance. They were asked to cover their right eye while looking with their left eye at a fixed placeholder that appeared in the center of the monitor, while a red circle moved to the left and participants were instructed to press the spacebar when they noticed that the circle disappeared. Screen distance was estimated by averaging five repetitions of this procedure.

The task was programmed in OpenSesame (Mathôt et al., 2012) and hosted in JATOS (Lange et al., 2015). A graphical representation of the procedure is presented in Figure 1. Each trial started with a central fixation cross, followed by a search display containing six shapes (2.3° * 2.3° visual angle) evenly arranged around an imaginary circle (10.1º). Five shapes were circles, each containing a segment tilted 45° randomly to the left or right. The target was a diamond-shaped stimulus containing a segment oriented randomly horizontally or vertically. In most trials, one of the circles was colored, while the other shapes were gray. Participants could be assigned to three conditions of color pairs: blue and orange, green and pink, or red and yellow. The colors of the high- and low-reward distractors were randomly assigned. The location of the target and the distractor were random on each trial.

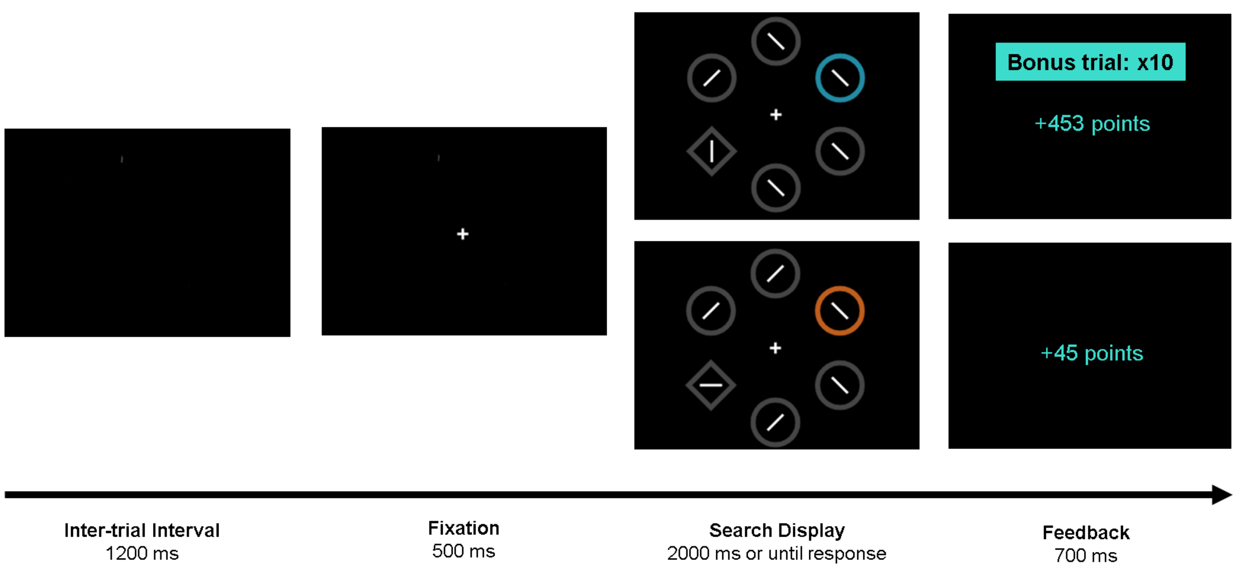

Figure 1. Example of the sequence of events in the experimental task. Participants could earn points based on performance, and when a high-value singleton appeared in the display, points were multiplied by 10. Feedback was provided in Spanish.

Participants were instructed to indicate, as quickly as possible, the orientation of the segment inside the diamond, by pressing either 'B' for horizontal or 'J' for vertical, with faster responses earning more points. Each block included 24 trials, comprising 10 trials with a distractor in the high-reward color (high-value singleton condition), 10 trials with a distractor in the low-reward color (low-value condition), and four distractor-absent trials (absent singleton condition) where all shapes were grey. During the first part of the task (rewarded phase) participants were awarded 0.1 points for every millisecond that their RTs were below 1000 ms on low-reward-distractor trials. On high-reward trials, the points were multiplied by 10. Responses with RT greater than 1000 ms were awarded no points, and errors led to the loss of the same number of points that would have been earned. The search display remained on-screen until the participant responded, or the trial timed out after 2000 ms. Feedback was then provided for 700 ms, indicating the number of points won or lost for correct and incorrect responses. The inter-trial interval was 1200 ms.

After the calibration described above, participants completed a small practice phase of 24 trials without singleton distractors. Afterward, instructions informed participants that they could earn points based on their performance in the following phase of the experiment (i.e., the rewarded phase). Participants were instructed that "faster and correct responses would result in more points, and that incorrect responses would result in the loss of the same points that would be earned". Importantly, they were not informed about the functional relationship between singleton color and reward. Then, participants completed the task with 12 blocks of trials.

Most narrative reviews about VMAC suggest that awareness is not relevant to its learning process (Failing & Theeuwes, 2018; Le Pelley et al., 2016). Nevertheless, if VMAC depends on the informational value of the color, spontaneous awareness about the stimulus-reward contingency could also explain the observed effects. Removing such information from the initial instructions thus allowed us to test the role of information on VMAC and potential individual differences between spontaneous awareness and VMAC. To that aim, once participants completed the task, we asked them to produce a contingency rating to assess their knowledge of the stimulus-reward contingency. We presented participants with each color and their total points earned through the task. Then, participants were asked to write the absolute number of points that they believed they had earned when each singleton distractor appeared on the screen. The order of presentation of the singletons in the contingency rating test was counterbalanced. After the contingency rating test, participants conducted another task that was beyond the scope of the present work.

Data analysis.

The analysis of performance in the VMAC task followed the same logic as in Garre-Frutos et al. (2024). We discarded incorrect responses (5.08%), very fast or slow responses (RT < 150 ms or RTs > 1800 ms; 0.08%), and we filtered RTs by 2SDs for each participant's mean (4.25%) to increase the signal-to-noise ratio in our data (Garre-Frutos et al., 2024).

We employed linear mixed models to analyze how VMAC evolved over blocks. Specifically, we included as predictors Singleton (high-value, low-value, absent singleton), Block (1-12), and the Singleton x Block interaction. We set the contrast hypothesis matrix for the Singleton predictor to have two coefficients: one for the VMAC effect (high vs. low) and the other for the attentional capture effect (low vs. absent; AC effect). We used repeated contrasts to set the hypothesis matrix, which allowed us to interpret the model intercept as the mean of overall log-RTs. Following (Barr et al., 2013), we fitted the maximal random effect structure derived from our research design supported by our data (Bates et al., 2018; Matuschek et al., 2017). As in Garre-Frutos et al. (2024), data were best fitted by a power function, so we decided to log-scale the Block predictor to approximate a power function. Following the notation of the *lme4* R package (Bates et al., 2015)[3], the model's formula for our maximal model is:

$$log(RT) \sim Singleton \ * \ log(Block) \ + (Singleton \ * \ log(Block) \mid Participant)$$

The analysis of response accuracy followed the same rationale as that for RTs, but we employed a mixed logistic regression model instead (Jaeger, 2008). The only difference with the previous rationale was that the Block predictor was not log-scaled. We employed non-parametric tests for mean comparisons or correlation whenever non-normality was detected to analyze the contingency rating. Lastly, as correlational research is highly influenced by measurement error, in the Supplementary Material, we included a multiverse reliability analysis[4] of the VMAC effect (high vs. low contrast) over a plausible range of data preprocessing specifications (as in Garre-Frutos et al., 2024).

Results

For the RTs analysis, the maximal feasible model included random slopes for both Singleton and Block. The coefficients of this model are presented in Table 1 and model predictions are presented in Figure 2a. Interestingly, only the low-absent contrast and the Block predictor were significant. We observed an AC effect, showing that the mere presence of a salient singleton distractor slowed RTs (M_{AC} = 16.60, 95% CI [11.4, 21.83]). In addition, RTs

[3] In this notation the parentheses denote the random effect structure and the rest of the right-hand side formula indicates the fixed effects.
[4] We calculated the split-half reliability using a modified version of the *splithalf* R package (Parsons, 2021) that allows stratification. This custom implementation can be found in the following github repository: https://github.com/franfrutos/multi.s

decreased across the task, but, interestingly, the VMAC effect was non-significant (M_{VMAC} = 1.39, 95% CI [-4.15, 6.93]). Regarding accuracy, the maximal feasible model included only the random slope of Block. As can be seen in Table 1 (right-hand side), the only significant predictor was lock, reflecting that accuracy generally increased across the task.

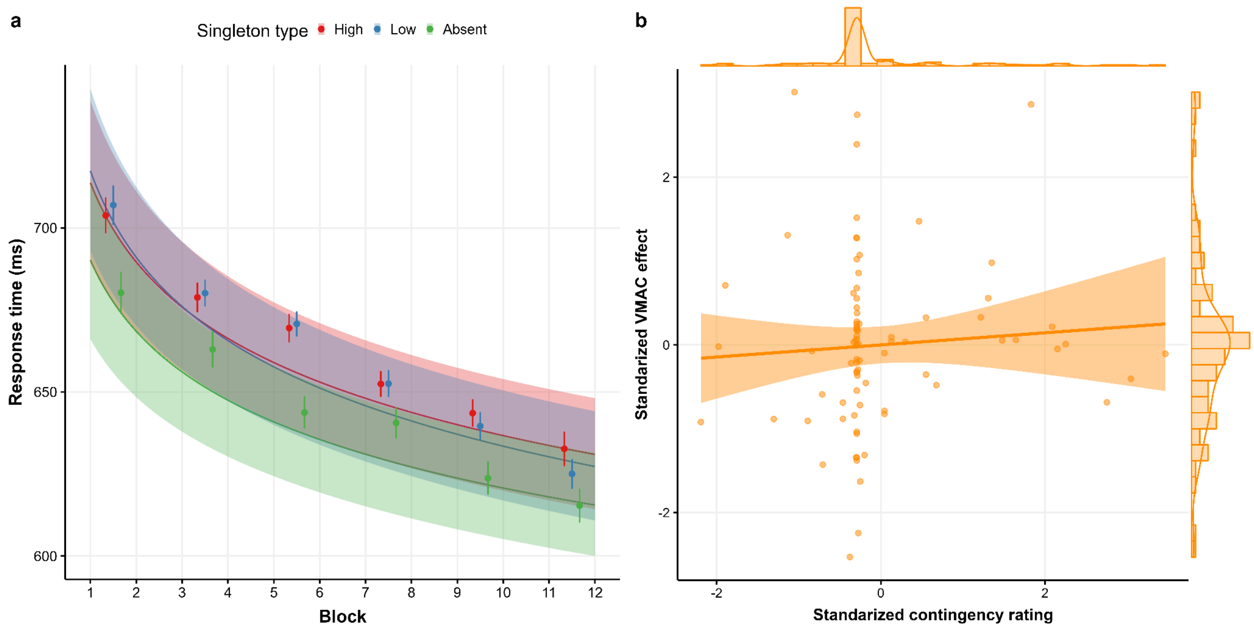

Figure 2. **a**) Model predictions as a function of singletons across blocks. Lines represent the predicted conditional mean in the response scale, while shaded areas indicate the 95% CI. Raw mean RTs using epochs of 2 blocks are indicated by dots, and error bars represent the standard error of the mean (SEM). **b**) Correlation between the VMAC effect and the contingency rating. The line intervals represent the linear prediction of the VMAC effect as a function of the contingency rating, while the shaded area is the CI. The margin shows the marginal distribution (histogram and density).

