The role of selection history in the learned predictiveness effect

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Abstract

Previous research has shown that cues that are good predictors of relevant outcomes receive more attention than nonpredictive cues. This attentional bias is thought to stem from the different predictive value of cues. However, because successful performance requires more attention to predictive cues, the bias may be a lingering effect of previous attention to cues (i.e., a selection history effect) instead. Two experiments assessed the contribution of predictive value and selection history to the bias produced by learned predictiveness. In a first task, participants responded to pairs of cues, only one of which predicted the correct response. A second task was superficially very similar, but the correct response was determined randomly on each trial and participants responded based on some physical characteristic of a target stimulus in each compound. Hence, in this latter task, participants had to pay more attention to the target stimuli, but these stimuli were not consistently associated with a specific response. Results revealed no differences in the attentional bias towards the relevant stimuli in the two tasks, suggesting that the bias induced by learned predictiveness is a consequence of deploying more attention to predictive stimuli during training. Thus, predictiveness may not bias attention by itself, adding nothing over and above the effect expected by selection history.

Public significance statement

Previous research has shown that we pay more attention to stimuli that are reliably associated with subsequent important events, commonly known as *predictive cues*. However, this effect is often studied in experimental tasks that force participants to pay attention to these stimuli to achieve successful performance, which introduces a potential confounding variable. Indeed, in the present study, we show that the attentional bias towards stimuli that are consistently associated with a subsequent event is probably not driven by their predictive value. Instead, it appears that once participants begin to focus on certain stimuli, they have a lingering tendency to continue paying attention to them, even when they are

no longer relevant. These findings are important as they challenge the current interpretation of attentional biases towards predictive cues.

Keywords: attention; dot probe; learned predictiveness; learning; selection history.

The role of selection history in the learned predictiveness effect

The complexity of the environment poses a challenge for our limited attentional resources. Different attentional biases help us to manage those resources and deal with the constant flow of stimulation. By focusing our attention on important stimuli, these biases maximize the likelihood that stimuli are processed and responded to appropriately, ultimately increasing the chances of survival. While some of these attentional biases take place with no specific training (e.g., attentional capture by salient stimuli), our experience with stimuli and what we learn about them provide a source of information for effective attentional selection.

Among the various determinants of attention, the ability of a stimulus to predict important events is one of the most studied and debated. This bias is particularly useful, as it allows attention to focus on the elements of the environment that signal potential sources of gratification, danger, or overall relevant events. In line with its relevance, the predictive value of stimuli has a central role in some of the most influential theories of associative learning, such as the one proposed by Mackintosh (1975; see also, e.g., Esber & Haselgrove, 2011; Kruschke, 1992; Le Pelley, 2004). In the vast body of research inspired by these theories, a stimulus is considered predictive when it consistently signals a subsequent outcome or correct response, enabling us to anticipate and prepare for what is to come.

According to Mackintosh (1975), the associability of a stimulus (i.e., its readiness to enter into associations with an outcome) varies depending on how effectively it has predicted the outcome on previous trials. More precisely, associability will increase for good predictors and decrease for poor predictors. Higher associability for predictive than for nonpredictive cues implies that learning will be faster for the former, as extensively demonstrated (e.g., Beesley & Le Pelley, 2010; Le Pelley et al., 2007, 2011; Le Pelley & McLaren, 2003; Lochmann & Wills, 2003; Mitchell et al., 2012).

A common interpretation in the literature is that the superior associability of predictive stimuli is grounded on the greater attention these stimuli receive. In line with this interpretation, it has been found that good predictors receive more attention than poor predictors (Cobos et al., 2018; Feldmann-Wüstefeld et al., 2015; Luque et al., 2017, 2018, 2020; Russo et al., 2019; for a review up to 2016, see Le Pelley et al., 2016). For example, the *learned predictiveness (LP) design* has been widely used to assess the effect of the predictive value of stimuli on attention (Le Pelley & McLaren, 2003; Lochmann & Wills, 2003). In these experiments, participants are trained with cue compounds where one of the cues is a reliable predictor of the correct response, while the other is irrelevant. To illustrate, participants in Le Pelley et al. (2013) were presented with a green square that varied in shade (green1 or green2) and another with oblique lines that varied in orientation (lines1 or lines2). One of the stimulus sets predicted the correct response (R1 or R2), while the other was always irrelevant. For instance, if the predictive stimulus was the green square, its shade determined the correct response in each trial (e.g., R1 for green1 and R2 for green2), regardless of the orientation of the lines in the other square. Thus, participants had to learn which stimuli were good or bad predictors based on their relationship with the correct response. Le Pelley et al. (2013) used a dot probe task to assess the effects of predictive value on attention. During this task, participants saw the same stimuli pairs but now they had to respond to a probe presented in the location previously occupied by one of the stimuli. In agreement with a learned-predictiveness attentional bias, participants responded faster when the probe was presented at the location of a (previously) predictive stimulus, despite the probe's position being completely unpredictable. This result dovetails with the predictions of Mackintosh's (1975) and related models, which suggest that attention is preferentially allocated to stimuli that reliably forecast the correct response during training.

Aside from the learned predictiveness effect[1], recent research has highlighted the importance of the selection history of the stimuli in shaping attention (e.g., Anderson et al., 2021; Awh et al., 2012;

[1] The learned predictiveness effect was originally defined as the influence of previous predictive value on new learning (Le Pelley & McLaren, 2003). After that, extensive research has explored the attentional bias produced by predictive value, with and without analyzing its impact on new learning (Le Pelley et al. 2016). Since the current study focuses solely on the effects of predictive value on attention, we will use the term 'learned predictiveness effect' to refer to the attentional effect—increased attention towards predictive cues.

Theeuwes, 2019; Wolfe, 2019), with this term referring to the individual's previous experience of attending to a stimulus (Awh et al., 2012). For instance, if participants must attend to stimuli A and B more than to C and D to solve a task, by the end of training there will be more trials in which A or B have been *selected* (attended), as compared to C or D. As Awh et al. (2012) contended, this attentional priority will tend to persist over time, so that A and B will capture more attention in future trials (e.g., at a subsequent test stage) than C and D, even when A and B are no longer task-relevant.

Studies showing more attention towards predictive stimuli, such as that of Le Pelley et al. (2013), provide evidence for an attentional bias produced by learned predictiveness. However, they do not rule out the possibility that selection history (and not the stimuli's predictive value) is responsible for the effect on attention. Note that in the first stage of a typical LP study, the predictive stimuli are the only source of information that participants can use to guess the correct response. Therefore, participants must pay more attention to the predictive than to the nonpredictive cues (Feldmann-Wüstefeld et al., 2015; Le Pelley et al., 2011; Lucke et al., 2013; Mitchell et al., 2012). From this point, according to Awh et al.'s (2012) proposal, attentional prioritization of the predictive stimuli might carry over to subsequent stages of the experiment, producing the observed attentional bias at test.

The objective of the present experiments was to assess whether selection history can account for the attentional bias observed towards predictive stimuli in an LP experiment. To do so, participants were trained in two tasks. The *categorization task* followed a standard LP design and therefore divided the stimuli into predictors and non-predictors. Within the theoretical and empirical tradition of studies on the LP attentional bias (e.g., Le Pelley & McLaren, 2003; Mackintosh, 1975) a stimulus is deemed predictive if it consistently precedes a relevant event in the task, such as an outcome or a correct response. In this task, two stimuli (A and B) fit this definition, as both perfectly signaled what was the correct response (R1 for A and R2 for B). The other two stimuli (C and D) were not consistently associated with any response in particular. Therefore, participants could use A and B to anticipate the correct response, while C and D were non-informative.

