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8 **Subjective Perception of Objects Depends on the Interaction Between the Validity of**
9 **Context-Based Expectations and Signal Reliability**

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18 **Author Note**

19 Declarations of interest: none

20 This study was not preregistered but stimuli, executable files of the experiment, data and
21 analysis scripts are available in the Open Science Framework repository at
22 <https://osf.io/mcv8p/>.

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1 **Abstract**

2 Predictive coding theories of visual perception assume that expectations based on prior
3 knowledge modulate the processing of information. However, the underlying mechanisms
4 remain debated. Some accounts propose that expectations enhance the perception of expected
5 relative to unexpected stimuli while others assume the opposite. Recently, the opposing process
6 theory suggested that enhanced perception of expected vs. unexpected stimuli may occur
7 alternatively depending upon the reliability of the visual signal. When the signal is noisy,
8 perception would be biased toward what is expected since anything else may be too noisy to
9 be resolved. When the signal is unambiguous, perception would be biased toward what
10 diverges from expectations and is more informative. Our study tested this hypothesis, using a
11 perceptual matching task to investigate the influence of expectations on the perceived
12 sharpness of objects in context. Participants saw two blurred images depicting the same object
13 and had to adjust the blur level of one object to match the blur level of the other one. We
14 manipulated the validity of expectations about objects by varying their scene context
15 (congruent or incongruent context leading to valid or invalid expectations about the object).
16 We also manipulated the reliability of the visual signal by varying the initial blur level of object
17 pairs. Results showed that expectations validity differentially affected the perception of objects
18 depending on signal reliability. Perception of validly expected objects was enhanced
19 (sharpened) relative to unexpected objects when visual inputs were unreliable while this effect
20 reversed to the benefit of unexpected objects when the signal was more reliable.

21 *Keywords:* Object perception; Predictive coding; Expectations; Opposing process theory;
22 Sharpening; Dampening

1 **1. Introduction**

2 Our visual system is constantly exposed to abundant streams of information which can
3 often be noisy or ambiguous due to signal constraints (e.g., masking of objects, dim light or
4 foggy weather) or sensory loss (e.g., in ageing or visual pathologies). To rapidly make sense
5 of it and adequately react, current models of visual perception assume that we constantly rely
6 on prior knowledge and expectations built upon regularities learnt from past perceptual
7 experiences. This assumption is supported by a large body of research which for example
8 showed improved performance during the processing of expected than unexpected visual
9 stimuli (see for example Brandman & Peelen, 2017; Davenport, 2007; Davenport & Potter,
10 2004; Greene et al., 2015; Joubert et al., 2008; Lai et al., 2020; Palmer, 1975; Roux-Sibilon et
11 al., 2019 in the context of object recognition).

12 Interestingly, recent studies suggest that expectations and prior knowledge can also
13 qualitatively affect the content of visual perception and the appearance of visual stimuli (Han
14 & VanRullen, 2016; Hansen et al., 2006; Lupyan, 2017; Perez et al., 2020; Rossel et al., 2022).
15 These studies addressed this question using tasks that directly tap into subjective perception
16 while minimising the influence of non-perceptual factors (e.g., decisional or semantic factors).
17 They for example used perceptual matching tasks or equal/same judgments based on different
18 visual properties (e.g., colour, blur or brightness) of visual stimuli that were associated or not
19 with prior knowledge (e.g., indicate whether silhouettes pairs of a meaningful and a
20 meaningless object composed of the same basic shapes are equally blurred or not; Perez et al.,
21 2020). These studies consistently showed that although objectively similar in their manipulated
22 perceptual properties, stimuli that could be expected or associated with prior knowledge were
23 subjectively perceived as different from stimuli that could not. Furthermore, expected stimuli
24 tended to be perceptually enhanced. For example, Lupyan (2017) used a perceptual matching
25 task in which participants had to adjust the blur level of a letter string (a Sample stimulus) in

1 order to match the blur level of another letter string (a Target stimulus). Letter strings could be
2 either meaningful words (e.g., “much”) or meaningless pseudowords composed of the same
3 letters in a randomised order (e.g., “mchu”). Results revealed that participants attributed more
4 blur than necessary to match a Sample word to a Target pseudoword and not enough blur to
5 match a Sample pseudoword a to Target word. These results suggest that at an objectively equal
6 level of blur, meaningful stimuli such as words for which we have semantic knowledge, were
7 subjectively perceived to be sharper than meaningless pseudowords, and that expectations
8 based on prior semantic knowledge influenced how we perceive.