Finally, we analyzed participants' contingency ratings. Overall, the estimated difference in points between the high and low-value singletons was significantly different from 0 (V=1,270.5, p = 0.019; $M_{\text{high-low}}$ = 3,478.9*,* $SD_{\text{high-low}}$ = 11,861.12). Nevertheless, only 40 participants (48.78%) estimated that the high-value singleton led to more points than a low-value singleton, and the median estimated difference was 0. In other words, the significant difference seems to be driven by some participants estimating that when the high singleton appeared in the display, they earned many more points than when the low-value singleton appeared. Lastly, no significant correlation was observed between the VMAC effect and the contingency rating test ($r_{Spearman} = 0.12$, $p = 0.29$; Figure 2b).

Table 1

Model summaries for the selected models for RTs and accuracy in experiment 1.

	RTs			Accuracy		
Predictors	*Estimates*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	6.462	6.435 – 6.488	**<0.001**	25.341	21.223 – 30.257	**<0.001**
VMAC	0.002	-0.006 – 0.011	0.589	1.042	0.916 – 1.186	0.633
AC	0.025	0.017 – 0.033	**<0.001**	0.911	0.6765– 1.085	0.297
Block	-0.036	-0.042 to -0.029	**<0.001**	1.126	1.030 – 1.230	**0.009**
VMAC × Block	0.003	-0.002 – 0.008	0.280	1.008	0.886 – 1.146	0.906
AC × Block	-0.006	-0.012 – 0.001	0.097	1.008	0.848 – 1.200	0.924
Random Effects						
σ^2	0.031			3.290		
τ_{00}	$0.015_{\text{Intercept}}$			$0.535_{\text{Intercept}}$		
τ_{11}	0.001_{VMAC}					
	0.0003_{AC}					
	0.001_{Block}			0.035_{Block}		
ρ_{01}	0.022			$0.052_{\text{Intercept}}$		
	0.349					
	-0.274					
ICC	0.343			0.148		
N	82			82		
Observations	21,445			23,554		
Marginal R^2 / Conditional R^2	0.030 / 0.362			0.004 / 0.151		

Note. Bold entries denote statistical significance. *p*-values were computed using Satterwhite correction. CI = Confidence interval; ICC = Intraclass correlation coefficient. τ = Random effects, ρ = correlation between random effects.

Discussion

In this first experiment, we showed the classical attentional capture effects typically observed in the additional singleton task (Theeuwes, 1992, 1994). In contrast, we did not observe a VMAC effect, even though participants attended to the colored singleton (as demonstrated by the AC effect) and were fully exposed to the contingencies. Moreover, contingency estimation did not correlate with the VMAC effect[5].

Although this result may seem surprising given the conceptualization of VMAC, other studies have found a similar pattern across experiments where removing instructions about stimulus-reward contingency abolished VMAC and only "aware" participants showed the effect (Failing & Theeuwes, 2017; Le Pelley et al., 2017; Meyer et al., 2020; see also Le Pelley et al., 2019, for a discussion). Our results, together with anecdotal evidence from other studies, suggest that instructed learning may affect the learning process of VMAC. The main problem with this literature is that this question has always been explored in a between-experiment fashion or comparing VMAC scores of "aware" and "unaware" participants based on a post-hoc awareness test. To our knowledge, no previous study has directly manipulated the content of instructions regarding stimulus-reward contingencies to experimentally test whether and how the explicit availability of information could modulate VMAC.

[5] Using an awareness measure where participants had to estimate the raw number of points earned with each distractor could be cognitively demanding. That is, even if participants actually knew the correct contingency, it may be hard for them to evaluate the number of points earned with each distractor in a raw scale. In addition, the fact that we only have one measurement of contingency makes it difficult to explore the extent to which our result could have been contaminated by measurement error. The previous caveats motivated us to change the contingency rating employed in Experiment 2.

Experiment 2

The contrasting results of Garre Frutos et al. (2024) and Experiment 1 of the present study suggest that explicit instructions about the stimulus-reward contingency could be an essential moderator of the VMAC effect. In Experiment 2, we manipulated experimentally the instructions given to participants. In one group, participants were informed in advance about the role of singleton color in the number of points they could earn, as in Garre-Frutos et al. (2024). On the contrary, another group of participants performed the task without this information about the stimulus-reward contingency, as in Experiment 1 in the present study.

Method

Participants.

We recruited 165 (148 self-identified as female; M_{age} = 20.3; SD_{age} = 6.05) participants from the University of Granada and the Autonomous University of Madrid. Participants were contacted from the mailing list of both universities and were offered to participate in the study in exchange for course credits. Approximately half of the participants were randomly assigned to the “Instructions group” (N = 82), and the other half were assigned to the “No Instructions group” (N = 83). Three participants (one from the instructions group and two from the no instructions group) were excluded due to exceptionally low response accuracy (< 70%).

Stimuli, Design, and Procedure.

Unless noted otherwise, the procedure of Experiment 2 was similar to Experiment 1. The main significant difference[6] was how instructions about stimulus-reward contingencies were

[6] In Experiment 2 we employed jspsych (de Leeuw, 2015) instead of OpenSesame. This allowed us to use the virtual-chinrest plugin (https://www.jspsych.org/7.0/plugins/virtual-chinrest/), which is a direct implementation of the procedure developed by Li et al. (2020) and not a custom implmentation that we createdby hand as in Experiment 1. We employed the psychophysics plugin for stimulus presentation (Kuroki, 2021), which have shown to have a remarkable performance in timing for web-based experiments. In addition, due to the high sample size in

provided to participants. Participants in the “No instructions group” did not receive explicit information about the role of the color of the singleton distractor in terms of performance (as in Experiment 1). In contrast, participants in the “Instructions group” were explicitly told that when a high-value singleton color appeared in the display, it would be a “bonus trial”, and they would earn 10 times more points than when the low-value singleton distractor was presented, like in Garre-Frutos et al. (2024). To avoid potential issues related to participants not reading the instructions, participants' knowledge about the instructions was tested using multiple-choice questions at the end of the practice block. Question order and correct response position within each question were randomized. If participants failed to answer correctly, they had to read the instructions again.

In Experiment 2, we also changed the contingency rating test. Data from Experiment 1 suggests that participants could have problems reporting contingency in the raw scale (i.e., the absolute number of points earned with each distractor). Therefore, in Experiment 2 we decided to use a relative scale instead. At the end of the VMAC task, participants were presented with a Visual Analog Scale (VAS). At each extreme of the VAS, each color singleton was presented with a percentage representing the relative number of points gained with each color. Participants were asked to place a dot on the location of the VAS that best represented the relative number of points gained when each color singleton appeared in the display. Therefore, if a participant moved the dot towards the high-value singleton color, the percentage for each singleton was updated accordingly (e.g., 70% points gained with the high-value singleton and 30% with a low-value singleton). After providing the contingency rating, participants were asked about their

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this second experiment. participants conducted the task without the experimenter presence. Nevertheless, instructions for the virtual chinrest were greatly improved to ensure that participants had enough information to understand the instructions.

confidence in their response. Participants were asked again to move a dot within the VAS to the left or the right on a scale ranging from 0 (“no confidence”) to 100 (“very confident”).

Data analysis.

The analysis performed in this second experiment only diverges from Experiment 1 regarding the inclusion of Group as an additional predictor and its interaction with the other coefficients in the models described in Experiment 1. Group was coded using deviation coding so that the rest of the coefficients could be interpreted for the overall mean of the log-RTs. As in the previous Experiment, for the RT analysis, we excluded incorrect responses (6.54%), outlier responses (RT < 150 ms or RTs > 1800 ms; 0.45%), and RTs outside each participant’s 2SDs (4.46%).

Results and Discussion

In the RTs analysis, the fitted models included a random slope for Singleton and Block. The model coefficients for RTs can be observed in Table 2 (left) and model predictions and conditional effects in Figure 3. Overall there is a significant AC effect (Instructions: M_{AC} = 19.65, 95% CI [13.18, 26.1]; No instructions: M_{AC} = 24.21, 95% CI [17.57, 30.8]) and a significant effect of Block, suggesting that RTs decreased across blocks. As for the interaction of Group with other factors, we only found a significant VMAC x Group interaction, with the Instructions group showing a significant VMAC effect (M_{VMAC} = 14.73, 95% CI [8.74, 20.7]) that was absent in the No Instructions group (M_{VMAC} = 3.91, 95% CI [-2.18, 10]). As can be seen in Figure 3b, there is also a nominal trend where the VMAC effect increased through time only in the Instructions group. However, this interaction did not reach significance (p = 0.16).

In the analysis of response accuracy, the maximal model included a random slope for Singleton and Block. Overall, we observed a marginal effect of Block due to an increase in accuracy across the task. There was also a significant Block x Group interaction, showing that an increase in accuracy through blocks was stepper for the No Instructions group. For the experimental effects of interests, we only found a significant AC x Group interaction, where the low singleton interfered more with performance in the No instructions group ($Accuracy_{\mathrm{AC}}$ = -1.02%, 95% CI [-1.7%, -0.02%]) than in the Instructions Group ($Accuracy_{\mathrm{AC}}$ = 0.23%, 95% CI [-0.54%, 0.99%]). We also observed a near-significant VMAC*Group interaction that, if anything, suggests that the high-value distractor interfered more strongly with performance in the Instructions ($Accuracy_{\mathrm{VMAC}}$ = -0.31%, 95% CI [-0.89%, 0.28%]) than in the No instructions group ($Accuracy_{\mathrm{VMAC}}$ = 0.23%, 95% CI [-0.54%, 0.99%]), showing that our results are not contaminated by speed-accuracy tradeoff.

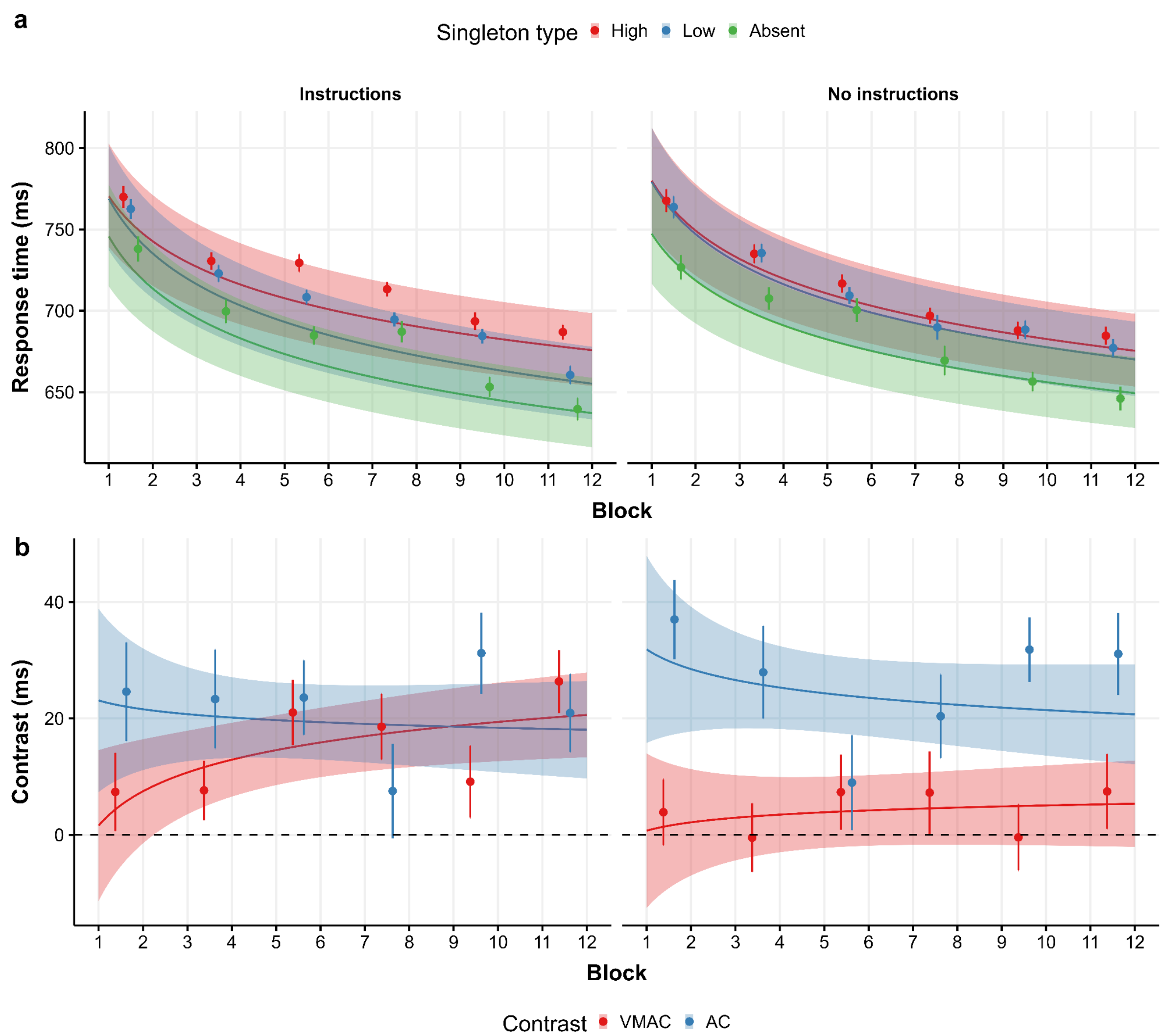

Figure 3. **a**) Model predictions as a function of singletons across blocks and groups. **b**) Conditional effects, which represent the conditional mean of the high-low (VMAC) and low-absent (AC) contrasts in the response scale.

