Humans show a higher preference for stimuli that are predictive relative to those that are predictable

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Abstract

Recent studies suggest that humans prefer information that is linked to the process of prediction. Yet it remains to be specified whether preference judgments are biased to information that can be predicted, or information that enables to predict. We here use a serial reaction time task to disentangle these two options. In a first learning phase, participants were exposed to a continuous stream of arbitrary shapes while performing a go/no-go task. Embedded in this stream were hidden pairs of go-stimuli (e.g., shape A was always followed by shape B). Data show faster reaction times to predictable shapes (i.e., shape B) as compared to random and predictive shapes (i.e., shape A), indicating that participants learned the regularities and anticipated upcoming information. Importantly, in a subsequent, unannounced forced-choice preference task, the shapes that were *predictive* of others were significantly more preferred over random shapes than shapes that could be predicted. Because both the reaction time benefit in the learning phase and the effect in the preference phase could be considered rather small, we studied the relation between both. Interestingly, the preference correlated with the reaction time benefit from the learning phase. A closer look at this correlation further suggested that the difference in preference was only observed when participants picked up the contingencies between predictive and predictable shapes. This study adds evidence to the idea that prediction processes are not only fundamental for cognition, but contribute to the way we evaluate our external world.

Keywords: Affect; Predictive coding; Emotion; Uncertainty; Choice; Prediction; Preference Judgments

Introduction

Which shoes would you prefer – the fancy green Mocassins, the clunky black Boots, or the comfortable white Sneakers? Just walking through a footwear store makes it impossible to imagine that there are general rules that determine our choices and preferences. Yet, the discovery of such rules has been a goal of psychological science almost since its very foundation (Fechner, 1876). Over the past decades, researchers have identified several factors that influence our preferences and aesthetic judgments, such as mere exposure (Zajonc, 1980), complexity (Frith & Nias, 1974), contrast (Reber, Winkielmann, & Schwarz, 1996), curviness (Bar & Neta, 2006), or processing fluency (Leder, Belke, Oeberst, & Austin, 2004; Reber, Schwarz, & Winkielman, 2004). Recently, it has been proposed that preference judgments are also linked to the process of prediction (Ogawa & Watanabe, 2011; Trapp, Shenhav, Bitzer & Bar, 2015).

Why should the process of prediction be an influential factor to begin with? There is considerable evidence that the brain does not passively perceive sensory input, but actively constructs hypotheses or predictions that are tested against sensory input (Alink, Schwiedrzik, Kohler, Singer, & Muckli, 2010; Bar et al., 2006; Knill & Pouget, 2004; Rao & Ballard, 1999; Todorovic, van Ede, Maris, & de Lange, 2011; Trapp & Bar, 2015). In other words, perception inherently requires and relies upon prior expectations that support the inference. It has even been suggested that the minimization of surprise is the major goal of the brain and accounts for a plethora of neuroanatomical and neurophysiological findings (Friston, 2005; 2009). Sensory information that contradicts with our current predictions will typically result in the sensation of surprise (e.g., Foerster, 2016; Horstmann, 2015; Schützwohl, 1998). To avoid surprise, an improved prediction of sensory input is mandatory, and we need to learn and use the statistical regularities in our environment that allow us to make correct predictions. Accordingly, one could assume that stimuli which are linked to the facilitation of this process receive positive valuation.

Indeed, two recent studies have supported this hypothesis. Using a visual search paradigm, Ogawa and Watanabe (2011) showed that humans preferred configurations of distractor stimuli that allowed them to predict the location of a target over configurations that did not. Similarly, Trapp and colleagues (2015) demonstrated how random shapes that had been presented in a fixed predictable context (i.e., always presented in the same group of shapes) were preferred over shapes that had been presented in a random context (i.e., always presented in a different group of shapes). However, in both studies, the predictive (i.e., the ability to predict) and predictable (i.e., the possibility to be predicted) aspect of the stimuli was embedded in one and the same stimulus. For example, it remains unclear whether participants' preference for a specific display was because it had helped them to predict the location of a target or because it contained the predictable location (Ogawa and Watanabe, 2011). Similarly, it could not be determined whether participants preferred certain shapes because the shape allowed them to predict the occurrence of other shapes or because the shape itself could be predicted based on the occurrence of other shapes (Trapp et al., 2015).