9 We recently adapted this perceptual matching paradigm on the perceived sharpness of
10 objects (Rossel et al., 2022). Two blurred versions of the exact same object (e.g., a car), one
11 being the Target and the other one the Sample, appeared on a screen. Participants had to adjust
12 the blur level of the Sample object to match the blur level of the Target object. We manipulated
13 the predictability of the two objects so that one of them was surrounded by an intact context
14 leading to valid expectations about the object (i.e., a highway context - predictable condition)
15 while the other one was surrounded by a meaningless context (e.g., phase-scrambled version
16 of the highway context - unpredictable condition). Similar to Lupyan (2017)’s findings, results
17 showed that participants attributed more blur to a predictable Sample object matched to an
18 unpredictable Target object than to an unpredictable Sample object matched to a predictable
19 Target object. This means that, at a physically identical blur level, objects that could be
20 predicted based on their intact context were subjectively perceived as sharper than objects that
21 could not (i.e., scrambled context).

22 Enhanced perception of expected stimuli in these studies is consistent with previous
23 findings of higher perceptual sensitivity to expected than unexpected features of visual stimuli
24 (e.g., Pinto et al., 2015; Stein & Peelen, 2015; Teufel et al., 2018; Wyart et al., 2012), giving
25 rise to the so-called “Sharpening” account of predictive processing theories. According to this

1 account, more weight is attributed to the processing of expected relative to unexpected features
2 of sensory inputs, such that the content of perceptual processing would be biased toward what
3 is consistent with expectations (de Lange et al., 2018; Kaiser et al., 2019; Kok et al., 2012; Lee
4 & Mumford, 2003). Given the highly probabilistic structure of the environment, such a
5 mechanism would enable to form accurate percepts in the vast majority of cases. Enhanced
6 perception of expected stimuli in the above-mentioned studies however appears to contradict
7 an alternative account of the predictive processing framework (so-called “Dampening”
8 account) which posits that more weight is attributed to the processing of – more informative –
9 unexpected features, such that the processing of expected features would be relatively
10 dampened. This account has been mainly supported by research in the action literature showing
11 that expected action’s outcomes tend to be perceptually suppressed (e.g., Blakemore et al.,
12 1998). In the vision domain, a few studies did suggest dampened processing of expected
13 relative to unexpected visual stimuli (Hollingworth & Henderson, 2000; LaPointe et al., 2013;
14 Mack et al., 2017; Spaak et al., 2022). For example, Spaak et al. recently showed that object-
15 related changes in visual scenes were better detected when objects were unexpected than
16 expected and unexpected objects were also better identified than expected ones. However,
17 these studies did not directly involve subjective perceptual reports and it remains unclear
18 whether surprising stimuli can be perceptually enhanced.

19 Although in apparent contradiction, the sharpening and dampening accounts may not
20 necessarily be mutually exclusive. Recent theoretical developments, the opposing process
21 theory (Press et al., 2020), propose that both expected and unexpected stimuli can be
22 perceptually enhanced alternatively according to time and signal constraints. Under this view,
23 perception would be initially biased toward what is expected, allowing to confirm valid
24 expectations. The processing of unexpected features would then be subsequently boosted
25 allowing to update expectations (e.g., Yon & Press, 2017). This sequence would be further

1 constrained by the quality (or reliability) of sensory inputs. Under this view, enhanced
2 processing of expected features would be mostly useful when sensory inputs are noisy or
3 ambiguous (as is the case for blurred stimuli), allowing to increase the signal-to-noise ratio.
4 Perception would therefore be biased toward what is expected since anything else may be too
5 noisy to be resolved. On the contrary, when sensory inputs are clear and unambiguous, there
6 would be less point in favouring the processing of expected signal features. Indeed, it would
7 be more relevant to favour the processing of what does not conform to expectations and what
8 is therefore more informative. In this case, perception should therefore be biased towards what
9 diverges from expectations. This is also in line with other accounts according to which the
10 relative weight of predictions and sensory signals are weighted by their respective reliability
11 (Feldman & Friston, 2010; Friston, 2005). Within this opposing process framework, enhanced
12 perception of expected visual stimuli reported in past studies could therefore be explained by
13 the fact that the stimuli used were generally noisy (e.g., blurred; Lupyan, 2017; Perez et al.,
14 2020; Rossel et al., 2022) while enhanced processing of unexpected stimuli was observed when
15 visual signals were unambiguous (e.g., Spaak et al., 2022).