The *selection task* was designed to draw attention only to certain stimuli. To do so, the task required participants to select only certain cues (W and X), while the other cues (Y and Z) could be ignored throughout the task. Therefore, by the end of training, only the former stimuli would have a history of being attended to. Crucially, the specific response required by the participants depended on the position (Experiment 1) or orientation of the stimuli (Experiment 2). Since these characteristics varied randomly across trials, the stimuli themselves were not associated with a specific response, as they were in the categorization task.

To sum up, in both tasks, certain stimuli demanded more attention than others (i.e., should have a larger history of being selected), but only in the LP task did the stimuli differ in their predictive value. Attention towards the relevant versus the irrelevant stimulus of each task was then assessed with a dot probe test.

We predicted that training in the selection task would result in an attentional bias towards the selected stimuli on dot probe trials. This result would be interesting as, although there is evidence of attentional capture by cues that have been consistently selected in a training phase (Kyllingsbæk et al., 2001; Qu et al., 2017; Sha & Jiang, 2016; Shiffrin & Schneider, 1977), there are also cases where no such an effect was found (Anderson et al., 2011) and, most importantly, the procedures used in those studies differ considerably from the procedures typically used to explore learned predictiveness. In our study, the selection and categorization tasks were very similar in all aspects, except for the predictive value of the stimuli. Therefore, finding an attentional bias towards previously selected stimuli would provide stronger evidence to the hypothesis that selection history can account for, at least, part of the attentional bias found towards the relevant stimuli of the categorization task, usually credited to the stimuli's predictive value.

It is relevant to determine whether the attentional prioritization of the predictive stimuli in the categorization task exceeds that observed towards the relevant stimuli in the selection task. A difference between these two biases, presumably in the sense of greater attentional capture by the predictive stimuli than by the simply selected stimuli, would support the traditional idea that the predictive value has a genuine and distinct effect on attention. Conversely, a lack of differences between the two effects would cast doubt on the predictive value having a direct impact on attention and support a selection-history account for the LP effect. That is, the predictive stimuli may capture attention simply because they have been attended to many times during training.

Experiment 1

Experiment 1 was conducted to determine whether the attentional modulation observed in an LP experiment is produced by differences in the stimuli's selection history. To compare both sources of attentional bias, participants were required to complete two tasks. In the *selection task*, they were presented with cue compounds and their task was simply to select one stimulus of the compound (hereafter, *selected* stimuli) while the other did not require any response (*unselected* stimuli). We expected this task to produce an attentional bias towards selected stimuli to the detriment of unselected ones, produced because of their different selection history.

In the *categorization task*, participants were required to give one of two possible responses to pairs of cue stimuli. The stimuli were different from those used in the selection task. Following an LP design, only one of the cues from each compound (the predictive cue) was informative about what the correct response was; the nonpredictive cue was uninformative. Note that this task should also endow the predictive and nonpredictive stimuli with different selection histories; however, it is only in this task that attention might be further affected by the predictive value.

The effects of initial training on attention were then assessed with a dot probe test. In this test, participants saw the same stimuli compounds used during training, but their task was to respond as fast as possible to a small probe appearing over one of the two stimuli. Reaction times (RT) to the probe provided a measure of differential attention to the stimuli so that RTs should be faster when the probe appears over the stimuli which is being attended (Le Pelley et al., 2013).

If training produces an attentional bias towards predictive cues, participants should detect the probe faster when presented over predictive vs. nonpredictive cues. Similarly, selection history effects should be evidenced by faster responses when the probe is presented over previously selected stimuli vs. unselected ones. Finally, and more important for our objective, if the LP attentional bias is simply the consequence of different selection histories, the advantage in detecting the probe on relevant cues should be the same regardless of whether such relevance arises from their predictive value or their selection history.

Method

Transparency and Openness

The two experiments reported in this manuscript were preregistered before data collection began (https://osf.io/adnbr/registrations). All documents, data, analysis scripts and materials are publicly available at https://osf.io/adnbr/. We provide information on how we determined the sample size, data exclusions, manipulations performed, the measures used in the study, and the year of data collection for each experiment.

Participants

Previous studies of the predictiveness-driven attentional bias with the dot probe tasks have found a range of effect sizes from medium, η_p^2 = .07 (Le Pelley et al., 2013), to very large, η_p^2 = .231 (Luque et al., 2020). However, because we were not aware of experiments measuring selection history effects with a similar procedure, instead of planning our sample for a particular effect size, we decided to collect data from at least 60 participants. This sample size granted 90% power to detect a small-to-medium effect size of d_z = 0.43 in a two-tailed *t*-test for paired samples and 80% power for an effect of d_z = 0.37. As mentioned in the pre-registration for this experiment, all participants that signed up for the study were included in the analyses, but no analyses were performed until data collection was completed.

Participants were undergraduate psychology students from the Autonomous University of Madrid (UAM). No volunteer who showed up for his/her appointment was turned away, resulting in 87 undergraduates (86.21% female) taking part in the experiment. All participants had normal (or corrected-to-normal) visual acuity and color vision. All signed a written informed consent form and received academic credit for their participation. The study was approved by the UAM's ethics committee (CEI-30-1473). Data for this study were collected in 2020.

Apparatus and Stimuli

Participants were run in individual desks equipped with a standard PC, a monitor (26.7 x 44.1), and a keyboard that registered the participants' responses. Vertical panels isolated each desk. The experimental room had 12 of these semi-isolated desks; however, no more than six participants were run at once. Stimulus generation and experimental control was carried out using PsychoPy (v2020.2.5). Participants wore face masks and were run in small groups following the COVID-19 protocols of the Autonomous University of Madrid.

Stimuli were eight colored circles whose diameter was set to be 50% of the height of the screen (12.5 cm). Their RGB values were red (R255, G0, B0), yellow (R230, G230, B51), green (R0, G204, B51), orange (R255, G128, B0), blue (R0, G128, B255), magenta (R255, G51, B255), brown (R153, G102, B0), and purple (R153, G51, B255). These cues were presented in pairs, with one of the cues placed on the left side of the screen and the other on the right side. The probe was a small white square, with width and height set to 0.02% the height of the screen (7 mm), presented in the middle of either the left or the right cue.

Procedure

Instructions written on the screen guided participants through the experiment. All instructions and messages were presented in Spanish. First, participants were instructed to respond to the categorization task. Instructions informed them that they were going to see pairs of colored circles (see Experiment 1 -

Categorization training in Figure 1). They were told that those circles would rapidly disappear and that, then, they would see the prompt "*A or Z*" on the screen. They were informed that their task was to press one of the keys specified on the prompt using their left hand and were encouraged to pay attention to the colors since they were relevant to anticipate the correct response. They were told that, if their response was not correct, an error message would appear, and were encouraged to use those messages to learn the correct response for each stimulus pair. Pictures showing how a categorization trial would look like accompanied these instructions. Then, participants had four practice trials with this task. The same pair of colored circles was used in the example pictures and in the practice trials. These colors were not used in the remainder of the experiment.

Figure 1. Appearance and timing of the categorization, selection, and dot probe trials (left, middle and right columns, respectively) for Experiments 1 (upper row) and 2 (lower row). Words in italics, not visible for the participants, summarize the task they were instructed to do on each trial.

Participants were then trained in the selection task. In this task, the circles appeared on the screen and were then replaced by the prompt "*O or P*". The color of the font matched the color of one of the circles (see Experiment 1 - Selection training in Figure 1). If the corresponding circle had been located on the right, they were to press the P key, if the circle had been located on the left, they were to press the O key. They received feedback if their response was incorrect. Participants were asked to use their right hand in this task and had four practice trials. The colors used in the example pictures that supported these instructions, and the colors used on practice trials differed from those used in the instructions of the categorization task and were not used during the experiment.