Table 2

Model summaries for the selected models for RTs and accuracy in experiment 2.

	RTs			Accuracy		
Predictors	*Estimates*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	6.519	6.495 – 6.543	**<0.001**	19.018	17.081 – 21.175	**<0.001**
VMAC	0.014	0.008 – 0.020	**<0.001**	1.018	0.933 – 1.109	0.692
AC	0.032	0.025 – 0.038	**<0.001**	0.917	0.817 – 1.030	0.143

Block	-0.042	-0.046 to -0.038	**<0.001**	1.053	0.996 – 1.113	0.070
Group	-0.012	-0.060 – 0.036	0.615	1.009	0.816 – 1.249	0.932
VMAC × Block	0.005	0.001 – 0.09	**0.020**	1.032	0.947 – 1.125	0.473
AC × Block	-0.002	-0.007 – 0.004	0.518	0.936	0.835 – 1.050	0.259
VMAC × Group	0.016	0.004 – 0.028	**0.010**	0.848	0.759 – 1.045	0.061
AC × Group	-0.006	-0.019 – 0.007	0.375	1.312	1.041 – 1.654	**0.021**
Block × Group	-0.001	-0.010 – 0.008	0.513	0.875	0.789 – 0.971	**0.012**
(VMAC × Block) × Group	0.006	-0.002 – 0.015	0.157	1.127	0.949 – 1.339	0.174
(AC × Block) × Group	0.002	-0.009 – 0.013	0.695	1.016	0.808 – 1.278	0.892
Random Effects						
σ^2	0.041			3.290		
τ_{00}	0.024 $_{\text{Intercept}}$			0.382 $_{\text{Intercept}}$		
τ_{11}	0.001 $_{\text{VMAC}}$					
	0.0005 $_{\text{AC}}$					
	0.001 $_{\text{Block}}$			0.029 $_{\text{Block}}$		
ρ_{01}	-0.148			0.269		
	0.351					
	-0.279					
ICC	0.377			0.111		
N	162			162		
Observations	41,489			44,129		
Marginal R^2 / Conditional R^2	0.030 / 0.396			0.003 / 0.114		

Note. Bold entries denote statistical significance. *p*-values were computed using Satterwhite correction. CI = Confidence interval; ICC = Intraclass correlation coefficient. τ = Random effects, ρ = correlation between random effects.

Regarding the awareness test, the contingency rating was positively correlated with confidence ratings in both groups (Instructions: $r = 0.35$, $p < 0.01$, CI 95% [0.14, 0.53]; No Instructions: $r = 0.55$, $p < 0.01$, CI 95% [0.38, 0.69]; Figure 4a), indicating that participants who were more confident in their response to the contingency rating also showed a better contingency estimation. Participants in the Instructions group showed higher contingency ratings

(t_{Welch}(154.86) = 4.023, $p < 0.01$, $M = 12.28$, 95% CI [6.25, 18.31]; Instructions: $M_{Instructions}$ = 67.80; No Instructions: $M_{No\ Instructions}$ = 55.52). Finally, the correlation between VMAC and contingency ratings was not significant in both groups (Instructions: $r = 0.016$, $p = 0.88$, CI 95% [-0.20, 0.23]; No Instructions: $r = 0.13$, $p = 0.250$, CI 95% [-0.09, 0.34]; Figure 4b).

As measurement error can hamper inferences from correlational analyses, we report an extensive multiverse analysis on the correlation coefficient between VMAC and the contingency rating in the Supplementary Materials. We generated 128 datasets orthogonally manipulating factors such as the use of fixed or relative filters in RTs, the averaging method, or the number of blocks[7] employed to calculate the VMAC effect (see Garre-Frutos et al., 2024). Interestingly, the correlation was close to 0 in the Instructions group in all specifications, while this correlation was often large in the other group, especially when only the last six blocks of trials were employed to calculate the VMAC effect (Figure 4c). This suggests that early and late blocks might be measuring a different latent construct. In other words, maybe participants with a high rating started to learn the association in later blocks. If true, one would expect that the contingency rating would predict the temporal dynamics of the VMAC effect in the No Instructions group. To test this hypothesis, we fitted the main model described above to data from the No Instructions group, adding contingency rating as an additional predictor. As expected, there was only a significant three-way VMAC x Block x Contingency interaction (Table S1), where the VMAC effect increased through blocks only for participants who showed a high contingency rating. For visualization purposes, in Figure 4d we presented the model

[7] In studies that use VMAC to explore individual difference is relatively common to compute the effect at the end of the learning stage (Albertella et al., 2019, 2020; Liu et al., 2021). This specification has been shown to reduce reliability (Garre-Frutos, 2024). On the other hand, given the temporal development of the VMAC effect, it is possible that the latent construct mapped in later trials is different from early trials, which makes it especially interesting to manipulate this factor in a multiverse analysis to explore correlations with other measures. This possibility has been extensively explored in supplementary materials.

conditional effect (arbitrarily) half-splitting the sample as a function of contingency rating. Critically, the same analysis was performed for Experiment 1, and we observed similar results (Table S2 and Figure S8).

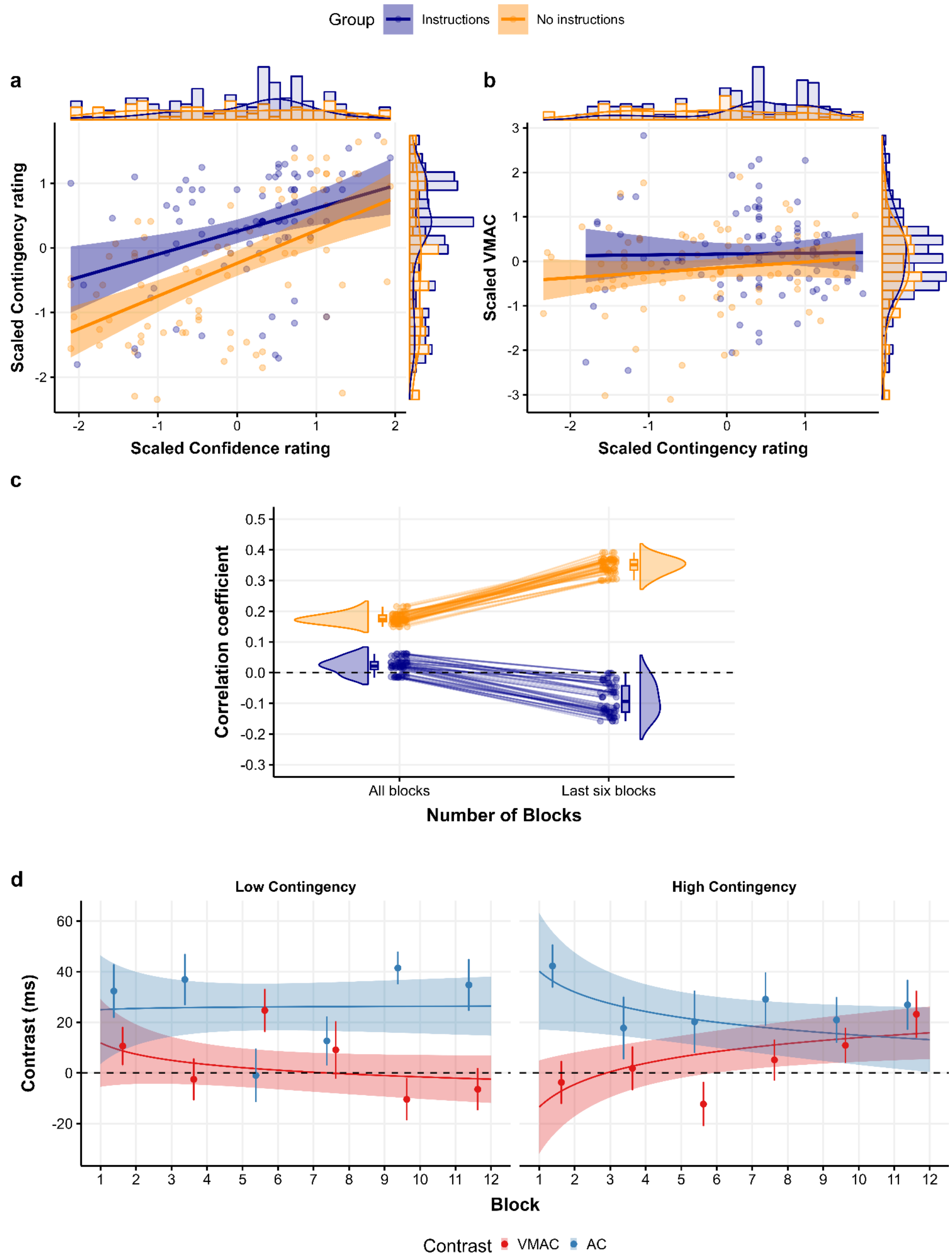

Figure 4. **a**) Scatterplot for the association between the contingency rating and the confidence rating, where group (Instructions or No instructions) is signaled by color. **b**) Scatterplot for the association between the VMAC effect and the contingency rating as a function of the group. **c**) Correlation coefficients between the VMAC effect and the contingency rating across 128 data preprocessing specifications as a function of group and the number of blocks employed for computing VMAC. **d**) Conditional VMAC and AC effect predictions for participants in the No Instructions group that indicated a high (80th quantile) or low (30th quantile) contingency rating. Raw data represents participants below ($N = 45$) or above ($N = 38$) the 60th quantile of the overall contingency rating distribution in the No Instructions group. The previous splitting procedure is arbitrary and only for visualization purposes.

General Discussion

In two experiments, we investigated the role of information value on VMAC. In Experiment 1, we observed that when instructions about the stimulus-reward contingency were removed, there was no VMAC effect at the group level. In Experiment 2, we directly manipulated the stimulus-reward contingency instructions in a between-participants fashion. Critically, we found that this manipulation modulated the VMAC effect, with only participants who received explicit instructions showing a VMAC effect. Furthermore, although participants who received no instructions did not show the VMAC effect at the group level, individual differences in contingency estimation seemed to influence the temporal dynamics of VMAC. Specifically, among participants who reported higher contingency estimates, spontaneous awareness of the stimulus-reward relationship may have triggered learning later in the task.