16 However, the interactions between prediction's validity and signal reliability and their
17 consequences for subjective perception have, to our knowledge, never been systematically
18 addressed within the same study. Indeed, the above-mentioned studies investigating perceptual
19 effects of expectations either used ambiguous stimuli (e.g., blurred; Lupyan, 2017; Perez et al.,
20 2020; Rossel et al., 2022) or unambiguous ones (e.g., Spaak et al., 2022) but did not directly
21 compare the two conditions. Furthermore, studies using ambiguous stimuli only manipulated
22 the presence vs. absence of prior knowledge or relevant information allowing to form
23 expectations. However, they did not address the effect of expectations validity by including a
24 condition in which the visual signal could be surprising and go against expectations (i.e., a
25 meaningful but incoherent/surprising stimulus). A comprehensive understanding of these

1 mechanisms is however important to better understand the determinants of subjective
2 perception of expected/unexpected visual stimuli under various constraints and how this may
3 in turn influence behaviour. These questions also more broadly tackle the long-standing debate
4 on whether (and how) cognition affects perception (Firestone & Scholl, 2016; Pylyshyn, 1999).

5 The present behavioural experiment aimed to address these issues and explicitly test
6 the assumption of the opposing process theory by comparing how the subjective perception of
7 ambiguous and unambiguous stimuli can vary according to their expected versus surprising
8 status. To this end, we adapted the perceptual matching task used in our previous study (Rossel
9 et al., 2022). Two blurred objects (a Target and a Sample) appeared simultaneously on the right
10 and left sides of the screen. The task consisted in adjusting the blur level of the Sample object
11 to match the blur level of the Target object. In contrast to our previous study, both the Target
12 and Sample objects were surrounded by an informative scene context. We manipulated the
13 validity of predictions about the objects by varying the congruence between the objects and
14 their scene contexts. One of the objects was surrounded by a congruent scene context (leading
15 to valid predictions about the object) while the other one was surrounded by an incongruent
16 context (leading to invalid predictions). In the present study, we also manipulated the reliability
17 of the visual signal by varying the initial blur level of object pairs, so that both objects could
18 have either a high signal reliability (i.e., relatively sharp objects) or a low signal reliability (i.e.,
19 blurry objects). Based on the opposing process theory (Press et al., 2020), we expected that at
20 a physically equal level of blur, participants should perceive objects in congruent contexts as
21 sharper than the same objects in incongruent contexts (i.e. perceptual enhancement of expected
22 stimuli) when the objects are blurry (low signal reliability) while the opposing effect should be
23 observed when objects are clearer (i.e., objects in incongruent contexts should be perceived as
24 sharper than objects in congruent contexts – perceptual enhancement of unexpected stimuli).
25 As a consequence, participants should compensate this perceived difference between objects

1 by attributing a higher blur level to congruent than incongruent Samples objects in the low
2 reliability condition while they should attribute a higher blur level to incongruent than
3 congruent Sample objects in the high reliability condition.

4 Additionally, it has been argued that if high-level factors (such as expectations based
5 on contextual information) influence the subjective perception of objects, such perceptual
6 effects should equally affect all objects in the visual display. For example, if an expected object
7 in a given context is perceived as sharper than it actually is, simultaneously displayed identical
8 objects sharing the same context should equally benefit from this perceptual enhancement,
9 resulting in the absence of perceived blur difference between them (cf. “El Greco fallacy”,
10 Firestone & Scholl, 2014 - but see Dubova & Goldstone, 2022 for recent empirical arguments
11 against this view). A secondary objective of this study was therefore to test this hypothesis. To
12 this end, we also included a condition in which the Target and Sample object shared the same
13 context (either congruent or incongruent with the object). We expected the perceived difference
14 in blur between the Target and Sample objects in these trials in both signal Reliability
15 conditions to be reduced relative to trials in which the Target and Sample object had a different
16 context.