After this training, participants were informed that trials from the two tasks would be presented in an alternated manner, and that they should withhold responding until they saw one of the prompts (A or Z / O or P) on the screen, as it would inform them of the task they had to do on that specific trial. Finally, they were reminded of the hand to use for each task and the experiment began.

Each categorization trial started with a central fixation cross. After 500 ms, two colored circles appeared at each side of the screen for two seconds. Then, the circles and the fixation cross disappeared and the prompt "*A or Z*", written in white font, was presented. Participants had no time limit to respond. However, if no response was registered within five seconds, the message "*Please, press one of the two keys, you will learn little by little*" appeared in the middle-bottom of the screen. Once a response was registered, the next trial began after an inter-trial interval (ITI) of one second. If the response was incorrect, the message "*Incorrect response*" appeared for three seconds in the middle of the screen followed by the ITI.

Categorization trials displayed four different stimuli combinations (see Table 1). If stimuli are labelled from A to D, the combinations were AC, AD, BC, and BD. A and B were the *predictive* stimuli so that any time A was present, one of the two possible responses (counterbalanced across participants) was required to solve the task regardless of the accompanying stimulus, and any time B was present, the alternate response was required. C and D did not inform about which was the correct response and, therefore, were *nonpredictive* stimuli.

The structure of the selection trials was the same as that of the categorization trials except for the identity of the colors and the response prompt which, in this task, read "*O or P*" written with the color font of one of the cues. Selection trials included four stimuli combinations: WY, WZ, XY and XZ (see Table 1). Along the experiment, participants were required to select colors W and X (whichever was present on the trial) as indicated by the color of the prompt. Participants did their selection response by pressing the keys O or P. They had to press O (i.e., “left”) if the response prompt had the same color as the circle on the left, and P (i.e., “right”) if it matched the color of the circle on the right. The prompt never adopted the color of the Y or Z stimuli, so participants were never required to select them. All other details (ITI, feedback for incorrect responses, etc.) were the same as in categorization trials. The specific color used for each of the eight stimuli stimulus was assigned to participants using a Latin-square design. Their left/right position on the screen was determined randomly on every trial.

Table 1. Types of training trials and their correct responses in Experiments 1 and 2.

Categorization task		Selection task	
Color pair	Correct Response	Color pair	Target color
AC	R1	WY	W
AD	R1	WZ	W
BC	R2	XY	X
BD	R2	XZ	X

Note. Letters A to D and W to Z refer to different colored cues. R1 and R2 denote two keys on the keyboard (A or Z, counterbalanced). A and B were predictive of the correct response; C and D were nonpredictive; W and X were the to-be-selected stimuli; Y and Z were the unselected stimuli.

Phase 1 had 280 trials, with half being categorization trials and the other half selection trials. These trials were organized in 35 eight-trial blocks with each block containing all eight possible combinations once (four from each task). Odd trials displayed the color combinations of the categorization task and even trials those of the selection task. After block 20, the message “*Now you can* *have a rest. Press the spacebar when you are ready to continue*" appeared in the middle of the screen. Once the participant pressed the spacebar, the next block began.

Before phase 2, participants read the instructions explaining the dot probe task on the screen. These instructions specified that, on each trial of this task a small white square would appear over one of the circles (see Dot probe test – Experiment 1 in Figure 1), and that they would have to press the left or right arrow of the keyboard to indicate the part of the screen in which it had appeared. Participants were told that the colors were completely irrelevant in this task and that they only had to consider the position of the probe. Example pictures showing both situations (probe presented on the left cue and on the right cue) accompanied these instructions. The colors used in these examples were the same as those used in the instructions of the selection task.

Participants were encouraged to respond as fast as possible but to hold any response until the square was presented. They were told that these trials would be signaled by two small arrows appearing in the middle of the screen (Figure 1) and were asked to respond with their right hand. Then, they had four practice trials. Final instructions told participants that, from that moment, they would receive blocks of dot probe trials and blocks of retraining trials (A or Z/O or P) in an alternating manner. After reminding them the hand to use in all three tasks, phase 2 started.

Dot probe trials began with a prompt formed by two small arrows (one pointing in each direction) presented in the middle of the screen (see Figure 1). After 500 ms, a cue compound appeared and, 250 ms later, the probe was superimposed over one of the cues. The interval between the onset of the cues and the appearance of the probe (250 ms) was determined following prior studies that have used the dot probe task to assess the LP attentional bias (Cobos et al., 2018; Le Pelley et al., 2013; Luque et al., 2020; Luque, Vadillo, et al., 2017; Vadillo et al., 2016). The ITI, feedback messages and other details were as in the other tasks. Phase 2 had 96 dot probe trials distributed in 12 blocks of eight trials each. The probe appeared over the relevant color (either previously predictive or previously selected) on half of the trials, and over the irrelevant color on the other half.

Dot probe trials displayed all eight color combinations with the probe appearing in the two possible locations (over a relevant/irrelevant color). Therefore, it took 16 trials to present all dot probe trials. Because each test block had 8 trials, two blocks were needed to present all the combinations. The 16 trial types were presented randomly without replacement with the only constraint that odd trials tested the colors previously used in the categorization task, and even trials those used in the selection task. The right vs. left position of the two cues of the compound was determined randomly on every trial.

To prevent unlearning of the effects established in training, dot probe blocks were alternated with blocks of categorization and selection trials. These *retraining blocks* proceeded exactly as the blocks in phase 1. Phase 2 began with a retraining block and, therefore, the sequence within this phase was retraining block – test (dot probe) block, and so on, with trials with the categorization and selection compounds being alternated in both block types. Each retraining block was preceded by the message “*Get ready to respond A or Z / O or P*” written in the middle of the screen, while the message “*Get ready to respond ←→*” was presented before each dot probe block. Those messages lasted four seconds.

Data analyses

Data was analyzed on a block-level basis with repeated measures analysis of variance (ANOVA). For results that were crucial for our hypothesis, Bayesian analyses were also conducted using JASP version 0.16.4 (JASP Team, 2022) with default priors. The resulting Bayes Factors (BF) were interpreted according to the rule of thumb where BFs less or equal than 3 provide weak evidence, BFs between 3 and 10 provide moderate evidence, and BFs larger than 10 provide strong evidence (Jeffreys, 1961; Wetzels et al., 2011).

The standard errors of the mean (SMEs) were corrected with the Cousineau-Morey approach (Cousineau, 2005; Morey, 2008) for repeated measure designs as described by Cousineau and O’Brien (2014) and O’Brien and Cousineau (2014). All the analyses presented in this manuscript were pre-registered (https://osf.io/adnbr/registrations).

Results

Accuracy in categorization and selection trials

As in experiments using similar procedures (e.g., Luque et al., 2020) participants with accuracies below 60% in either the categorization or the selection task were removed from this and the following analyses. Applying this criterion resulted in seven participants being removed, all due to poor performance in the categorization task. Therefore, 80 datasets were used in these analyses.

Response accuracy in the categorization and selection tasks of phase 1 was assessed with a Task (categorization vs. selection) × Block (35) ANOVA. This analysis yielded a main effect of Task, $F(1,79) = 83.567$, $p < .001$, $\eta_p^2 = .514$, as accuracy was better in the selection than in the categorization task (Figure 2, top panel), a main effect of Block, $F(34,2686) = 39.727$, $p < .001$, $\eta_p^2 = .335$, as performance improved with training, and a significant Task × Block interaction, $F(34,2686) = 36.535$, $p < .001$, $\eta_p^2 = .316$. This interaction resulted from a better performance on the selection task on blocks 1-12, 14, 16, 18, 19 and 21, $F(1,79)_{range} = 5.444 - 223.112$, $p_{range} = 1.012 \times 10^{-24} - .022$, $\eta^2_{p\,range} = .064 - .739$. This difference tended to disappear with training, being absent in the rest of blocks, ps $\geq .057$ (block 13).