To test this, we designed a paradigm that allows dissociating these two options. Specifically, we used a serial reaction time task with hidden regularities, i.e., a shape always predicted the occurrence of another, subsequent shape. In line with the proposal that the brain tries to minimize surprise, we hypothesized that participants would prefer information that supports this process over information that can be predicted.

Method

Participants. 94 students (range = 17-36 years, 68 female, 85 right-handed) took part in return for course credits. Participants gave informed consent prior to the study, and the procedures were approved by the local ethics committee of Ghent University.

Stimuli and material. We used the same stimuli as used by Trapp, Shenhav, Bitzer & Bar (2015), which consisted of 64 shapes with no semantic meaning or apparent affective value. For each participant separately, two shapes were randomly assigned as no-go stimuli, and 32 as go-stimuli. The

32 go-stimuli were further randomly subdivided in eight predictive go-stimuli, eight predictable go-stimuli, and 16 random go-stimuli. All instructions and stimuli were presented on a black background. Stimuli were presented on a CRT monitor located 60 cm away from the eyes using Tscope software (Stevens, Lammertyn, Verbruggen, & Vandierendonk, 2006). Participants used the spacebar on a standard QWERTY keyboard for responding to the go-stimuli in the learning phase, and the letters F and J, as their left and right response key respectively, for indicating their preference in the preference judgment task.

Procedure. During the instructions, participants were first presented with the two no-go shape stimuli and instructed to withhold response whenever one of these two stimuli was presented on screen, but press spacebar whenever another shape would be presented on screen. After these instructions, we presented 840 trials with self-paced brakes in between every 120 trials, resulting in seven blocks of 120 trials. Per 40 trials, each of the 32 go-stimuli was centrally presented once and each of the two no-go stimuli was presented four times. Importantly, the stimuli were presented in a random order with the following exception: a predictive go-stimulus always preceded a predictable stimulus. Specifically, eight pairs were formed to ensure that each specific predictive stimulus was always uniquely followed by one of the specific predictable go-stimuli (e.g., predictive shape A was always followed by predictable shape B, predictive shape C always by predictable shape D, etc.). The stimuli remained on screen until participants pressed spacebar or the response deadline of 1200 ms had passed. Next, there was a 500 ms inter-trial interval during which nothing was presented on screen, and after which the next stimulus appeared on screen. During breaks, participants were informed about the amount of response errors they made and remembered to avoid making errors as much as possible.

After this learning task, participants were presented with a second unannounced preference judgment task. In this task, subjects had to indicate their preference for one out of two shape stimuli. The 16 random go shapes were divided in two groups of 8 shapes (i.e., r1 and r2). Next, each of the eight predictive shapes was presented next to one of the r1 shapes, and each of the eight predictable shapes were presented next to one of the r2 shapes. These 16 pairs were presented in a random order, after which another 16 comparisons were made by pairing each of the predictive and predictable stimuli with a shape from the alternative random group. In fact, for each specific predictive-predictable stimulus pair (i.e., shape A was always followed by B), both shapes were compared to the same random stimuli across all 32 trials (i.e., if A was compared to random shape X and B to Y in the first 16 trials, A would be compared to Y and B to X in one of the next 16 trials). This way, the predictive and predictable stimuli were compared to the same baseline.

Finally, in the first 49 subjects, we also collected two post-interview questions from the participants to assess awareness of contingencies. First, they were asked whether they noticed something about the order in which the stimuli were presented. Thereafter, they were told that some participants were assigned to a group with a random order condition, while other participants were assigned to a group for which there was something programmed in the order of stimuli. They were then asked to which group they thought they belonged. If they correctly answered that they belong to the non-random group, they were further asked which order in the sequence they noticed. Importantly, while 37% of the participants (n = 18) thought they might have belonged to the non-random group, none of the subjects reported any order effect related to the order of go-trials. If anything, the participants thought there might have been a pre-programmed sequence in which the no-go trials occurred (e.g., "the figures to which I should not react seemed to purposely repeat one another", "the figures to which I should not react sometimes occurred three times in a row"). These results strongly suggest that none of the participants were aware of the motivation for this experiment, let alone the comparison they were subjected to in the preference judgment task.

Results

All data can be found on the open science framework (https://osf.io/w2bef/). The subjects were recruited in two samples. A subset of the analyses was performed twice (all but the correlation analysis): once after a first sample of 49 subjects, and once after collecting another 45 subjects. While the main effects of interest (learning effect and preference effect) already reached significance after the first sample (both *p*s < .05), the sample was further increased in response to a reviewers' suggestion to increase the reliability of this result. We report the uncorrected p-values, but note that the main results also reached significance when using a Bonferroni correction (multiplying p-values by two). Similarly, a mini meta-analysis (e.g., Goh, Hall, & Rosenthal, 2016) treating the two samples as independent experiments reached significant results. One participant was excluded from the analysis because (s)he responded to the preference phase using the spacebar (which was only relevant in the learning phase).