17

18 **2. Method**

19 **2.1. Participants**

20 Fifty-three undergraduate students of Psychology from University Grenoble Alpes (50
21 women, $M_{\text{age}} = 21.43$, $SD_{\text{age}} = 5.54$) with normal or corrected to normal vision participated in
22 the experiment. The sample size was set based on an estimated effect size of $d_z = 0.45$ from the
23 simple effect of objects predictability on blur perception for Target-Sample pairs with different
24 contextual information (i.e., comparison between -1- the blur level attributed to a Sample object
25 with informative contextual information matched to a Target object with uninformative

1 contextual information and -2- the blur level attributed to a Sample object with uninformative
2 contextual information matched to a Target object with informative contextual information) in
3 Experiment 1 of Rossel et al. (2022) to achieve a power (i.e., corresponding to $1 - \beta$, with β
4 being the risk of Type-2 error) of 0.8 with an alpha level of .025 after Bonferroni correction
5 for the two planned non-orthogonal analyses ($.05/2 = .025$). The study was approved by the
6 ethics committee of the University Grenoble Alpes (CER-Grenoble Alpes, COMUE University
7 Grenoble Alpes, CERGA-Avis-2020-4) and was conducted in agreement with the Declaration
8 of Helsinki for experiments involving human subjects. All participants involved in the study
9 gave their informed written consent before taking part in the experiment. They received course
10 credits for their participation.

11

12 **2.2. Stimuli**

13 The stimuli consisted of 20 colour photographs of scenes (10 indoor and 10 outdoor
14 scenes) and 20 colour photographs of objects (10 animated and 10 non-animated objects). The
15 photographs were downloaded from Pixabay (<https://pixabay.com/fr/>), a Creative Commons
16 Zero (CC0) licensed photo sharing site, and from the Google Images database by filtering for
17 the CC0 licence. The stimuli were created using MATLAB R2019b (The Mathworks, Natick,
18 MA).

19 The original photographs of the scenes were first cropped to a square format and resized
20 to 700×700 pixels. They were converted to 256-level grey-scale images by averaging the
21 values of the three colour channels for each pixel. The average luminance of each image was
22 equalised to 0.5 (for pixel intensity values between 0 and 1) and the average Root Mean Square
23 (RMS) contrast value of all images (0.1947) was applied to each image. For each scene image,
24 we then constructed a 700×700 pixels disc containing the scene.

1 The original photographs of the objects were also cropped to a square format and
2 resized to 120×120 pixels which corresponded to the maximum size of objects (either in width
3 or height). The objects were then isolated from their background by outlining them on GIMP
4 software (The GIMP Development Team, 2019) and applying transparent pixels to their
5 background. They were then converted to greyscale images. The average luminance and RMS
6 contrast of each object were also equalised to 0.5 (for pixel intensity values between 0 and 1)
7 and the average RMS contrast value of all images (0.2117) was applied to each image.

8 Each object was then blurred using 2D Gaussian filters (*imgaussfilt* function in Matlab)
9 of increasing size (i.e., with increasing standard deviation - SD) to obtain 22 versions of the
10 object ranging from a sharp object (close to intact; blur level 1, SD = 1) to a very blurred and
11 hardly recognisable object (blur level 22, SD = 10, see Rossel et al., 2022 for a similar
12 procedure). We then assembled the object and scene images to construct final stimuli
13 containing a central object surrounded by the circular scene context. To this end, we placed at
14 the centre of each scene a 250×250 pixels grey disc of luminance 0.5 that was spatially filtered
15 by a Gaussian with a standard deviation of 2 to smooth the edge of the disc. We then added the
16 blurred object to the centre of the grey disc. This grey disc allowed us to isolate the object from
17 the background and avoid local contrast differences between the object and the scene in the
18 different conditions.

19 The object and scene images were paired so that each object appeared either surrounded
20 by a semantically congruent scene (e.g., a boat in a harbour scene), an experimental condition
21 that should lead to valid predictions about the object, or surrounded by a semantically
22 incongruent scene (e.g., a boat in a kitchen scene), an experimental condition that should lead
23 to invalid predictions about the object (Fig. 1).

24

25 **2.3. Procedure**

1 The experiment was constructed using the Psychtoolbox (Brainard, 1997; Pelli, 1997)
2 implemented in MATLAB R2019b (MathWorks, Natick, MA, USA). Stimuli were displayed
3 on a 30' monitor (DELL ULTRASHARP) with a resolution of 2560×1600 pixels. Participants
4 put their head on a chin rest 72 cm away from the screen so that the grey disc containing the
5 object corresponded to an angular size of 5° visual angle, the object corresponded to a maximal
6 angular size of 2.4° visual angle and the circular scene corresponded to an angular size of 14°
7 visual angle.