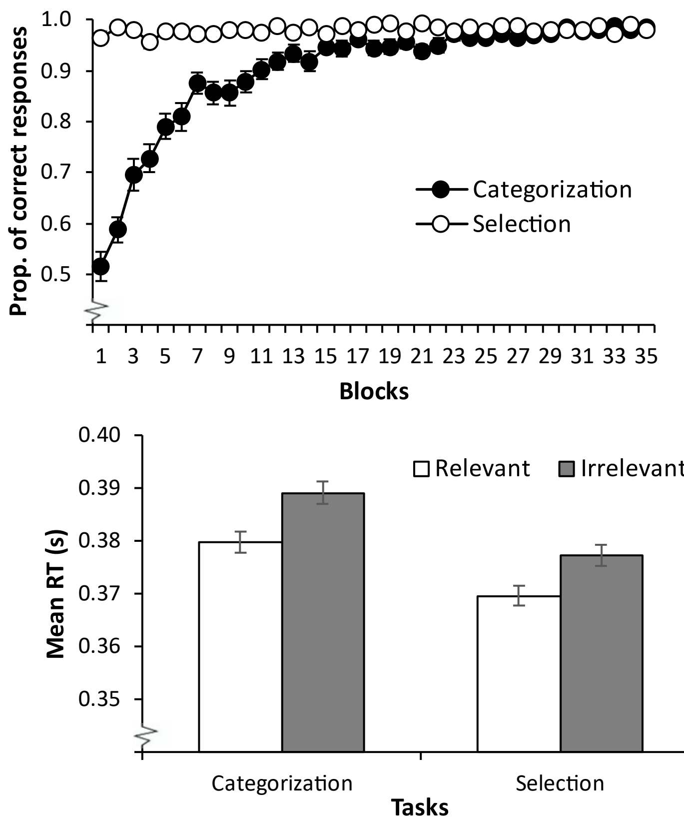

Figure 2. Top: Accuracy (proportion of correct responses) across the 35 training blocks of training in the categorization and selection tasks of Experiment 1. *Bottom*: RTs on dot probe trials of Experiment 1, collapsed across blocks. Bars represent the Cousineau-Morey SME for repeated measures.

Given the increased difficulty observed in the categorization task, it was important to verify that task accuracy was firmly established before the test phase began. Therefore, although not initially planned, we conducted a series of exploratory analyses to determine the point at which performance in the categorization task reached stability. To do so, we contrasted the accuracy observed in the final block against that of preceding blocks through pairwise comparisons, utilizing a series of one-way ANOVAs with Block as factor. That is, we started by comparing the accuracy of block 35 (the final block) with that of block 34, and then proceeded to compare block 35 with block 33, continuing this sequence until a significant difference was found between a particular block and the final block. The first significant difference was observed between blocks 35 and 21, $F(1,79) = 7.882$, $p = .006$, $\eta_p^2 = .091$. This indicates that a stable level of accuracy was reached 13 blocks prior to the initiation of the test phase.

Another Task (categorization vs. selection) × Block (12) ANOVA was conducted considering the retraining trials of phase 2 (not shown in the figure) to see whether the relationships learned during training were maintained once the dot probe task was introduced. None of the factors was significant, *F*s < 1. The mean accuracy during this phase was 98% in each of the tasks.

Dot probe trials

Trials with incorrect responses (0.84% of the data) were not considered in the analysis of RTs. Following similar studies (Le Pelley et al., 2013; Luque et al., 2020), to prevent the impact of outlying responses, trials were also removed if RTs were faster than 200 ms, or greater than 2000 ms (0.23% of the remaining data), or if they were either below or above 2.5 SDs from the participants' mean RT (2.7% of the remaining data).

Performance at test (collapsed across blocks) is shown in Figure 2 (bottom panel). RTs were assessed with a Task (categorization vs. selection) × Relevance (probe on predictive/selected vs. nonpredictive/unselected colors) × Epoch (6) ANOVA. Epochs were formed collapsing the data from every 16 trials (two blocks), because that was the number of trials needed to present all possible test trials once (see Procedure). This analysis yielded a significant effect of Task, $F(1,79) = 44.269$, $p < .001$, $\eta_p^2 = .359$, which, as shown in the figure, indicates slower RTs when the test involved the colors of the categorization task. The factor Relevance was also significant, $F(1,79) = 15.051$, $p < .001$, $\eta_p^2 = .160$, indicating faster responses when the cue was presented over a relevant color (either predictive or previously selected). Importantly, the Task × Relevance interaction was not significant, $F < 1$, $p = .680$, $\eta_p^2 = .002$, indicating a similar advantage in RTs in detecting the probe when presented over a predictive or a previously selected color. Given the relevance of this result for our objective, the BF was calculated to estimate the evidence in favor of the null. The odds favored the model including only the main effects of Task and Relevance over the model also including their interaction with a BF of 8.328, which represents evidence for the lack of an interaction. No other significant effects were found, Fs ≤ 2.176, ps ≥ .056 (Epoch).

Discussion

Experiment 1 was conducted to determine whether the attentional prioritization of predictive stimuli results from those cues being selected (attended) more often during training. The categorization task followed a typical LP design and served to endow some stimuli with greater predictive value and selection history than others. In the selection task, participants had to select certain stimuli and ignore others, and was used to establish differences between the stimuli in terms of just their selection history. A dot probe task was used to assess the extent to which good predictors and frequently selected stimuli captured attention.

Results showed that both tasks had an impact on attention. Participants responded faster to the probe when presented over relevant stimuli (predictive or selected) than over irrelevant ones (nonpredictive or unselected), indicating greater attention to the formers. Interestingly, the magnitude of the two attentional biases did not differ. RTs were reduced to the same extent when the probe was presented over a predictive vs. nonpredictive stimulus than over a selected vs. unselected color.

These results suggest that both forms of experience affected attention in a similar manner, raising the possibility that the attentional bias toward predictive stimuli in LP designs is due just to differences in the selection history (more selections for predictive stimuli). A caveat, however, is necessary, as a closer look at our procedure reveals an alternative explanation for this pattern of results. In the selection task, participants had to press O or P to select the cue on the left or the cue on the right, respectively. Similarly, a left/right response was required on dot probe trials (though in this case by using the arrow keys) to indicate the probe location. Therefore, it is possible that the selection and dot probe responses have interfered with each other.

Take for instance the compound XZ, where X is the to-be-selected cue. The correct response to this stimulus pair during phase 1 was to press O (i.e., left) if X is presented on the left (XZ), and P (right) when presented on the right (ZX).The problem with this response arrangement is that on dot probe trials that presented the probe over the relevant color (X), the correct response is the same as that of training: to press “left” when X (and therefore the probe) is on the left, and “right” when X is on the right. Conversely, on trials where the probe appears over the unselected color (Z), locating the probe implies signaling the place where the unselected stimulus (and thus the probe) is located, which is exactly the opposite response that was required during training.

The presence of a facilitatory effect on trials presenting the probe over a previously selected color, along with a response interference on trials where the probe appeared over an unselected one, may have yielded shorter RTs in the former than in the later type of trials regardless of any actual attentional bias. That is, what seems to be an attentional bias driven by selection history may be simply the result of a response overlap between training and test trials, or maybe a mixture of the two processes. Note that this problem does not affect the results that refer to the categorization task, as the responses to that task (press A or Z) had nothing to do with the left/right position of the stimuli on the screen. Therefore, in agreement with prior literature, Experiment 1 provides a demonstration of an attentional bias towards predictive cues. What is under question is the evidence in favor of selection history effects in the selection task.