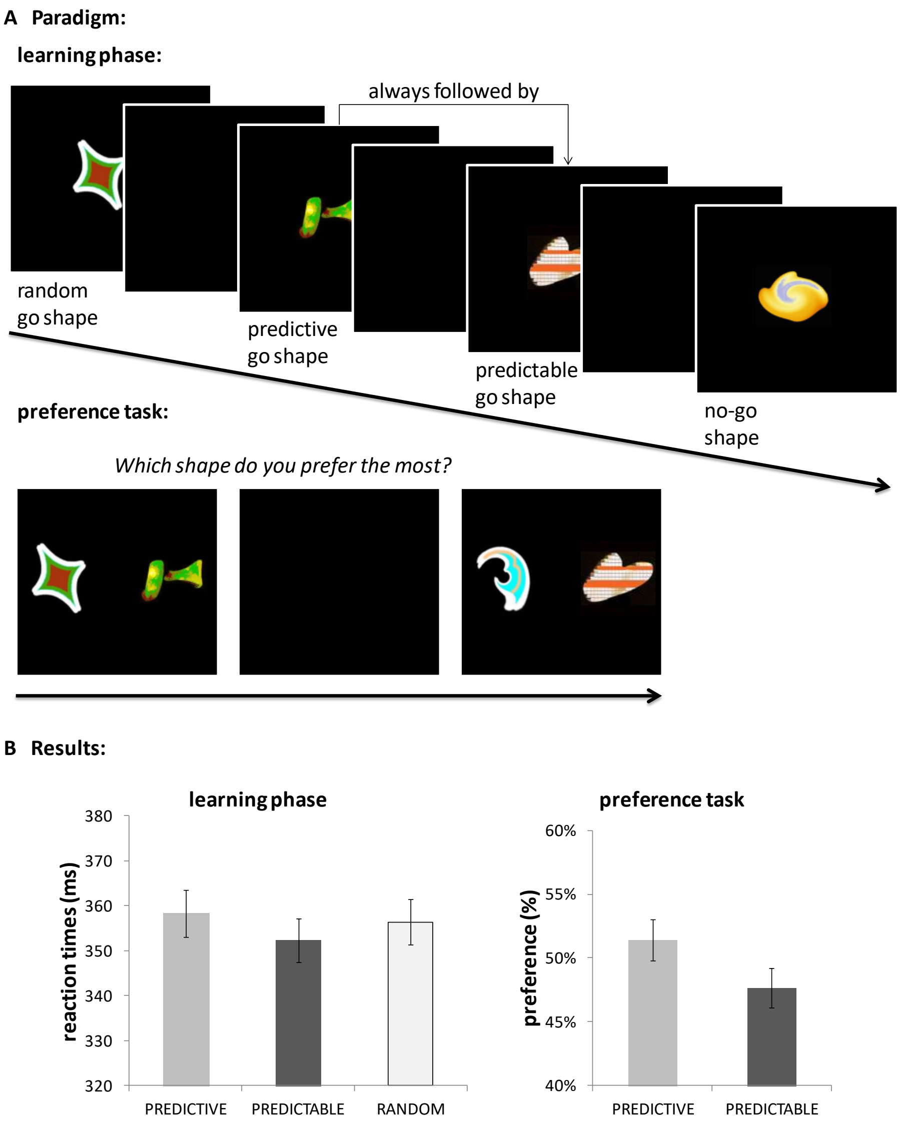

Figure 1. General paradigm and results. A. *Task and procedure*. The experiment consisted of a training phase and a subsequent, unannounced preference judgment task. In the training phase, participants had to respond to each shape as fast as possible, except for two previously instructed no-go shapes. Unknown to the participant,

some (predictive) shapes were always followed by the same (predictable) go-shape. In the preference judgment task, participants had to indicate their preference for one out of two shapes, of which one was always a random shape, and the other either a predictive or predictable shape. **B.** ***Differences between predictive and predictable shapes***. ***Left.*** Mean reaction times for each go-shape separately: Although participants were unable to correctly report any contingencies, reaction times were fastest for predictable shapes, and slowest for random shapes, indicating that contingencies had been learned. ***Right.*** Preference judgments as a function of shape type (predictive versus random, predictable versus random shape). Participants preferred predictive shapes over random shapes more than they preferred predictable images over random shapes.