Based on the present results, one might think that the variable we manipulated in the present study is a strong moderator of the VMAC effect. In a recent meta-analysis on this phenomenon, Rusz et al. (2020) showed that reward-driven distraction is robust to many methodological details of the experiment, such as task type, learning conditions (Pavlovian or instrumental), and even whether participants were explicitly told that looking at the high-value distractor is a suboptimal search strategy. Although none of these factors modulated the effect, the meta-analysis did not test whether instructions about stimulus-reward contingencies were provided. To explore the extent to which our results generalize to the literature as a whole, we re-analyzed the data gathered by Rusz et al. (2020) coding the inclusion of instructions about stimulus-reward contingencies in all the studies in their meta-analysis[8]. Supporting our findings, instructions about stimulus-reward contingencies significantly increased the effect size across studies ($Q(1) = 6.53$, $p = 0.01$), which suggests that the present findings may be extrapolated to other studies in the literature.

VMAC is thought to reflect a form of human sign tracking (Colaizzi et al., 2020; Le Pelley et al., 2015; Pelley et al., 2024). In other words, VMAC may reflect increased attention to stimuli that have gained incentive salience through Pavlovian learning. However, other authors have suggested that VMAC may also reflect the automatization of an instrumental response to the high-value distractor (Anderson, 2016; Failing & Theeuwes, 2018). Although in the paradigm developed by Le Pelley et al. (2015), the predictive features are always task-irrelevant, awareness of the stimulus-reward contingency could induce strategic attention to the high-value stimulus.

Habitual behaviors are formed based on extensive training in stimulus-response pairings, and typical paradigms to study habit formation usually employ several days of training (Hardwick et al., 2019; Luque et al., 2020). In contrast, we generally observe that VMAC unfolds relatively fast, without extensive training (Garre-Frutos et al., 2024; Le Pelley et al., 2015; Watson et al., 2019). Moreover, if VMAC represents a goal-directed action that becomes habitual, one would expect the VMAC effect to be present from the beginning of the learning phase, reflecting participants' knowledge. On the contrary, VMAC typically develops progressively over time (Failing & Theeuwes, 2017), suggesting a gradual learning mechanism based on Pavlovian learning that may depend on the individual motivational state (Anderson,

[8] The code and material regarding this analysis is presented in the following OSF repository: https://osf.io/4wdpv/.

2016), and not necessarily habit-like attention. In other words, it could be the case that Pavlovian learning itself could be modulated by explicit information.

It has been proposed that associative learning in humans could be entirely propositional (Mitchell et al., 2009) and that conscious awareness may be necessary (but not sufficient) in several phenomena related to Pavlovian learning (Lovibond & Shanks, 2002). However, one of the major issues in evaluating the potential role of awareness is the intrinsic difficulty of measuring awareness in implicit cognition research (Shanks et al., 2021). Other visual statistical learning effects, such as contextual cueing (Chun & Jiang, 1998) or probability cueing (Geng & Behrmann, 2002) of visual attention, have been claimed to be unconscious because a robust significant effect on RTs and null results in an awareness test is usually observed (but see Meyen et al., 2023). Sadly, most common tests of explicit awareness are severely underpowered (Vadillo et al., 2016, 2020), and lack the psychometrics properties necessary for the analysis of individual differences (Vadillo et al., 2022). Although most of the narrative reviews about reward-related distraction have highlighted that there is no or little influence of explicit awareness on VMAC (Anderson, 2016; Anderson et al., 2021; Failing & Theeuwes, 2018; Le Pelley et al., 2016), the extent to which this literature suffers from the above issues is unknown.

In conclusion, the present findings suggest that conscious awareness about the stimulus-reward relationship may be necessary in the learning process underlying VMAC. Although VMAC has been considered a highly automatic and implicit process, the concept of automaticity is complex (Moors & De Houwer, 2006). Once learned, the expression of VMAC may share features of typically automatic processes, but its learning process may not be entirely automatic. Perhaps only when participants are instructed (or they spontaneously become aware) about the functional relationship between color and reward, the color feature is selectively attended and learning occurs. In any case, further research is needed to elucidate the role of explicit awareness in VMAC.

References

Albertella, L., Le Pelley, M. E., Chamberlain, S. R., Westbrook, F., Lee, R. S. C., Fontenelle, L. F., Grant, J. E., Segrave, R. A., McTavish, E., & Yücel, M. (2020). Reward-related attentional capture and cognitive inflexibility interact to determine greater severity of compulsivity-related problems. *Journal of Behavior Therapy and Experimental Psychiatry*, *69*, 101580. https://doi.org/10.1016/j.jbtep.2020.101580

Albertella, L., Watson, P., Yücel, M., & Le Pelley, M. E. (2019). Persistence of value-modulated attentional capture is associated with risky alcohol use. *Addictive Behaviors Reports*, *10*, 100195. https://doi.org/10.1016/j.abrep.2019.100195

Anderson, B. A. (2016). The attention habit: How reward learning shapes attentional selection: The attention habit. *Annals of the New York Academy of Sciences*, *1369*(1), 24-39. https://doi.org/10.1111/nyas.12957

Anderson, B. A., Kim, H., Kim, A. J., Liao, M.-R., Mrkonja, L., Clement, A., & Grégoire, L. (2021). The past, present, and future of selection history. *Neuroscience & Biobehavioral Reviews*, *130*, 326-350. https://doi.org/10.1016/j.neubiorev.2021.09.004

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011a). Learned Value Magnifies Salience-Based Attentional Capture. *PLOS ONE*, *6*(11), e27926. https://doi.org/10.1371/journal.pone.0027926

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011b). Value-driven attentional capture. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(25), 10367-10371. https://doi.org/10.1073/pnas.1104047108

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437-443. https://doi.org/10.1016/j.tics.2012.06.010

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Lemguage*, *68*(3). https://doi.org/10.1016/j.jml.2012.11.001

Bates, D., Kliegl, R., Vasishth, S., & Baayen, H. (2018). *Parsimonious Mixed Models* (arXiv:1506.04967). arXiv. https://doi.org/10.48550/arXiv.1506.04967

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1), 1-48. https://doi.org/10.18637/jss.v067.i01

Chun, M. M., & Jiang, Y. (1998). Contextual Cueing: Implicit Learning and Memory of Visual Context Guides Spatial Attention. *Cognitive Psychology*, *36*(1), 28-71. https://doi.org/10.1006/cogp.1998.0681

Colaizzi, J. M., Flagel, S. B., Joyner, M. A., Gearhardt, A. N., Stewart, J. L., & Paulus, M. P. (2020). Mapping sign-tracking and goal-tracking onto human behaviors. *Neuroscience & Biobehavioral Reviews*, *111*, 84-94. https://doi.org/10.1016/j.neubiorev.2020.01.018

de Leeuw, J. R. (2015). jsPsych: A JavaScript library for creating behavioral experiments in a Web browser. *Behavior Research Methods*, *47*(1), 1-12. https://doi.org/10.3758/s13428-014-0458-y

Della Libera, C., & Chelazzi, L. (2009). Learning to attend and to ignore is a matter of gains and losses. *Psychological science*, *20*(6), 778-784. https://doi.org/10.1111/j.1467-9280.2009.02360.x

Failing, M., & Theeuwes, J. (2017). Don't let it distract you: How information about the availability of reward affects attentional selection. *Attention, Perception, & Psychophysics*, *79*(8), 2275-2298. https://doi.org/10.3758/s13414-017-1376-8

Failing, M., & Theeuwes, J. (2018). Selection history: How reward modulates selectivity of visual attention. *Psychonomic Bulletin & Review*, *25*(2), 514-538. https://doi.org/10.3758/s13423-017-1380-y

Garre-Frutos, F., Vadillo, M. A., González, F., & Lupiáñez, J. (2024). On the reliability of value-modulated attentional capture: An online replication and multiverse analysis. *Behavior Research Methods*. https://doi.org/10.3758/s13428-023-02329-5

Geng, J. J., & Behrmann, M. (2002). Probability Cuing of Target Location Facilitates Visual Search Implicitly in Normal Participants and Patients with Hemispatial Neglect. *Psychological Science*, *13*(6), 520-525. https://doi.org/10.1111/1467-9280.00491

Hardwick, R. M., Forrence, A. D., Krakauer, J. W., & Haith, A. M. (2019). Time-dependent competition between goal-directed and habitual response preparation. *Nature Human Behaviour*, *3*(12), 1252-1262. https://doi.org/10.1038/s41562-019-0725-0

Jaeger, T. F. (2008). Categorical data analysis: Away from ANOVAs (transformation or not) and towards logit mixed models. *Journal of memory and language*, *59*(4), 434-446. https://doi.org/10.1016/j.jml.2007.11.007

Kuroki, D. (2021). A new jsPsych plugin for psychophysics, providing accurate display duration and stimulus onset asynchrony. *Behavior Research Methods*, *53*(1), 301-310. https://doi.org/10.3758/s13428-020-01445-w

Lange, K., Kühn, S., & Filevich, E. (2015). " Just Another Tool for Online Studies”(JATOS): An easy solution for setup and management of web servers supporting online studies. *PloS one*, *10*(6), e0130834. https://doi.org/10.1371/journal.pone.0134073

Le Pelley, M. E., Mitchell, C. J., Beesley, T., George, D. N., & Wills, A. J. (2016). Attention and associative learning in humans: An integrative review. *Psychological bulletin*, *142*(10), 1111—1140. https://doi.org/10.1037/bul0000064

Le Pelley, M. E., Pearson, D., Griffiths, O., & Beesley, T. (2015). When goals conflict with values: Counterproductive attentional and oculomotor capture by reward-related stimuli. *Journal of Experimental Psychology: General*, *144*(1), 158-171. https://doi.org/10.1037/xge0000037

Le Pelley, M. E., Seabrooke, T., Kennedy, B. L., Pearson, D., & Most, S. B. (2017). Miss it and miss out: Counterproductive nonspatial attentional capture by task-irrelevant, value-related stimuli. *Attention, Perception & Psychophysics*, *79*(6), 1628-1642. https://doi.org/10.3758/s13414-017-1346-1

Le Pelley, M. E., Ung, R., Mine, C., Most, S. B., Pearson, D., & Theeuwes, J. (2022). Reward learning and statistical learning independently influence attentional priority of salient distractors in visual search. *Attention, Perception & Psychophysics*, *84*(5), 1446-1459. https://doi.org/10.3758/s13414-021-02426-7

Le Pelley, M. E., Watson, P., Pearson, D., Abeywickrama, R. S., & Most, S. B. (2019). Winners and losers: Reward and punishment produce biases in temporal selection. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *45*(5), 822-833. https://doi.org/10.1037/xlm0000612

Li, Q., Joo, S. J., Yeatman, J. D., & Reinecke, K. (2020). Controlling for Participants' Viewing Distance in Large-Scale, Psychophysical Online Experiments Using a Virtual Chinrest. *Scientific Reports*, *10*(1), 904. https://doi.org/10.1038/s41598-019-57204-1

Liu, C., Yücel, M., Suo, C., Le Pelley, M. E., Tiego, J., Rotaru, K., Fontenelle, L. F., &

Albertella, L. (2021). Reward-Related Attentional Capture Moderates the Association between Fear-Driven Motives and Heavy Drinking. *European Addiction Research*, *27*(5), 351-361. https://doi.org/10.1159/000513470

Lovibond, P. F., & Shanks, D. R. (2002). The role of awareness in Pavlovian conditioning: Empirical evidence and theoretical implications. *Journal of Experimental Psychology: Animal Behavior Processes*, *28*(1), 3-26. https://doi.org/10.1037/0097-7403.28.1.3

Luque, D., Molinero, S., Watson, P., López, F. J., & Le Pelley, M. E. (2020). Measuring habit formation through goal-directed response switching. *Journal of Experimental Psychology. General*, *149*(8), 1449-1459. https://doi.org/10.1037/xge0000722

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior research methods*, *44*(2), 314-324. https://doi.org/10.3758/s13428-011-0168-7

Matuschek, H., Kliegl, R., Vasishth, S., Baayen, H., & Bates, D. (2017). Balancing Type I error and power in linear mixed models. *Journal of Memory and Language*, *94*, 305-315. https://doi.org/10.1016/j.jml.2017.01.001