Another potential problem with our procedure relates to the sequential presentation of the cues and the response prompt in the selection task. While the prompt in the categorization task was always the same, in the case of the selection task the color of the prompt matched the color of the relevant cue. For instance, if the green circle was the to-be-selected stimulus, then that stimulus was consistently followed by a green prompt. Note that this procedural detail does not imply a predictive relationship between the cues and the correct response, as the correct response depended on the position of the circle, which was randomly determined on every trial. However, it would be reasonable to think that our to-be-selected cues were perfect predictors of the color of the prompt. Therefore, the attentional bias towards the selected colors could be simply another example of the learned predictiveness effect, what may explain the lack of differences in the attentional biases observed at test. A recent study by Eatherington and Haselgrove (2022) shows that the concurrent presentation of events is not sufficient to produce an attentional bias in a LP design. The bias only appears if the events are presented sequentially so that one event, indeed, predicts the other. Therefore, in Experiment 2 the cues and the prompt were presented simultaneously.

Experiment 1 also showed that participants responded faster to the probe when using the color combinations of the selection task than those of the categorization task (the Task effect found at test). We do not have a clear interpretation of this result. It could be that because the categorization task was more complex than the selection task, participants may have remained more doubtful at test when facing the colors of this task, though this interpretation is only speculative. Importantly, the presence of a Task effect does not affect the comparison between the two attentional biases; the interpretation of our main contrast (the Task × Relevance interaction) would be the same regardless of the presence or absence of a main effect of Task.

Experiment 2

Experiment 2[2] was conducted with the same objective as Experiment 1 while trying to prevent any response interference between training and testing. To do so, selection trials required participants to give an up/down response to the stimuli, which, in this case, were equilateral triangles oriented either up or down. Categorization trials also made use of those triangles, but the response required was the same as in Experiment 1 (A/Z) since it did not hold any relationship with the position of the stimuli on the screen.

[2] An additional experiment was conducted before what here is presented as Experiment 2. However, a problem with programing resulted in a significant alteration of the test phase and the loss of a large proportion of data per participant. That experiment is not reported in this series, but its pre-registration and results can be found at the following link: https://osf.io/adnbr/.

Another difference with respect to Experiment 1 was that the prompt (e.g., “A or Z”) was presented along with the cues, while in Experiment 1 the prompt appeared when the cues had already been removed from the screen. The reason for doing so in Experiment 1 was that we expected participants to need more time to respond to the categorization than to the selection task because of its greater difficulty, leading to more exposure of some cues over others. Given that selection history is “the bias to prioritize items that have been previously attended” (Awh et al., 2012, p. 437), the amount of attention allocated to the cues during training was essential in our experiments. Thus, it was important to ensure that both sets of cues had the same opportunity to be attended to. Otherwise, a different attentional bias towards the two types of relevant cues at test could be attributed to their unequal exposure during training. By presenting the response prompt after the cues, we were sure that participants were exposed to all the cues for the same amount of time (2 s) regardless of the time they needed to respond.

This feature of Experiment 1, however, may complicate the interpretation of the results of the selection task. First, if participants responded without the cues being on the screen, to what extent were the colors actually selected by the participants? Second, if participants are informed about the relevant cue once it has disappeared from the screen, can we be sure that the selected colors had received more attention than the unselected ones? Finally, and more importantly, the sequential presentation of the cues and the prompt might have established the to-be-selected cues as perfect predictors of the color of the prompt. To prevent these problems, Experiment 2 presented the cues and the prompt simultaneously and participants were required to respond to the cues in their presence. To ensure the same time exposure to the two sets of colors, the cues and the response prompt were on the screen for two seconds regardless of whether the participant responded earlier or later within the trial.

Method

Participants

In Experiment 1 we decided to collect data from at least 60 participants to achieve 90% power to detect a small-to-medium effect size. However, screening resulted in 8% of the sample being removed. To compensate for that percentage of removal, in this experiment we planned to collect data from at least 70 participants. As in Experiment 1, participants were undergraduate psychology students from the UAM. Because no participant that signed up for the study was turned away, the final sample size was 75 (70.67% female). No analyses were performed until data collection was completed. Data were collected in 2021. All other issues related to participants proceeded as in Experiment 1.

Apparatus and Stimuli

The apparatus was the same as in Experiment 1 except for the version of PsychoPy used (v2020.2.6). Stimuli had the same visual attributes as in the previous experiment except that, instead of circles, each stimulus display contained two equilateral triangles (see Figure 1 – Experiment 2), with one of them being oriented upwards and the other downwards.

Procedure and data analyses

As in Experiment 1, participants were first instructed in the categorization task. Briefly, they were required to press either A or Z to pairs of triangles based on their color. Participants were informed that the cues would remain on the screen for two seconds and that they must respond within such time frame. Experiment 1 did not make it explicit that the left/right position of the two colors on the screen was irrelevant in this task. Some participants in Experiment 1 indicated to the experimenter that they did not fully understand this point after initial instructions, in this experiment they were explicitly informed that the position was unimportant. As in Experiment 1, participants had practice with this task before receiving the instructions for the selection task.

Categorization trials began with the fixation cross, then, the cues and the response prompt “A or Z” appeared and remained on the screen for two seconds. In each trial, one of the triangles was oriented upwards and the other downwards. These trials displayed the same stimuli combinations as Experiment 1 (see Table 1). Feedback was provided when the response was not correct or if participants did not respond during the trial, in which case, the message read “*The time for responding is over*”.

Instructions for the selection task told participants that they would see two triangles with the prompt “*K or M*” written on the screen (see Selection training – Experiment 2 in Figure 1). They were required to pay attention to the color font of the prompt as they would have to indicate whether the triangle whose color matched that of the prompt was oriented upwards (in which case they would have to press K) or downwards (press M). They were also informed that the left/right position of the stimuli on the screen was irrelevant. After the practice trials with this task, the main points of the two tasks were summarized and the experiment began. For both tasks, the number of practice trials was increased from four (Experiment 1) to eight, and participants were given the opportunity to repeat the instructions and practice trials if they wanted to.

In selection trials, after the fixation cross, the cues appeared along with the response prompt “*K or M*” presented with the color font of one of the cues. These trials displayed the same stimuli combinations as in Experiment 1 (Table 1). Participants had to indicate whether the triangles W or X (whichever was present) was oriented upwards (press K) or downwards (press M). Feedback was provided as in categorization trials.

Unlike Experiment 1, for both tasks, the left/right position of the triangles on the screen was not determined randomly but counterbalanced across trials. The same applies to the orientation of the triangles. Additionally, the feedback messages remained on the screen for two seconds, instead of the three seconds used previously.

Each block of phase 1 trained all eight color combinations with the categorization and selection compounds being presented in an alternated manner. Counterbalancing of the two possible positions of the triangles (relevant left-irrelevant right, or vice versa) and its orientation (left triangle up-right triangle down, or vice versa) produced four possible versions of each color pair. The specific version of each compound used on a given block was determined randomly without replacement. Phase 1 contained 32 training blocks with a rest after block 16. After the rest, participants were reminded of the main instructions of the categorization and selection tasks and training continued until the end.

After training, participants were instructed to respond to the dot probe task as in Experiment 1. In this case the number of practice trials continued to be four, as in Experiment 1. Participants were given the opportunity to repeat the instructions and practice trials of this task.

Dot probe trials resembled those of Experiment 1 with the only exception that participants had a time limit of two seconds to give a response (the two seconds the stimuli were on the screen). If no response was registered during such period, the message "*ERROR. Use the arrow keys to indicate the position of the small square as soon as possible*" appeared for two seconds.

As in Experiment 1, phase 2 alternated test and retraining blocks. However, while in that experiment each retraining and test block contained all eight color combinations, in Experiment 2 the color combinations from the two tasks were trained and tested in separate blocks. The sequence during this phase was: categorization retraining block – categorization test block – selection retraining block – selection test block, and so on. This cycle was repeated 16 times with each block containing four trials. In retraining blocks, the 16 types of retraining trials per task (four color combinations × two positions × two orientations) were presented randomly without replacement.