8 On each trial, two images containing the same object were displayed on the left (the
9 Target) and right (the Sample) sides of the screen against a grey background (average
10 luminance of 0.5). To test the effect of visual signal reliability on the perceived sharpness of
11 objects, the Target object appeared in the first half of the trials at a blur level of 18 (SD of
12 Gaussian filter = 7.6, low signal reliability) and in the second half of the trials at a blur level of
13 5 (SD of Gaussian filter = 2.2, high signal reliability). In a pilot study, we found that the
14 minimum difference in blur required to perceive a blur difference between two objects was of
15 0.3 SD when the objects had a blur level of less than 4.6 SD (as in the high reliability condition)
16 and of 0.6 SD when the objects had a blur level of 4.6 SD or more (as in the low signal reliability
17 condition). The size of Gaussian filters used to obtain the blur levels of Target and Sample
18 therefore varied in increments of 0.3 SD in the high signal reliability condition and of 0.6 SD
19 levels in the low signal reliability condition. This resulted in a total of 22 blurred versions of
20 each object used in the experiment. We did not counterbalance the order of the reliability
21 conditions to avoid that the prior perception of sharp objects of the high reliability condition
22 could be later used to disambiguate the signal of blurred objects of the low reliability condition
23 if performed next. Concerning the initial blur level of the Sample object which had to be
24 matched to the Target, it varied randomly between three blur levels above or below the blur
25 level of the Target object. However, the levels varied according to the signal reliability