Meyen, S., Vadillo, M. A., von Luxburg, U., & Franz, V. H. (2023). No evidence for contextual cueing beyond explicit recognition. *Psychonomic Bulletin & Review*. https://doi.org/10.3758/s13423-023-02358-3

Meyer, K. N., Sheridan, M. A., & Hopfinger, J. B. (2020). Reward history impacts attentional orienting and inhibitory control on untrained tasks. *Attention, Perception, & Psychophysics*, *82*(8), 3842-3862. https://doi.org/10.3758/s13414-020-02130-y

Mitchell, C. J., Houwer, J. D., & Lovibond, P. F. (2009). The propositional nature of human associative learning. *Behavioral and Brain Sciences*, *32*(2), 183-198.

https://doi.org/10.1017/S0140525X09000855

Moors, A., & De Houwer, J. (2006). Automaticity: A Theoretical and Conceptual Analysis. *Psychological Bulletin*, *132*, 297-326. https://doi.org/10.1037/0033-2909.132.2.297

Parsons, S. (2021). splithalf: Robust estimates of split half reliability. *Journal of Open Source Software*, *6*(60), 3041-3041. http://dx.doi.org/10.21105/joss.03041

Pearson, D., Osborn, R., Whitford, T. J., Failing, M., Theeuwes, J., & Le Pelley, M. E. (2016). Value-modulated oculomotor capture by task-irrelevant stimuli is a consequence of early competition on the saccade map. *Attention, Perception, & Psychophysics*, *78*(7), 2226-2240. https://doi.org/10.3758/s13414-016-1135-2

Pelley, M. L., Watson, P., & Wiers, R. (2024). *Biased choice and incentive salience: Implications for addiction*. https://doi.org/10.31234/osf.io/vf3rd

Rusz, D., Le Pelley, M. E., Kompier, M. A. J., Mait, L., & Bijleveld, E. (2020). Reward-driven distraction: A meta-analysis. *Psychological Bulletin*, *146*(10), 872-899. https://doi.org/10.1037/bul0000296

Shanks, D. R., Malejka, S., & Vadillo, M. A. (2021). The Challenge of Inferring Unconscious Mental Processes. *Experimental Psychology*, *68*(3), 113-129. https://doi.org/10.1027/1618-3169/a000517

Theeuwes, J. (1992). Perceptual selectivity for color and form. *Perception & Psychophysics*, *51*(6), 599-606. https://doi.org/10.3758/BF03211656

Theeuwes, J. (1994). Stimulus-driven capture and attentional set: Selective search for color and visual abrupt onsets. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(4), 799-806. https://doi.org/10.1037/0096-1523.20.4.799

Theeuwes, J. (2018). Visual Selection: Usually Fast and Automatic; Seldom Slow and Volitional.

Journal of Cognition, *1*(1), 29. https://doi.org/10.5334/joc.13

Vadillo, M. A., Konstantinidis, E., & Shanks, D. R. (2016). Underpowered samples, false negatives, and unconscious learning. *Psychonomic Bulletin & Review*, *23*(1), 87-102. https://doi.org/10.3758/s13423-015-0892-6

Vadillo, M. A., Linssen, D., Orgaz, C., Parsons, S., & Shanks, D. R. (2020). Unconscious or underpowered? Probabilistic cuing of visual attention. *Journal of Experimental Psychology: General*, *149*(1), 160-181. https://doi.org/10.1037/xge0000632

Vadillo, M. A., Melejka, S., Lee, D. Y. H., Dienes, Z., & Shanks, D. R. (2022). Raising awareness about measurement error in research on unconscious mental processes.*Psychonomical Bulletin & Review, 29*, 21-43. https://doi.org/10.3758/s13423-021-01923-y

Watson, P., Pearson, D., Most, S. B., Theeuwes, J., Wiers, R. W., & Le Pelley, M. E. (2019). Attentional capture by Pavlovian reward-signalling distractors in visual search persists when rewards are removed. *PLOS ONE*, *14*(12), e0226284. https://doi.org/10.1371/journal.pone.0226284

Watson, P., Pearson, D., Theeuwes, J., Most, S. B., & Le Pelley, M. E. (2020). Delayed disengagement of attention from distractors signalling reward. *Cognition*, *195*, 104125. https://doi.org/10.1016/j.cognition.2019.104125

Open Practices Statement

All data, materials, and analysis scripts related to the present study are publicly available at https://osf.io/4wdpv/. All data exclusions, manipulations, and measurements are reported in the main text. None of the experiments was formally preregistered before data collection.

Declaration of interests

The authors report there are no competing interests to declare.

Author contribution

Author roles were classified using the Contributor Role Taxonomy (CRediT; https://credit.niso.org/) as follows: *Francisco Garre-Frutos*: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, and Writing - original draft; *Juan Lupiañez*: Conceptualization, Funding acquisition, Supervision, and Writing - review & editing; *Miguel A. Vadillo*: Conceptualization, Funding acquisition, Supervision, and Writing - review & editing

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Supplementary Materials to accompany

Value-modulated attentional capture depends on explicit awareness

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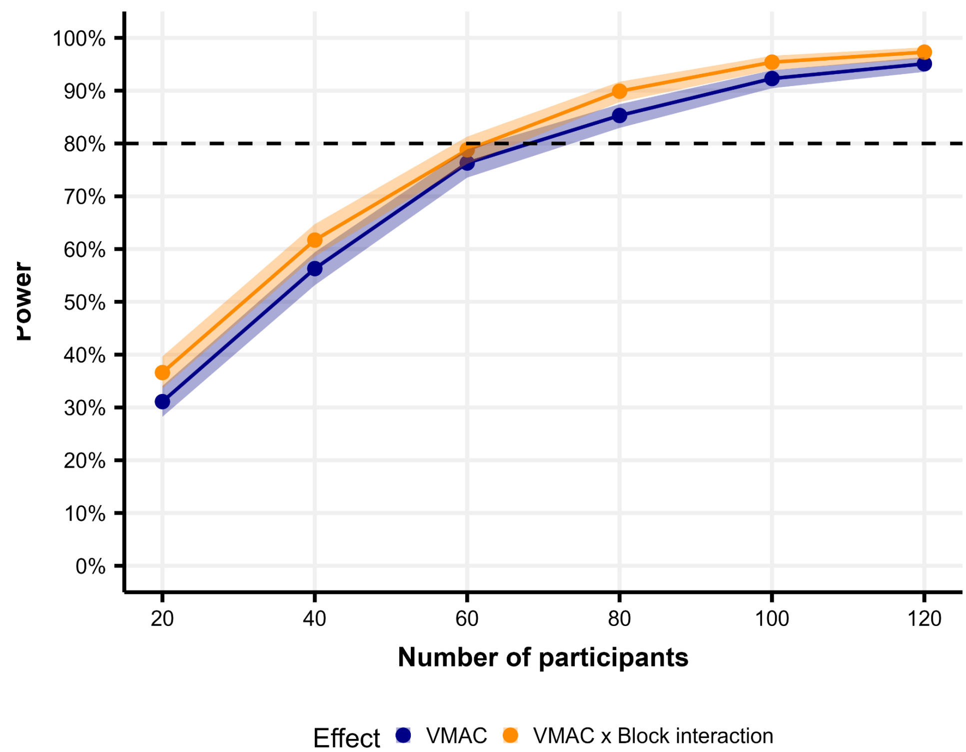
Power analysis

As this first experiment is based on Garre-Frutos et al. (2024), we performed a simulation-based power analysis using their results as a reference. We assumed the same model structure and effect sizes observed in Garre-Frutos et al. (2024) and then we tested the significance of the VMAC effect and its interaction with Blocks of trials in 1000 simulations with varying sample sizes (from 20 to 120). Figure S1 shows the proportion of significant results as a function of the statistical test and the number of participants. The power analysis shows that at least 80 participants would be necessary to achieve sufficient power to detect both the VMAC effect (Power = 85.3% 95% CI [83%, 87.4%]) and its interaction with the block of trials (Power = 89.9% 95% CI [87.9%, 91.7%])[9].



[9] In the context of the VMAC*Block interaction, the VMAC effect calculated in this power analysis is conditional to the higher-order interaction. In other words, as the Block predictor is centered, the VMAC effect here refers to the VMAC effect in block six/seven, which may be a more conservative power calculation given that VMAC increases over time. Taking the averaged VMAC effect across blocks would result in an increase in statistical power.

Figure S1. Power curve for the VMAC effect and its interaction with Block predictor. Dots indicated the observed proportion of significant results as a function of the effect and the number of participants employed in the simulation. Shaded segments represent the 95% CI for a binomial proportion.

Multiverse reliability analysis for Experiments 1 and 2

Here we present a multiverse reliability analysis exploring the reliability of our measures under a plausible range of data-preprocessing specifications (Parsons, 2022). Similar to Garre-Frutos et al. (2024), we orthogonally manipulated the following factors:

- Relative filter for RTs: none, 2 SDs, 2.5 SDs, or 3 SDs.
- Fixed filter for RTs: none or (RT > 150 and RT < 1800),
- Averaging method: mean or median.
- Log-transform RTs: yes or no.
- Filter the first two trials of each block: yes or no.
- Number of blocks used to calculate the effect: 6 or 12.

The combination of the previous factors gives rise to 128 possible data preprocessing specifications. For every specification, we calculated random permutated split-half reliability using 5000 random permutations (Parsons, 2021). Then, we corrected the reliability estimates using the Spearman-Brown formula. Figures S1, S2, and S3 (top row) show the mean Spearman-Brown estimates across permutations and the 95% bootstrapped CIs ordered as a function of reliability. In contrast, the bottom row shows the corresponding specification for each reliability estimate in the top row.