Regarding test blocks, counterbalancing of the color combinations (four per task), two possible locations of the probe, two orientations of the triangles, and two positions of the stimuli on the screen, resulted in 32 types of test trials per task. As each block had four trials, eight blocks were needed to present all possible test trials once. Those types were presented randomly without replacement along test blocks with the only restriction that each block contained one instance of each color combination. The different versions of each color pair as defined by the other three counterbalancing variables were presented in a random order but was equal across the experiment. Changes between retraining and test blocks were signaled with the message "*Get ready to respond…"* followed by the corresponding prompt (*A or Z* / *K or M* / ←→) and a reminder of the hand the participants had to use. These messages lasted three seconds.

Data analyses was the same as for Experiment 1 with the exception that four-trial blocks were used at test. Unless otherwise noted, all analysis presented in the following section were pre-registered (https://osf.io/adnbr/registrations).

Results

Accuracy in the categorization and selection trials

Four participants failed to achieve a 60% accuracy in the categorization task and were not considered in this nor in the following analyses. Hence, the final analyses included 71 datasets.

Accuracy during training (shown in the top panel of Figure 3) was analyzed with a Task (categorization vs. selection) × Block (32) ANOVA. The analyses yielded a main effect of Task, $F(1,70) = 119.171$, $p < .001$, $\eta_p^2 = .630$, as participants made more errors in the categorization task, Block, $F(31,2170) = 53.809$, $p < .001$, $\eta_p^2 = .435$, reflecting an overall improvement with training, and a significant Task × Block interaction, $F(31,2170) = 24.598$, $p < .001$, $\eta_p^2 = .260$, as the difference in accuracy between tasks disappeared with training. A follow-up analysis of this interaction revealed significant differences between the tasks on blocks, 1-14, 16, 17, 20, 22 and 31, $F(1,70)_{range} = 4.716 - 150.628$, $p_{range} = 4.058 \times 10^{-19} - .033$, $\eta^2_{p\,range} = .063 - .683$, and no differences on the remainder of blocks, $ps \leq .073$. Performance in the two tasks did not differ by the end of training, at block 32, $F<1$.

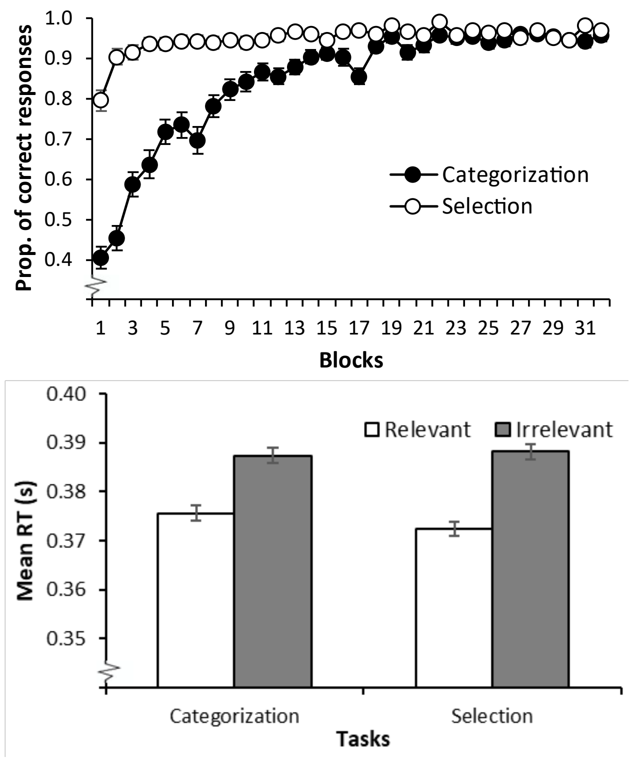

Figure 3. Top: Accuracy (proportion of correct responses) across the 32 blocks of training in the categorization and selection tasks of Experiment 2. *Bottom*: RTs on dot probe trials of Experiment 2, collapsed across blocks. Bars represent the Cousineau-Morey SME for repeated measures.

As in Experiment 1, to determine the block at which performance stabilized in the categorization task, several unplanned one-way ANOVAs contrasted the accuracy observed in the final block (block 32) against that of preceding blocks until a significant difference was found. The first significant difference was observed between blocks 32 and 21, $F(1,70) = 15.599$, $p < .001$, $\eta_p^2 = .182$. This result suggests that stability in task accuracy was established 11 blocks before the test phase commenced.

Retraining trials (not shown in the figure) were also analyzed with a Task (categorization vs. selection) × Block (16) ANOVA. These analyses did not yield any significant effect, *F*s < 1, indicating that during phase 2 (when test trials were presented) performance in the two tasks was at asymptotic level, with no differences between them. The mean accuracy was 97% and 96% in the categorization and selection task, respectively.

Dot probe trials

Trials with incorrect responses (1.05% of the total data), trials with RTs faster than 200 ms (0.03% of the remaining data), and trials with RTs below or above 2.5 SDs from the participants' mean RT (2.63% of remaining data) were excluded from the analysis. As participants had a time limit of two seconds to respond, the filter used in Experiment 1 concerning slow RTs (> 2000 ms) was no longer relevant. Approximately one quarter (23.76%) of the incorrect responses mentioned previously were due to participants not responding within the two-second timeframe.

RTs on test trials, collapsed across blocks, are depicted in Figure 3 (bottom panel). These data were analyzed with a Task (categorization vs. selection) × Relevance (probe on relevant vs. on irrelevant) × Epoch (8) ANOVA. The Epoch factor here represents groups of four blocks, as this is the number of four-trial blocks required to test all the color combinations (8), with the probe appearing over the relevant vs. irrelevant cue (×2). This analysis yielded a main effect of Relevance, $F(1,70) = 81.117$, $p < .001$, $\eta_p^2 = .537$, as participants were faster responding when the probe appeared over a relevant color. There was also a main effect of Epoch, $F(7,490) = 2.263$, $p = .028$, $\eta_p^2 = .031$. Though performance across epochs was fairly constant, with the epochs means ranging from 0.373 to 0.386 seconds, there was a significant increase in RTs between epochs 2 and 3, $F(1,70) = 6.751$, $p = .011$, $\eta_p^2 = .088$, no other significant differences were found between consecutive epochs, ps $\geq .102$. The Task factor was not significant, $F < 1$. There was, however, a Task × Epoch interaction, $F(7,490) = 2.790$, $p =.007$, $\eta_p^2 = .038$, due to differences between the two tasks on the first epoch, $F(1,70) = 4.264$, $p = .043$, $\eta_p^2 = .057$, with faster RTs to the selection ($\bar{x}$ = 0.368) than to the categorization colors ($\bar{x}$ = 0.377), that were absent in the remainder of epochs, ps $\geq .146$.

Importantly, consistent with Experiment 1, the Task × Relevance interaction was not significant, $F(1,70) = 2.071$, $p = .155$, $\eta_p^2 = .029$, indicating a similar attentional bias towards predictive and selected cues. Bayesian analyses supported the model including only the main effects of Task and Relevance over the model also including their interaction with a BF of 6.803, which provides moderate evidence for the lack of an interaction. No other effects in the overall ANOVA were significant, $ps \geq .126$.

Discussion

The objective of Experiment 2 was to test whether learning about the predictive value of a stimulus yields a larger attentional bias than the one that arises from simple selection history effects. Importantly, this experiment was conducted in conditions that allowed us to rule out that response interference/facilitation was the source for the effect. The results showed that differences in selection history produce an attentional bias that does not differ from that obtained in a typical LP design. These results are consistent with those of Experiment 1, and further support the possibility that the LP attentional bias is produced because of differences in selection history—and not because attention is shaped by the cues' predictive value.