Learning phase. Participants were successful in withholding their response on 76.7% (SD = 11.3%) of the no-go trials and responded within the response deadline of 1200 ms to 99.8% (SD =.4%) of the go trials. Reaction times faster than 100 ms or slower than the mean plus two SDs were excluded from the analyses. When comparing the mean reaction times per go-shape, predictable shapes (352 ms) were significantly faster responded to than both random (360 ms), $t(92) = 5.204$, $p < .001$, or predictive shapes (361 ms), $t(92) = 4.633$, $p < .001$.Reaction times were not significantly different between responses to predictive shapes were versus random shapes, $t(92) < 1$.

Notably, it has been observed before that people tend to slow down after having inhibited their response on a previous trial (e.g., Bissett & Logan, 2011), and in the present experiment only predictive or random shapes could follow a no-go trial. Therefore, to ensure that the present effects are not a side-effect of post-no-go slowing, we repeated this analysis using only predictive or random shape trials that followed a predictable trial. Even when using this conservative criterion, predictable shapes (352 ms) were still significantly faster responded to than both random (358 ms), $t(92) = 2.508$, $p = .014$, or predictive shapes (356 ms), $t(92) = 2.867$, $p = .005$ (see Figure 1B, left panel).

Preference judgments. Predictive shapes were preferred over random shapes 51.4 % of the time and predictable shapes were preferred over (the same) random shapes in 47.7 % of the time (see Figure 1B, right panel). While these individual preference rates were not significantly different from 50 %, both ps > .1, the difference between both preference rates was significant, as indicated by the Wilcoxon signed rank test, $Z = 2.401$, $p = .016$, effect size $r = .249$ (Rosenthal, 1994).

Correlation analysis. While we did observe a significant preference for predictive over predictable shapes, the effect was rather small: predictive shapes were only preferred 3.7% more than predictable shapes. Interestingly, however, so was the effect of learning, i.e., using predictive information to predict upcoming stimuli. The difference between random and predictable trials was only 6 ms, and a substantial number of subjects did not show any learning effect. Therefore, to determine whether the preference effect related to the degree to which they picked up the contingencies between predictive and predictable shapes, we performed a correlation analysis between this difference in preference and the learning effect in milliseconds (by subtracting mean reaction times on predictable shapes from those on random shapes). Indeed, participants showing a larger reaction time benefit in the learning phase, showed a larger difference in preference in the preference phase, $r = .224$, $p = .031$ (see Figure 2). Following the reasoning that implicit learning effects are more expressed over time (Abrahamse, Jiménez, Verwey, & Clegg, 2010), this correlation was replicated when using only the reaction times from the second half of the learning phase, $r = .273$, $p = .008$, but not when using those of the first half, $r = .111$, $p = .288$. As can be seen on Figure 2, this correlation could potentially be driven by the one participant that showed a difference in preference of 56.25%. However, we note that both a Spearman rank-ordered correlation, which is minimally sensitive to outliers, $\rho = .226$, $p = .030$, as well as a correlation analysis excluding this participant, $r = .250$, $p = .016$, reached similar conclusions.

In addition, to further determine to which extent having a learning effect (i.e., the reaction time benefit on predictable trials as an index of whether somebody picked up the contingency or not) determines the preference effect, we also re-analyzed our preference effect on the subset of participants that had a learning effect larger than 0 ms, and the set of participants that did not. In line with our above interpretation, the people that did show a learning effect larger than 0 ms (n = 53) showed a significant difference between their preference for predictive (45.9 %) versus predictable shapes (52.7 %), $Z = 3.002$, $p < .005$, effect size $r = .412$, whereas the other group (n = 40) did not (49.7 % vs. 50.0 %), $Z < 1$, effect size $r = .028$.