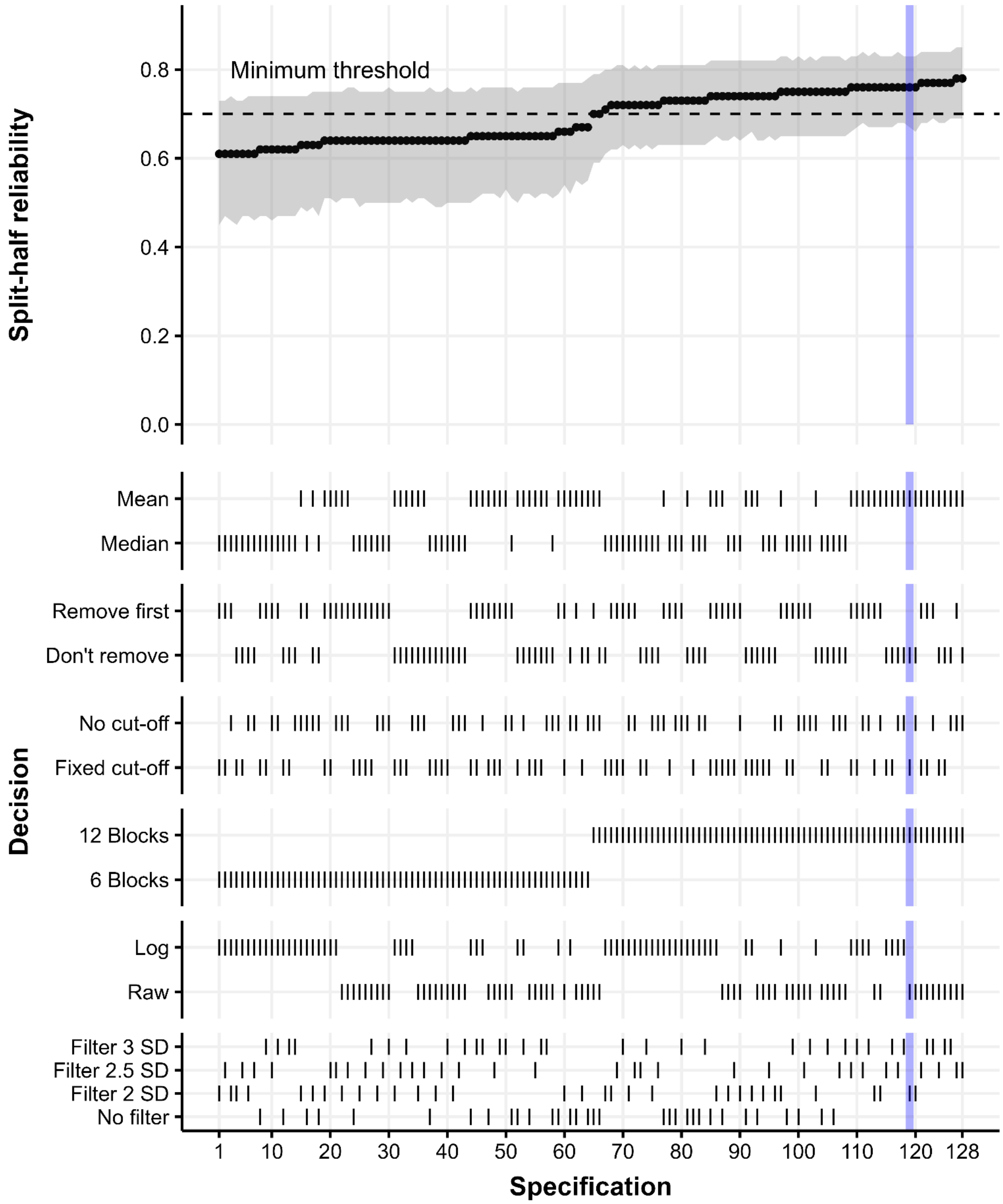


Figure S2. In the top panel, each dot represents a Spearman-Brown reliability estimate in Experiment 1, and shaded areas represent 95% CI. Regarding the bottom panel, the different combinations of specifications are signaled with a vertical line. The line in the top panel highlights 0.7, as the minimum threshold for studies on individual differences, and the vertical shaded segment represents the specification used in the main analysis.

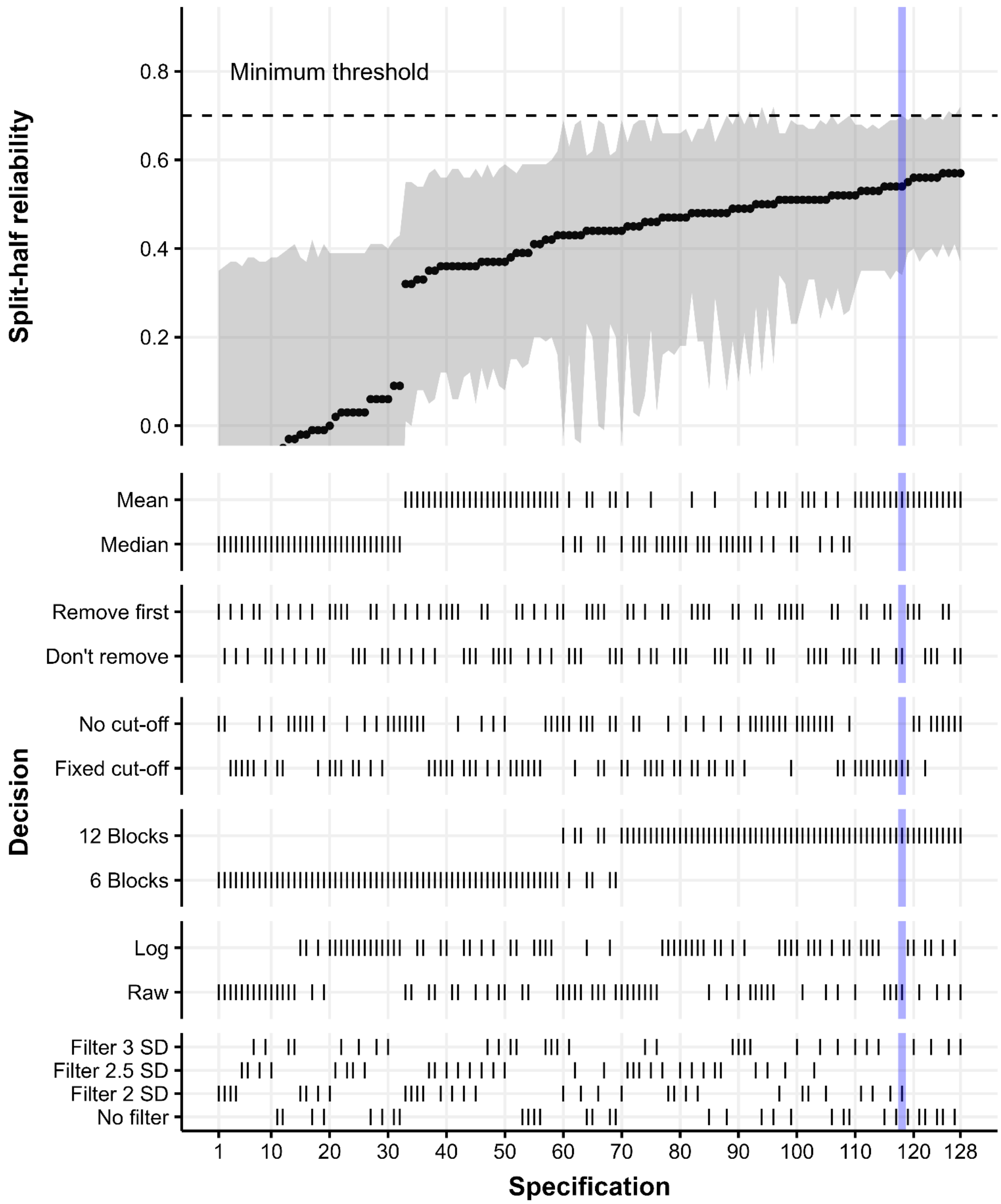


Figure S3. In the top panel, each dot represents a Spearman-Brown reliability estimate for the Instructions group in Experiment 2. Shaded areas represent 95% CI. The bottom panel depicts the different combinations of specifications signaled with a vertical line. The line in the top panel highlights 0.7, as the minimum threshold for studies on individual differences, and the vertical shaded segment represents the specification used in the main analysis.

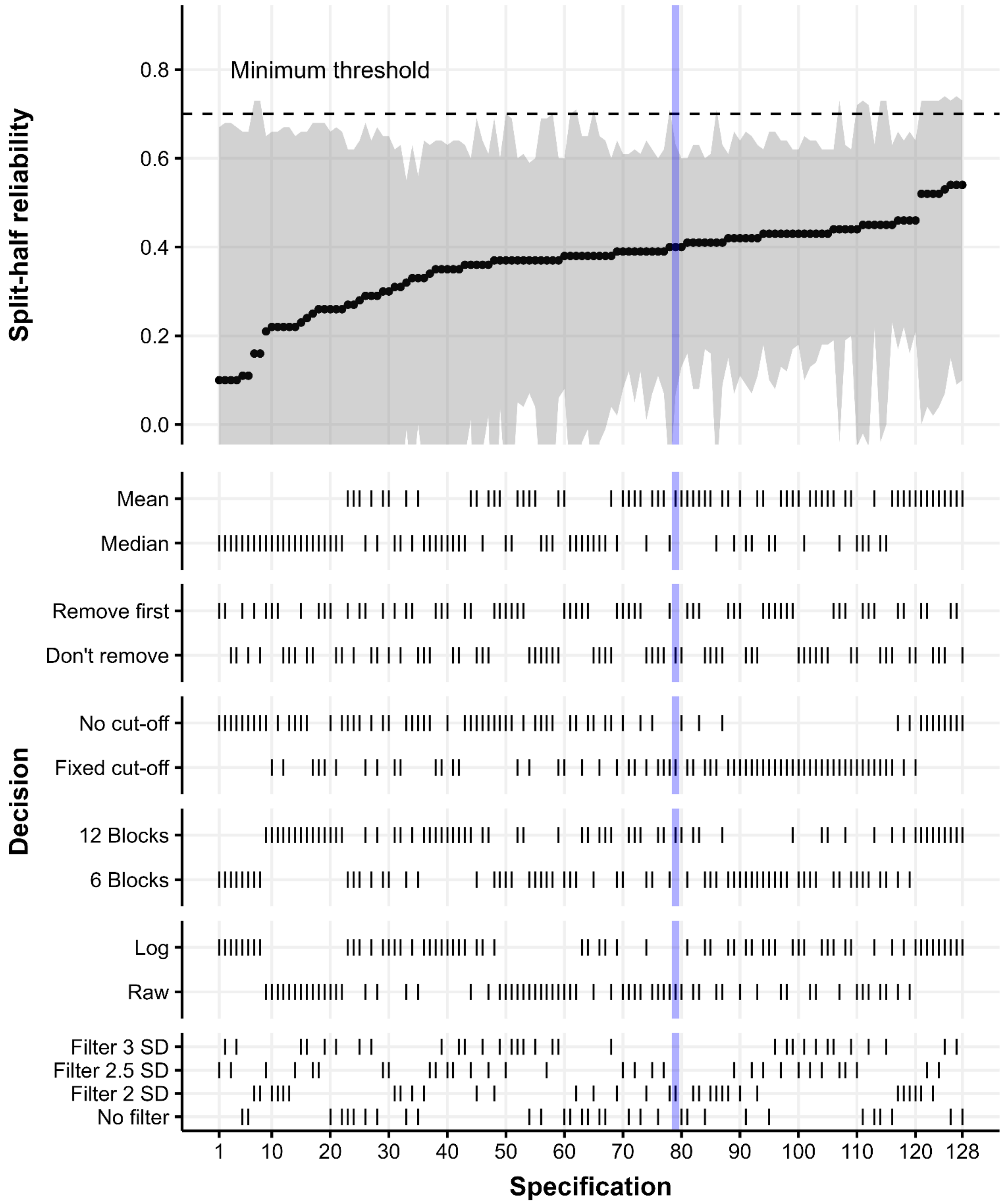


Figure S4. In the top panel, each dot represents a Spearman-Brown reliability estimate for the No Instructions group in Experiment 2. Shaded areas represent 95% CI. The bottom panel depicts the different combinations of specifications signaled with a vertical line. The line in the top panel highlights 0.7, as the minimum threshold for studies on individual differences, and the vertical shaded segment represents the specification used in the main analysis.

In Experiment 1 (Figure S2), the median reliability is r_{sb} = 0.67, 95% CI [0.55, 0.78], and the range of reliabilities is [0.61, 0.78], with 48.43% of the estimates above the usual recommended minimum threshold for individual difference research (0.7, following Nunnally, 1978). For Experiment 2, we show the reliability of our measures in Figures S3 (Instruction group: median of r_{sb} = 0.44, 95% CI [0.23, 0.61], range of [-0.14, 0.57]) and S4 (No instructions group: median of r_{sb} = 0.38, 95% CI [-0.1, 0.64], range of [0.1, 0.54]). As can be seen, in general, reliability in either group of Experiment 2 is lower than that observed in Experiment 1. This may be related to the experimenter's presence via the online meeting in Experiment 1 compared to Experiment 2 (the main difference in both experiments). Nevertheless, the reliability of the particular specification employed in the analysis of experiment 2 is quite high considering the overall range of reliabilities.

Multiverse analysis for the correlation between VMAC scores and contingency rating

Given the null correlation between the VMAC scores in Experiment 2 and that the measure of contingency is highly correlated with the confidence rating, we decided to examine the extent to which this correlation could be attenuated by measurement error. To do this, we used the data sets generated for the previous multiverse analysis and computed the correlation between the VMAC scores and the contingency rating for each group. If the observed correlation is attenuated by measurement error, it should increase as a function of the reliability of the VMAC scores, especially for the No Instructions group (since we expect the contingency rating to measure awareness only for participants who did not receive explicit instructions).