General Discussion

There is strong evidence supporting the hypothesis that predictive stimuli are more attended than nonpredictive stimuli (e.g., Cobos et al., 2018; Feldmann-Wüstefeld et al., 2015; Luque et al., 2017, 2018, 2020; Russo et al., 2019; for a review up to 2016, see Le Pelley et al., 2016). In addition, there is growing evidence that stimuli that have been attended to in the past are more likely to capture attention than those which have not, an effect driven by the *selection history* of the stimuli (e.g., Anderson et al., 2021; Awh et al., 2012; Theeuwes, 2019; Wolfe, 2019). Both sources of attentional bias are confounded in the experimental paradigm that has been traditionally used to assess the effects of the predictive value on attention and learning, as the predictive stimuli must be preferentially attended to perform the task. To disentangle these two types of attentional bias, we compared the bias towards two types of stimuli: stimuli that demanded attention *and* were predictive, versus stimuli that required attention but did not convey predictive information despite being relevant. These two types of relevant stimuli were presented in separate tasks during training. In the tradition of studies on the LP attentional bias (e.g., Le Pelley & McLaren, 2003; Mackintosh, 1975) a stimulus is considered predictive if consistently precedes a certain outcome or response. Therefore, to endow only one type of relevant stimuli with predictive value, we manipulated the contingencies between the stimuli and the response required from the participants, with these contingencies differing between tasks.

In the *categorization task*, the relevant stimuli predicted the response required from participants afterwards, while the irrelevant stimuli were not informative. The perfect contingency between the relevant stimuli and the correct response endowed these stimuli with predictive properties. This task mirrored the tasks that have been widely used to study the effects of learned predictiveness on attention (e.g., Le Pelley et al., 2013; Luque, Vadillo, et al., 2017).

In the *selection task*, participants were required to report the position (Experiment 1) or orientation (Experiment 2) of the relevant stimuli; the irrelevant stimuli could be ignored. Crucially, the position and orientation were randomly determined on each trial, leading to a random variation in the correct response in this task. Given the absence of a contingency between the relevant stimuli and the correct response, these stimuli were deemed relevant, but lacked predictive value. Attention towards all stimuli was then assessed with a dot-probe task.

Given that both types of relevant stimuli required attention, an attentional bias driven by selection history was anticipated for both. The absence of differences between the two attentional biases would suggest that selection history alone accounts for the attentional prioritization of predictive stimuli. Conversely, should predictive value influence attention, a greater attentional bias is expected towards the relevant stimuli in the categorization task.

Experiment 1 showed that both tasks produced an attentional bias of the same magnitude. That is, the relevant predictive stimuli captured attention to the same extent as the relevant stimuli that lacked predictive value. This suggests that the critical factor driving the bias is the attention the stimuli received during training (their selection history), with predictiveness adding nothing over and above this effect. Experiment 1, however, posed a problem for our conclusions. In that experiment, the stimuli and the response prompt were presented sequentially, allowing predictive relationships to emerge, and obscuring the interpretation of the bias observed in the selection task. In this task, the response prompt matched the color of the previously presented relevant stimulus. Thus, while the stimuli did not predict the correct response, they were perfect predictors of the prompt's color. Considering that sequential presentation of events (as opposed to mere correlation) is critical for obtaining an attentional bias driven by predictiveness (Eatherington & Haselgrove, 2022), Experiment 2 presented the stimuli and the response prompt simultaneously, therefore eliminating any predictive relationship between them. Additional minor adjustments were made to avoid a response overlap between training and test in the selection task. Experiment 2 replicated the same pattern of results as Experiment 1: there was no difference between the attentional bias towards the two types of relevant stimuli. Importantly, this experiment ruled out that the attentional bias generated by the selection task was produced by an unintended predictive relationship or by a response overlap between the training and test tasks.

Our findings provide relevant insights on the role of selection history in the learned predictiveness effect. However, there are potential alternative interpretations of our findings that are worth discussing. First, the absence of a significant difference between the two attentional biases could be due to the bias reaching its ceiling. This scenario, however, appears unlikely given that larger effect sizes have been reported in comparable experiments using the dot probe task (e.g., Le Pelley et al., 2013; $\eta_p^2 = .69$). A related concern is that the attentional bias produced by selection history effects may be so strong that it leaves no room to observe an additional influence of predictiveness in the categorization task. However, given that the effect size for the Relevance effect in the categorization task –which reflects the combined impact of both sources of attentional bias– was η_p^2 =.108 in Experiment 1 and η_p^2 =.326 in Experiment 2, and considering the larger effect sizes observed in the literature, this possibility seems unlikely.

Another potential concern with our findings is that the 250 ms interval between the onset of the cues and the appearance of the probe might have been long enough for participants to have already allocated their attention to both types of relevant stimuli by the time the probe appeared. If so, the interval length would have rendered the dot-probe task insensitive to detect differences in attentional biases. However, the Task effect observed in the analysis of the dot probe task in both experiments contradicts this possibility. If 250 ms is indeed long enough to pre-allocate attention to both types of relevant stimuli, participants should be equally prepared to respond as soon as the probe appears. However, the analyses revealed that participants required more time to respond when the test involved the colors of the categorization task, indicating that attention was not already biased by the time the probe appeared.

Finally, another potential concern is related to the relative difficulty of the categorization task compared to the selection task. Its increased difficulty resulted in errors persisting longer during training, which raises the question of whether the attentional bias was fully established by the onset of the dot-probe test. To address this concern, we conducted exploratory analyses to determine when accuracy in the categorization task stabilized during training. Our findings indicate that, in both experiments, accuracy had stabilized at least 10 blocks before the test phase began. It is also important to note that, in both experiments, performance between tasks was equally accurate during the retraining trials that were intermixed with the test trials. Finally, the number of training trials in our studies exceeded that of previous significant experiments in this field aimed at determining the impact of learned predictiveness on attention and learning (e.g., Beesley et al., 2015; Le Pelley et al., 2011, 2013; Luque et al., 2017). Therefore, we measured the LP effect in standard conditions.

To our knowledge, the present study is the first assessing the role of selection history in the LP attentional bias. Further research might complement the current results. For instance, if predictive value affects attention by means of selection history, stimuli with different predictive values should capture attention to the same extent at test if equal attention towards them is (somehow) guaranteed during the training phase. In other words, when the history of selection is equal for predictive and nonpredictive stimuli during training, no attentional bias should be found at test. Another prediction is that, if two cues are equally predictive, but only one of them must be attended for solving the task, attention should be biased only towards the attended predictive cue, while no attentional prioritization should be observed to the unattended cue—despite being also predictive.

Interestingly, a series of experiments published by Eatherington and Haselgrove (2022) provides an insight about what would happen in these situations. In their Experiment 2, participants were presented with pairs of letters followed by one of two possible target letters, with each target requiring a different response. The task was arranged so that one of the letters in the pair (in their terms, the correlated stimuli) predicted the identity of the upcoming target, and the other (the uncorrelated stimuli) was completely irrelevant. Importantly, while one group of participants (the Target group[3]) was instructed to respond in the presence of the target, the other group (the Stimuli group) was encouraged to respond during presentation of the stimuli pair (i.e., in anticipation to the target) provided that they could guess the upcoming target. Dwell time spent looking at the correlated and uncorrelated stimuli was used as a measure of attention during the training trials described above, and on test trials in which the letter pair was not followed by any target.