Last, we wanted to study whether the above-mentioned correlation was primarily driven by an increased preference for predictive stimuli when having learned the regularities, or a decreased preference for predictable stimuli. To this end, we ran the above-mentioned correlation analyses again, but, this time, for the preference for predictive stimuli and preference for predictable stimuli separately. This analysis hinted at a positive relation between the learning effect and a preference for predictive stimuli, $r = .180$, $p = .085$, while no such trend was observed for the relation between the learning effect and a preference for predictable stimuli, $r = -.057$, $p = .587$. In close analogy to the above-mentioned correlation analyses, similar results were observed when focusing on the second half only, $r = .189$, $p = .070$, and $r = -.100$, $p = .341$, respectively. In fact, when only focusing on the participants that did show a positive learning effect to begin with, this positive relation between the size of this learning effect and a preference for predictive stimuli was yet more prominent, $r = .270$, $p = .045$, while still no relation between the learning effect and a preference for predictable stimuli was observed, $r = .073$, $p = .604$.

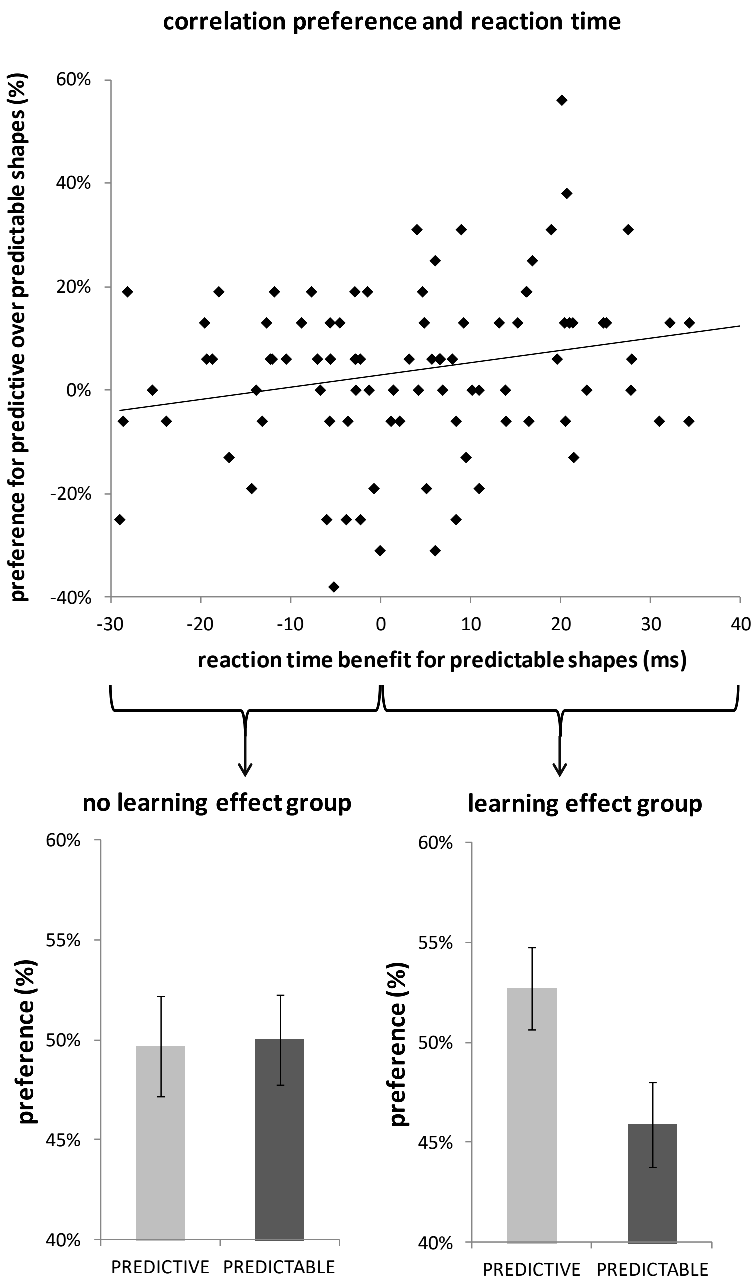

Figure 2. Individual differences in (implicit learning) and shape preference. The learning effect (i.e., reaction time benefit for predictable shapes) correlated positively with the preference for predictive shapes over predictable shapes (upper panel). When comparing the subject that did show an effect (learning effect > 0 ms) to those that did not (learning effect </= 0 ms), it becomes evident that only the former group showed a difference in preference between both types of shapes (lower panel).

Discussion

The proposal that the brain constantly predicts its own sensory input suggests that we may also value information that supports this process. Two studies indicate that human preferences are indeed biased towards information that is linked to predictive processing (Ogawa & Watanabe, 2011; Trapp et al., 2015). Here, we addressed the question whether preference is higher for information that is predictive or information that can be predicted. By using a serial reaction time task with hidden regularities that allowed the anticipation of upcoming information, we found that participants chose information that promoted predictions over information that could be predicted.