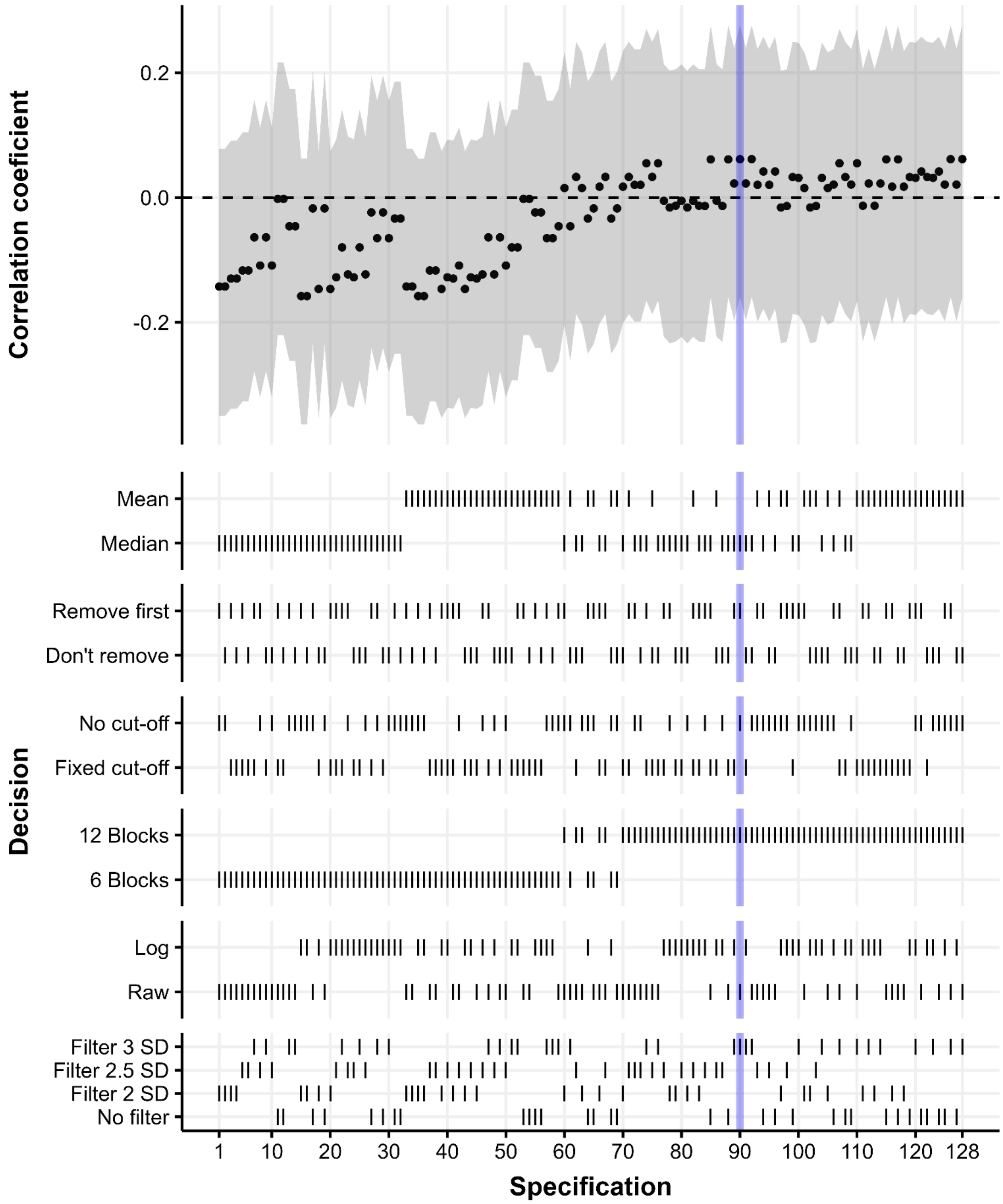


Figure S5. In the top panel, each dot represents the correlation between VMAC and the contingency rating for the Instructions group ordered by the reliabilities of different data preprocessing specifications. Shaded areas represent 95% CI for the same correlation. The bottom panel illustrates different specifications, where the vertical line signals the possible combinations of factors employed for each specification.

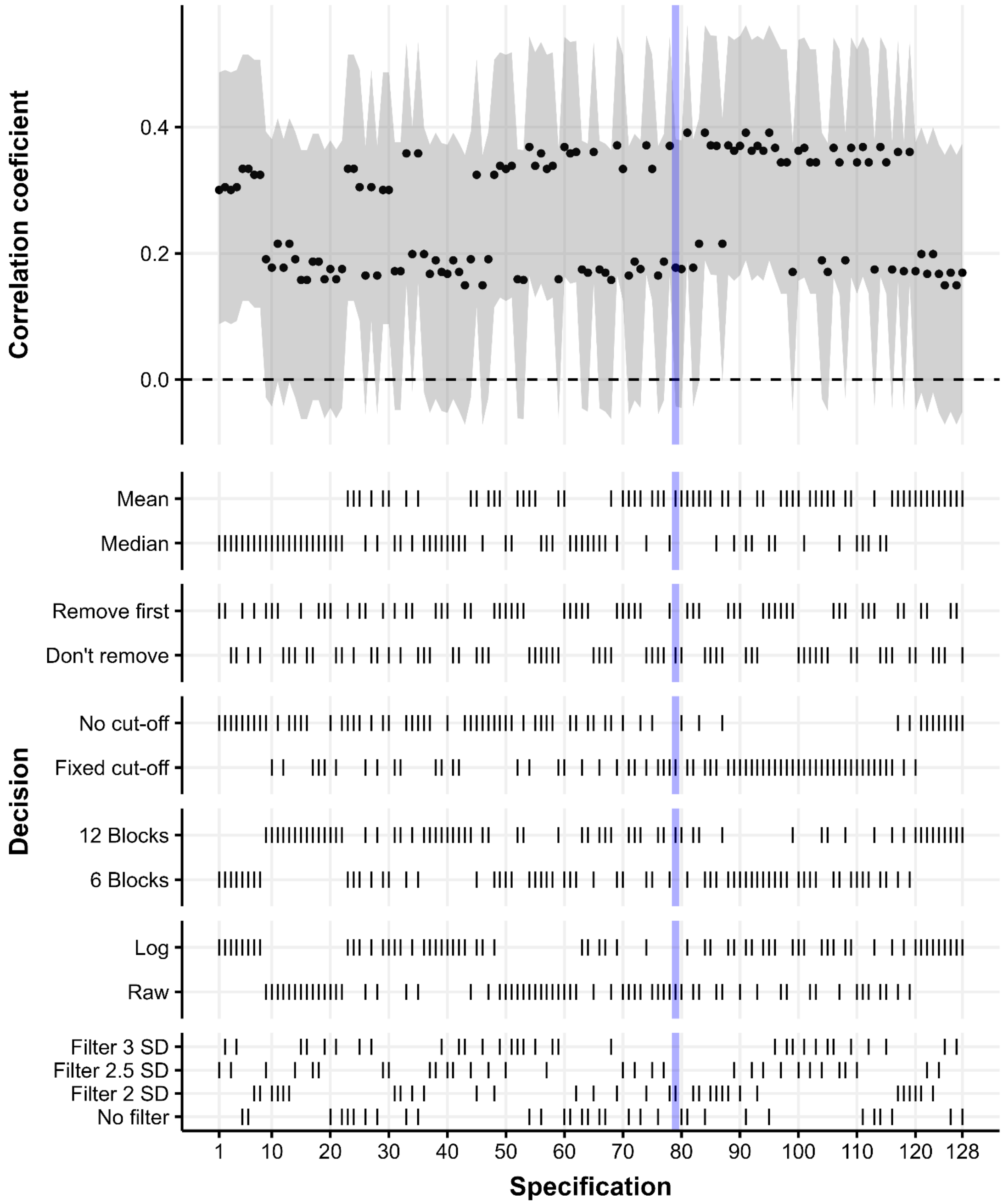


Figure S6. In the top panel, each dot represents the correlation between VMAC and the contingency rating for the Instructions group ordered by the reliabilities of different data preprocessing specifications. Shaded areas represent 95% CI for the same correlation. The bottom panel illustrates different specifications, where the vertical line signals the possible combinations of factors employed for each specification.

Figures S5 and S6 show the correlation between VMAC and contingency ratings as a function of the reliability of each specification for both groups, respectively. In the Instructions group, there is a clear pattern where specifications with lower reliability tend to show a negative correlation. Additionally, these specifications often use the last half of the task to calculate the VMAC effect. This pattern could resemble regression to the mean due to high measurement error (Shanks, 2017). Specifically, participants with extreme VMAC scores may have less extreme contingency ratings, creating a spurious negative association. In contrast, in the No Instructions group, the correlation coefficient systematically increases for every specification when VMAC scores are computed using the last six blocks of trials. This pattern is more evident in Figure 4c of the main text.

Table S1

Model summaries for the selected models for RTs and accuracy in experiment 2.

		RTs			**Accuracy**	
Predictors	*Estimates*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	6.525	6.495 – 6.555	**<0.001**	18.672	15.894 – 21.935	**<0.001**
VMAC	0.006	-0.003 – 0.014	0.177	1.105	0.970 – 1.246	0.105
AC	0.035	0.024 – 0.045	**<0.001**	0.800	0.678 – 0.944	**0.008**
Block	-0.041	-0.048 – -0.035	**<0.001**	1.106	1.010 – 1.197	**0.012**
Contingency	-0.039	-0.069 – -0.009	**0.011**	1.004	0.858 – 1.175	0.769
VMAC × Block	0.002	-0.004 – 0.008	0.537	0.929	0.789 – 1.095	0.678
AC × Block	-0.003	-0.011 – 0.005	0.488	0.929	0.789 – 1.095	0.381
VMAC × Contingency	0.005	-0.004 – 0.013	0.274	0.913	0.813 – 1.025	0.123
AC × Contingency	-0.003	-0.013 – 0.008	0.618	0.998	0.951 – 1.171	0.983
Block × Contingency	0.005	-0.002 – 0.012	0.130	0.935	0.970 – 1.005	0.0068

(VMAC × Block) × Contingency	0.010	0.003 – 0.016	**0.003**	0.983	0.875 – 1.103	0.769
(AC × Block) × Contingency	-0.007	-0.015 – 0.001	0.109	1.025	0.876 – 1.200	0.759
Random Effects						
σ^2	0.043			3.290		
τ_{00}	0.016 $_{\text{Intercept}}$			0.431 $_{\text{Intercept}}$		
τ_{11}	0.001 $_{\text{VMAC}}$					
	0.001 $_{\text{AC}}$					
	0.001 $_{\text{Block}}$			0.032 $_{\text{Block}}$		
ρ_{01}	-0.038			0.381		
	0.146					
	-0.224					
ICC	0.319			0.116		
N	81			81		
Observations	20,644			21,997		
Marginal R^2 / Conditional R^2	0.052 / 0.355			0.006 / 0.121		

Note. Bold entries denote statistical significance. *p*-values were computed using Satterwhite correction. CI = Confidence interval; ICC = Intraclass correlation coefficient. τ = Random effects, ρ = correlation between random effects.

The previous analysis suggests that the underlying construct might vary depending on whether all trials or only the last half of the task are included in the calculation of the VMAC effect. In the No Instructions group, where this relationship is stronger, later trials may reflect that some participants become spontaneously aware of the contingency and start to learn later. Consequently, individual differences in contingency estimation could reliably predict VMAC scores. This means the underlying correlation may consistently change because later trials may better capture true individual differences in the learning process of VMAC. This temporal dependency suggests that the temporal dynamics of the VMAC effect should vary as a function of the contingency rating test.