Eatherington and Haselgrove (2022) found that only participants who were encouraged to anticipate their response (the Stimuli group) spent more time looking to the correlated than to the uncorrelated cue. The group that responded directly to the target attended both cues in a similar manner. This occurred even though both groups demonstrated good learning of the relationship between the

[3] The group names in the original manuscript were Serial-Stimuli and Serial-Target. Those groups have been relabeled here for convenience as Stimuli and Target groups, respectively.

correlated and target cues in a final questionnaire. The authors interpreted this result as evidence that the mere existence of a predictive relationship between the correlated stimuli and the target is insufficient for attention to be modulated by the predictive value of the stimuli. Instead, for that to occur, a *predictive response* (one that is performed before the target appears) is required.

The results of Eatherington and Haselgrove (2022), however, can also be explained because of differences in selection history. Note that for both groups one of the cues in the pair was a perfect predictor of the target. However, while attending the correlated cue was irrelevant for participants in the Target group (they were instructed to respond to the target), attending and responding based on the identity of the correlated cue was fostered by instructions in the Stimuli group. Indeed, measures of visual attention during training revealed that only the Stimuli group attended the correlated cue more than the uncorrelated one. Thus, the correlated cues had the same predictive value in both groups, but different selection histories. The results showed that participants paid more attention to the correlated cue only in the group in which the task demanded more attention (selections) towards it, as expected if selection history is driven attention. The results of the Target group are also relevant by themselves. In this group the correlated and uncorrelated stimuli had different predictive values but the same history of being attended, as demonstrated by no differences in dwell times on training trials. As predicted by a selection-history account of the LP effect, no difference in attentional bias was observed at test.

Finally, it is also worth mentioning the procedure and results of Eatherington and Haselgrove's Experiment 3. In this case, training was split into two phases. First, participants had to wait for the target to respond, like in the Target group of the prior Experiment 2. Then, in the second phase, participants were encouraged to respond in the presence of the correlated and uncorrelated cues, like in the Stimuli group of Experiment 2. The results showed that participants attended the correlated and uncorrelated cues similarly in the first phase, but an attentional bias towards the correlated cue was observed in the second phase and at test. Again, they interpreted these results as evidence that, for the predictive value to modulate attention, a predictive response should be performed before the target appears. But another reading of these results is that an attentional bias did not appear until the correlated and uncorrelated stimuli differed in the number of selections and responses they received (i.e., until selection history operated). Unfortunately, none of their experiments included a condition that enables an assessment of these two potential interpretations of their results (e.g., by including a group where a *nonpredictive* response is done in anticipation to the target). Nevertheless, their results question that learned predictive value affects attention by itself, and are consistent with the idea that, in the absence of selection history differences, the predictive value is not sufficient to generate an attentional bias.

Our results suggest a common source for attentional prioritization in our tasks and support a selection-history account for the LP effect. However, the definition provided by Awh et al. of the term selection history is rather phenomenological (in his own words, "the bias to prioritize items that have been previously attended" [Awh et al., 2012, p. 437]), and does not appeal to the mechanisms underlying this bias (though see Anderson et al., 2021). In line with other authors (Anderson, 2016; Jiang & Sisk, 2019; Luque, Beesley, et al., 2017), we contend that our results would be fully expected if attention is regarded as an instrumental response that is amenable to be reinforced and, eventually, susceptible to acquire habit-like features. According to this view, during training with the categorization task, on trials with correct responses participants have probably attended the predictive cue more than the nonpredictive one. Consistent with this assumption, greater attention towards predictive cues during training trials has been demonstrated in eye tracking studies (Beesley et al., 2015; Le Pelley et al., 2011; Lucke et al., 2013; Mitchell et al., 2012). Therefore, as participants solve the trial successfully, the attentional response to the predictive cues gets reinforced, increasing the probability of its occurrence on future trials. And just as occurs with instrumental habitual responses, the response is eventually detached from the reinforcer and is triggered by the stimuli, resulting in the persistence of this attentional pattern on dot-probe trials even when is no longer advantageous (see Luque et al., 2020). Because the attentional response directed towards the selected cues will be reinforced through the same mechanisms, a similar attentional bias is observed in both tasks. That is, the instrumental reinforcement of the attentional responses directed towards the relevant stimuli establishes a common mechanism for our tasks that can explain both attentional biases and the lack of differences between them.

Notably, the results of Eatherington and Haselgrove (2022) mentioned above are also expected under this hypothesis. Take for example their Experiment 2, where the Target group had to respond to the target and the Stimuli group had to respond in an anticipatory manner. In this situation, if attention is unavoidably attracted by predictive stimuli, then an attentional bias towards the correlated cue should be observed in both groups. However, the attention habit hypothesis predicts a difference between conditions, as instructions fostered attention towards the stimuli compound (including the correlated cue) in the Stimuli group, but towards the target in the other group, something that very possibly resulted in different attentional responses being reinforced in each group.

Our results point towards reinforcement of the attentional response as the primary factor producing the attentional bias towards the stimuli. Another phenomenon in the realm of attentional bias and reward processing is the value-modulated attentional capture (VMAC), by which stimuli are attended to if they consistently signal reward. Note however that there are relevant differences between these phenomena and the mechanisms underlying them. In the VMAC, stimuli predicting reward are attended to even when irrelevant to the task, so the participant's active engagement or response to these stimuli is not required or even punished (Le Pelley et al., 2015, 2017; Pearson et al., 2015; see also, e.g., Bucker & Theeuwes, 2017; Failing & Theeuwes, 2017). Given that it seems to be the mere association with reward what makes these stimuli potent in drawing attention, it has been suggested that Pavlovian associations are responsible for the effect (Le Pelley et al., 2015). In our experiments, in contrast, the reward is contingent upon the active engagement with the relevant stimuli. To obtain the reward, the participant must attend to the stimuli and respond accordingly. To the extent that attention can be considered a type of response, this scenario sets the occasion for the reward to act as an instrumental reinforcer. Therefore, this approach aligns with a more instrumental conditioning framework, where the reward is not merely predicted but is a consequence of specific behaviours or responses. While in the VMAC attention is just passively drawn, attentional habits reflect a dynamic interplay between attention and behavior. Taken together, these phenomena suggest that the mechanisms driving attentional biases are multifaceted, involving both passive and active components of reward.

The idea that the LP effect does not depend on the predictive value of the stimuli but on attention towards the predictive cues being reinforced does not conflict with prior demonstrations of the effect, as in common LP studies the stimuli that are relevant to solve the task are the predictive stimuli. However, the explanatory scope of this viewpoint is broader, as it accounts for unexpected results, as this experimental series and that by Eatherington and Haselgrove (2022) and provides a common mechanism for explaining the LP effect and other forms of learned attentional bias, such as the bias driven by former targets that is implicit in our selection task.

Lastly, it is important to acknowledge two constraints in the scope of our conclusions. First, our claims are supported by the data to the extent that the predictive value is understood as the ability to forecast a subsequent relevant outcome or response. If an alternate definition of predictive value is adopted, then different interpretations of our results are possible. For instance, one might consider that two events which are presented simultaneously are both predictors of each other. This approach does not take into account the importance of a predictor being able to anticipate the predicted event. If we adopt this alternative definition, then our strategy (and the one used by Eatherington and Haselgrove, 2022) might not effectively distinguish between predictive value and selection history. And second, participants in these studies were mainly female Western university students. Though we do not have reasons to expect a different pattern of results in individuals with different demographic characteristics, the sample used in these experiments may constrain the generalizability of the results.

To sum up, this series of experiments suggests that selection history effects alone, as defined by Awh et al. (2012) can account for all the attentional effects observed in LP designs and, therefore, that the LP effect might be considered an attentional pattern that develops during training to meet the task demands carrying over to the test. Finally, we propose that the attentional prioritization of predictive stimuli might depend on attention towards these stimuli being reinforced during training. To extract clear conclusions, future research on the learned attentional biases should take careful consideration of the task used in training and the attentional patterns it reinforces.

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