As the effect was rather small, and some participants did not pick up the contingencies in our task, future studies may use more straightforward or explicit manipulations of predictable relations to demonstrate larger effects, and effects across all individuals. Another way to strengthen the current finding could be to prolong the learning session and/or use less fixed pairs of predictive and predictable shapes (e.g., four instead of eight, as used in the present study).

The positive evaluation of information that triggers predictions aligns nicely with a framework which conjectures that perceptual inference incorporates expectations during the interpretation of sensory input (Friston, 2005; 2009; Rao & Ballard, 1999; Trapp & Bar, 2015). Another account of preference and aesthetic judgments suggests that humans rely on their processing experience for evaluation – the easier a stimulus is processed, the higher it is valued (Leder, Belke, Oeberst, & Austin, 2004). However, our findings here disfavor the proposal that increased processing fluency contributed to the preference of predictive stimuli, as these were processed *slower* than predicted stimuli, yet were *more* preferred. Trapp et al. (2015) already provided evidence that predictability may be an influential factor in the context of preference judgments. They asked participants to decide which of two pictures of daily objects they prefer (e.g., image of a pizza or a cactus). Importantly, these objects were matched for several low-level features, and were rated beforehand on the degree to which they elicit associations. The finding was that the amount of associations is a significant predictor of preference choices. However, the link to prediction in their study was rather indirect – associative information is assumed to promote predictions (Bar, 2007). By using a serial reaction time task, we here manipulate predictive processes directly, and show a preference for information that is linked to the process of *using* predictive information, rather than to the result hereof.

One possible limitation of the present experiment is that it cannot unequivocally establish whether predictable stimuli were simply preferred *less* because the task was subjectively experienced as boring, and the stimuli accordingly became associated with less excitement. We conducted correlation analyses that focused on both preference measures separately, and the results disfavor this account: Specially, participants who were more likely to pick up the relation between predictive and predictable stimuli showed a change in preference of the *predictive* stimulus, rather than a change in their preference of the *predictable* stimulus. If the effect was really driven by disfavoring predictable stimuli, one would expect a change in the latter as well, as putative effects of boredom would magnify with increasing strength of being able to predict the stimuli following the predictors. Furthermore, if the effects are driven by disfavoring the predictable stimuli, one would also expect less positive evaluation of predictors, as those are associated with and announce the putatively less exciting event. A more direct way to address this issue in follow-up studies could be to employ stimulus ratings where each stimulus type (predictive, predictable, and random) is rated independently (if possible, both before and after the learning phase).

Our study also points towards the importance of taking into account individual differences. Specifically, the present data showed that only some participants were able to pick up the contingencies, suggesting that the present paradigm was not successful in triggering contingency learning in each and every participant. However, by taking into account these individual differences, we were able to demonstrate that size of this implicit learning effect showed a positive relation with the preference for predictive stimuli over predictable stimuli, further supporting our main hypothesis. Usually, serial reaction time tasks and studies investigating behavioral and neural correlates of predictions and prediction errors only report group averages, but it can also be an exciting avenue to investigate whether and why inter-individual differences in these low-level implicit learning exist (see also Kaufman et al., 2010). One step further, individual differences in preferences for predictable or predictive information may help us in understanding different traits, or potentially even certain clinical disorders that are linked to predictive processes (e.g., see Goris, Deschrijver, Trapp, Brass, & Braem, 2017).

Another exciting aspect that can be addressed in follow-up studies relates to the fact that both the predictive and predictable stimuli were associated to a task-relevant action (i.e., pressing the spacebar as fast as possible). It remains to be tested whether similar changes in preference could be observed for relations that are not tied to specific actions, or that are not task relevant at all. If so, this could suggest that the affective tagging of predictive stimuli is inherent to the way we process any type of information, irrespective of their goal or task relevance.

Taken together, this study supports the idea that the rather neglected dimension of valence is important in the context of a 'predictive brain' (Chetverikov & Kristjánsson, 2016; Feldman-Barrett & Bar, 2009; Schäfer, Overy, & Nelson, 2013; Trapp et al., 2015). Future studies should address how these and related findings resonate with the idea that humans can also prefer and seek out uncertain, novel and surprising events (Berlyne, 1971; Van de Cruys & Wagemans, 2011).

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Compliance with Ethical Standards

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Ethical approval: All procedures performed were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent: Informed consent was obtained from all individual participants included in the study.

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