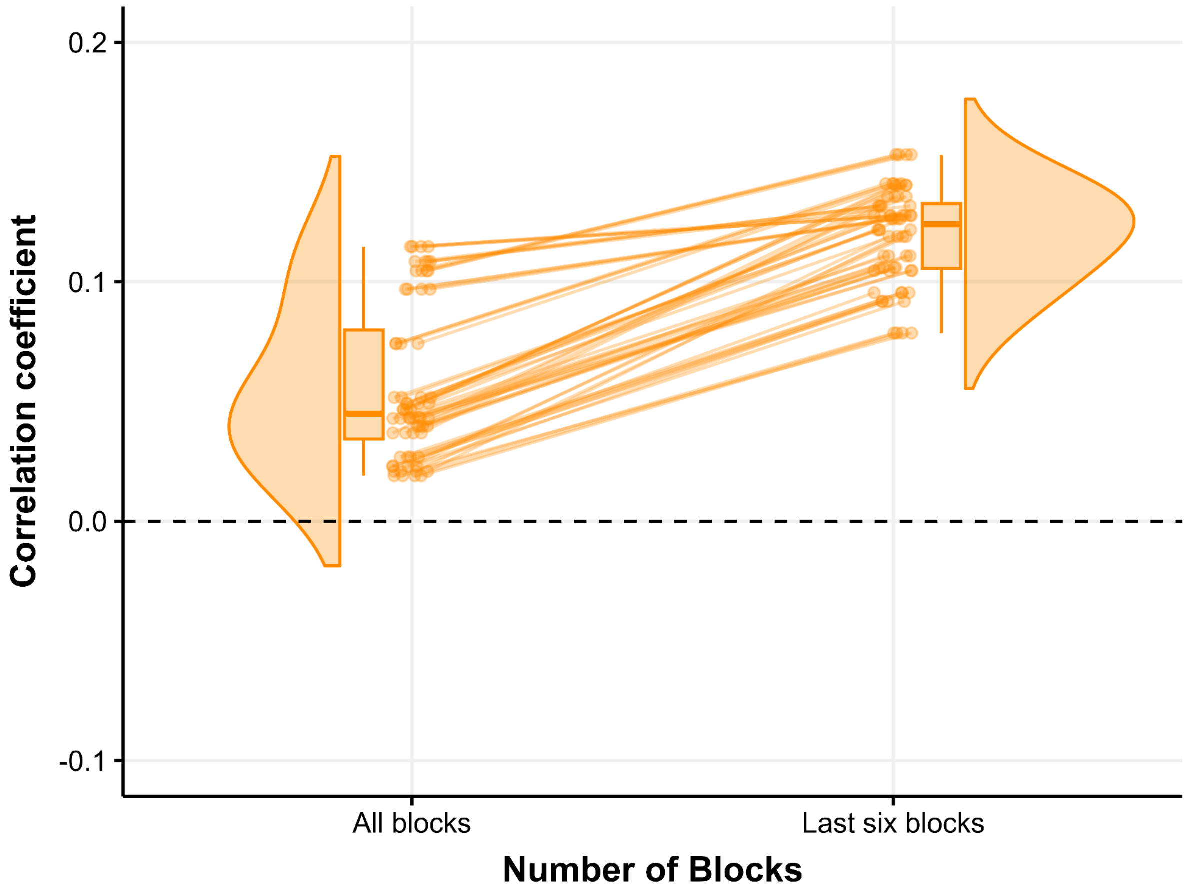


Figure S7. Spearman Correlation between VMAC effect and the contingency rating in Experiment 1 across different sets of data preprocessing specifications. The x-axis subsets these correlations as a function of the number of blocks employed to calculate the VMAC effect.

To investigate this possibility, we fit a linear mixed model following the same structure used in the analysis of Experiment 2 for the No Instructions group, adding the scaled contingency rating as a predictor. Table S1 (left) shows the model coefficients. We observed a significant effect of the contingency predictor, where participants with a higher contingency rating had faster RTs than participants with a lower contingency rating. Critically, there was only a significant VMAC x Block x Contingency interaction, which is visualized in Figure 4d of the main text. Table S1 (right) presents the accuracy analysis, also including the contingency rating as a predictor. This analysis reveals no significant effect or interaction with the Contingency predictor, suggesting that the previous analysis does not reflect a speed-accuracy tradeoff.

Table S2

Model summaries for the selected models for RTs and accuracy in experiment 1.

	RTs			Accuracy		
Predictors	*Estimates*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	6.462	6.435 – 6.488	**<0.001**	20.343	16.070 – 25.754	**<0.001**
VMAC	0.002	-0.006 – 0.011	0.590	1.025	0.787 – 1.335	0.855
AC	0.025	0.017 – 0.033	**<0.001**	0.893	0.624 – 1.278	0.538
Block	-0.036	-0.042 – -0.029	**<0.001**	1.035	1.009 – 1.062	**0.009**
Contingency	-0.003	-0.032 – 0.026	0.765	0.963	0.771 – 1.202	0.736
VMAC × Block	0.003	-0.002 – 0.008	0.226	1.003	0.966 – 1.041	0.891
AC × Block	-0.006	-0.012 – 0.001	0.099	1.003	0.953 – 1.055	0.913
VMAC × Contingency	0.003	-0.006 – 0.011	0.537	0.870	0.664 – 1.139	0.310
AC × Contingency	-0.003	-0.012 – 0.004	0.320	1.321	0.928 – 1.879	0.122
Block × Contingency	0.000	-0.006 – 0.007	0.878	1.007	0.984 – 1.031	0.557
(VMAC × Block) × Contingency	0.006	0.001 – 0.011	**0.020**	0.995	0.959 – 1.035	0.854
(AC × Block) × Contingency	0.003	-0.003 – 0.010	0.304	0.972	0.923 – 1.024	0.281
Random Effects						
σ^2	0.031			3.290		
τ_{00}	0.015 Intercept			0.632 Intercept		
τ_{11}	0.001 VMAC					
	0.0001 AC					

	0.001_{Block}	0.003_{Block}
ρ_{01}	0.025	-0.393
	0.346	
	-0.272	
ICC	0.346	0.148
N	82	82
Observations	21,445	21,554
Marginal R^2 / Conditional R^2	0.030 / 0.365	0.006 / 0.153

Note. Bold entries denote statistical significance. *p*-values were computed using Satterwhite correction. CI = Confidence interval; ICC = Intraclass correlation coefficient. τ = Random effects, ρ = correlation between random effects.

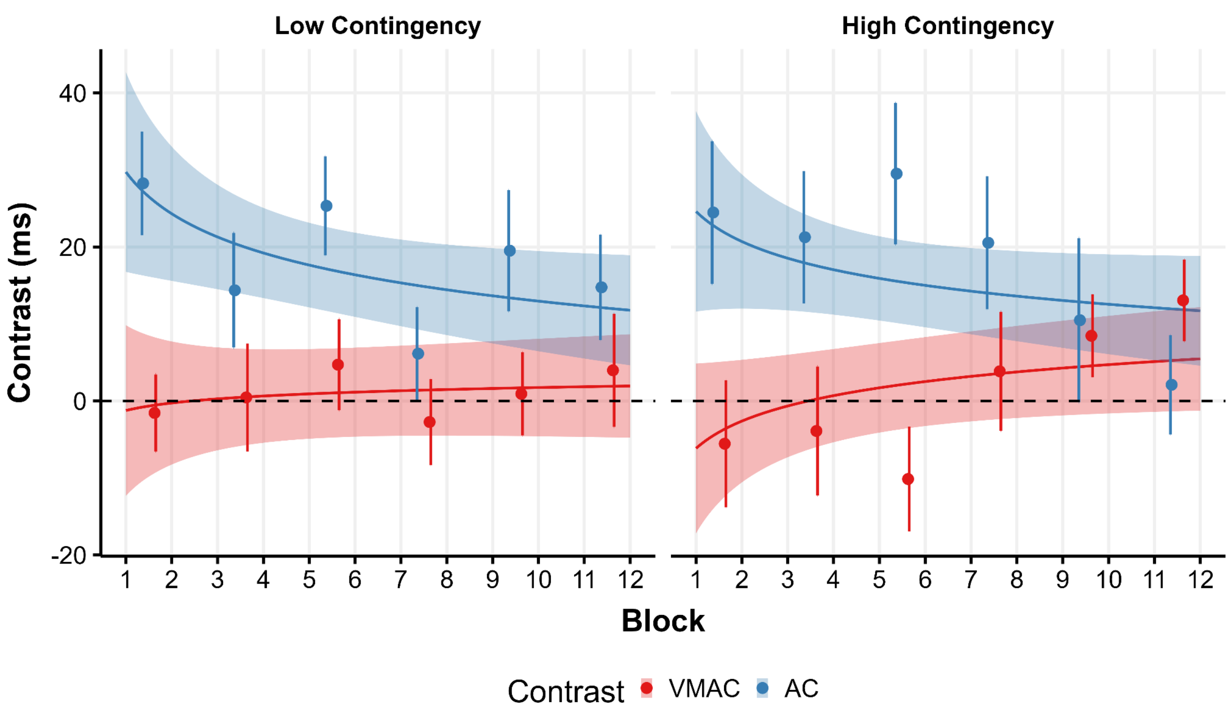


Figure S8. The conditional mean of the high-low (VMAC) and low-absent (AC) contrasts in the response scale as a function of the contingency rating in Experiment 1. As in Figure 5d of the main text, we generated predictions for a high (80th quantile) or low (30th quantile) contingency rating. Raw data represents participants below (*N* = 49) or above (*N* =33) the 60th quantile of the overall contingency rating distribution for participants in Experiment 1. This splitting procedure is arbitrary and only for visualization purposes.

Due to the interesting insights about the temporal dynamics of the VMAC effect in Experiment 2 for participants who did not receive information about the color-reward contingency, we checked if the same pattern could be observed in Experiment 1. As in the previous analysis, Figure S6 shows that the correlation between the VMAC effect and the contingency rating increases when VMAC scores are computed in the last half of the task compared to the whole task. Therefore, we fit the same models described in the main text for Experiment 1, adding the scaled Contingency rating as a predictor. Critically, in the RTs analysis, the contingency rating predictor only significantly interacted with the VMAC x Block interaction (Table S2, left), and there was no significant effect nor interaction with the contingency rating in the accuracy analysis (Table S2, right). In Figure S8 we visualized this interaction as is presented in Figure 5d of the main text. This analysis further suggests that a high contingency rating is associated with an increased VMAC effect later in the task and that the true correlation between our measures of awareness and the VMAC effect seems to be time-dependent, as has been proposed in other learning-dependent attentional effects (Meyen et al., 2023; Vadillo et al., 2022).

References

Garre-Frutos, F., Vadillo, M. A., González, F., & Lupiáñez, J. (2024). On the reliability of value-modulated attentional capture: An online replication and multiverse analysis. *Behavior Research Methods*, 1-18. https://doi.org/10.3758/s13428-023-02329-5

Meyen, S., Vadillo, M. A., von Luxburg, U., & Franz, V. H. (2023). No evidence for contextual cueing beyond explicit recognition. *Psychonomic Bulletin & Review*, 1-24. https://doi.org/10.3758/s13423-023-02358-3

Nunnally, J. C. (1978). *Psychometric theory* (2d ed). McGraw-Hill.

Parsons, S. (2022). Exploring reliability heterogeneity with multiverse analyses: Data processing decisions unpredictably influence measurement reliability. *Meta-Psychology*, *6*. https://doi.org/10.15626/MP.2020.2577

Parsons, S. (2021). Splithalf: Robust estimates of split half *reliability. Journal of Open Source Software, 6*(60), 3041.http://dx.doi.org/10.21105/joss.03041

Shanks, D. R. (2017). Regressive research: The pitfalls of post hoc data selection in the study of unconscious mental processes. *Psychonomic Bulletin & Review*, *24*, 752-775. https://doi.org/10.3758/s13423-016-1170-y

Vadillo, M. A., Malejka, S., Lee, D. Y., Dienes, Z., & Shanks, D. R. (2022). Raising awareness about measurement error in research on unconscious mental processes. *Psychonomic Bulletin & Review*, *29*(1), 21-43. https://doi.org/10.3758/s13423-021-01923-y