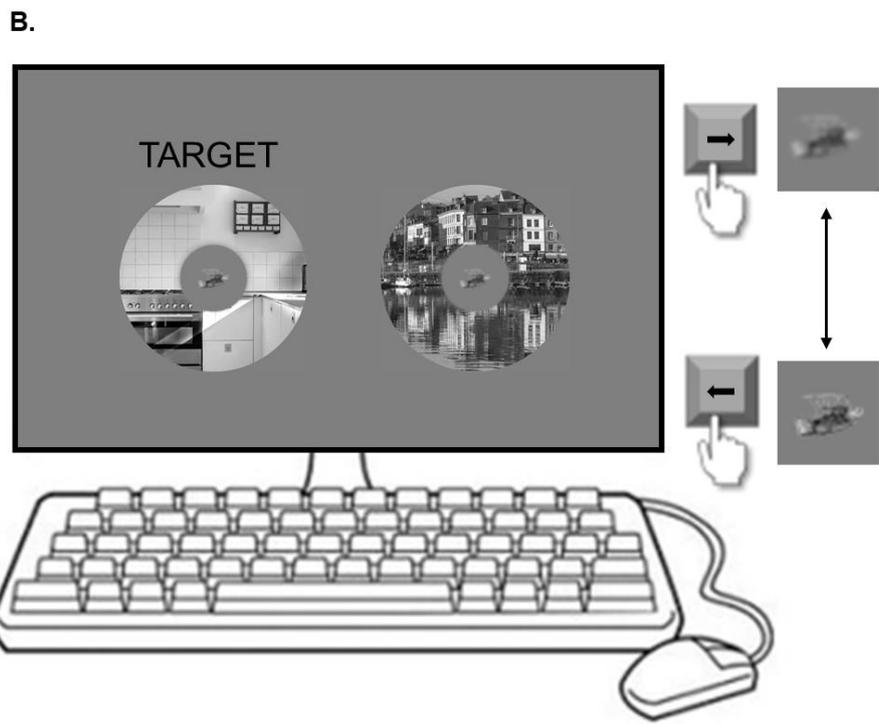
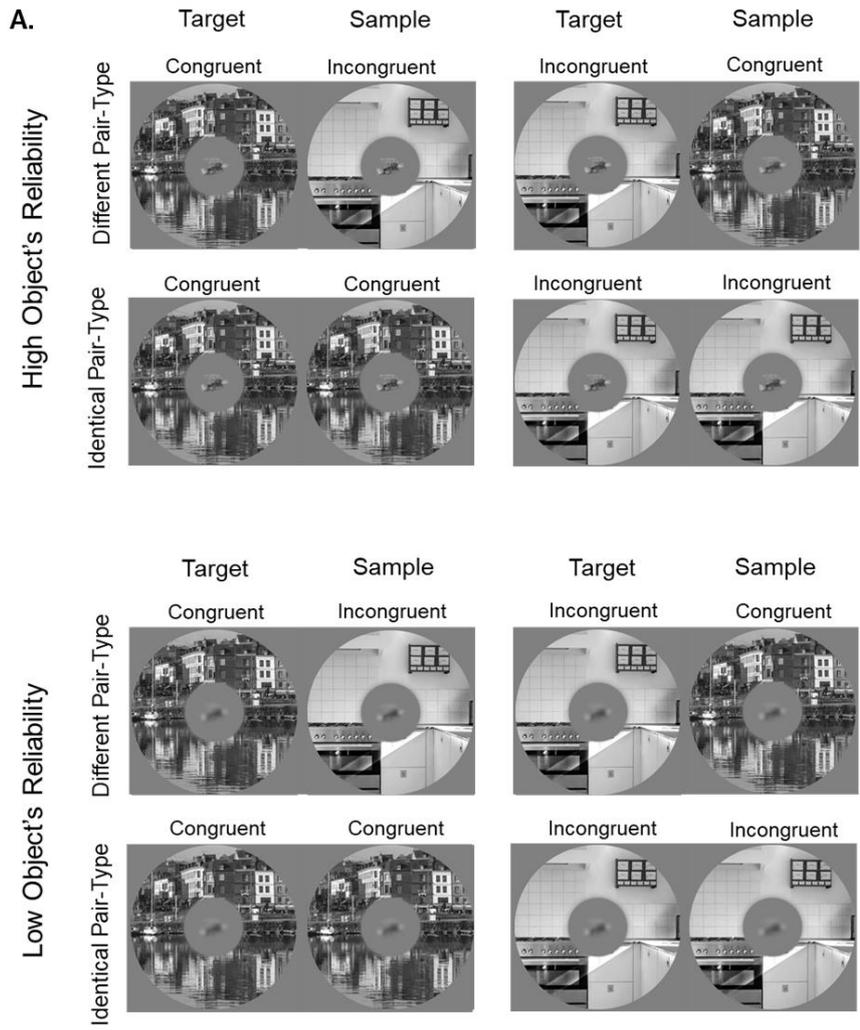
1 condition of the Target (low vs. high). Indeed, it is possible that in the low reliability condition
2 of the Target object (i.e., when the object is very blurred and therefore ambiguous), having the
3 same object in Sample at a medium blur level and therefore better identifiable, would bias the
4 processing of the Target which would then become less ambiguous, even if very blurred. To
5 avoid this, the initial blur level of the Sample object remained close to the one of the Target
6 object in the low reliability condition. Therefore, the Sample object could have a blur level
7 between 16 (SD = 5.5) and 21 in the low signal reliability condition and a blur level between 3
8 (SD = 4.6) and 8 (SD = 3.1) in the high signal reliability condition. Participants had to adjust
9 the blur level of the Sample object to match the blur level of the Target object by increasing or
10 decreasing the blur of the Sample object in steps of one blur level in the high reliability
11 condition and in steps of two blur levels in the low reliability condition, using the left and right
12 arrows on the keyboard respectively. In the low reliability condition, the Sample object could
13 be adjusted to a maximum blur corresponding to level 22 (SD = 10) and a minimum blur
14 corresponding to level 15 (SD = 5.8) and in the high reliability condition, the Sample object
15 could be adjusted to a maximum blur corresponding to level 14 (SD = 5.2) and a minimum blur
16 corresponding to level 1 (SD = 1). Participants were asked to press the spacebar to validate
17 their response once they judged that the objects in the Sample and Target were equally blurred.
18 Participants were encouraged to rely on their subjective judgement to match the blur level of
19 the objects and were not limited in time at each trial.

20 It can be noted that in the present study, blur was used both as the signal to be processed
21 to perform the matching task and as a way to modulate object reliability. Given that our main
22 assumption was that the exact same blurred object can be subjectively perceived as different
23 according to its contextual information, we needed to ensure that any perceived difference in
24 blur between object pairs could not be attributed to other objective differences between them.
25 For example, manipulation of other perceptual variables (e.g., contrast) as a way to modulate

1 signal reliability may have unevenly affected object perception at different blur levels.
2 Furthermore, manipulation of blur was preferred to other perceptual variables (e.g., brightness
3 or orientation) because blur is a fundamental feature of vision that can be easily transposed to
4 ecological conditions (e.g., small or distant objects in our visual field may initially appear
5 blurry before they can be resolved as we get closer or change viewpoint).

6 For each trial, the objects in Target and Sample had either a different scene context (one
7 congruent and one incongruent with the object, i.e., Different Target-Sample pair-types) or the
8 same scene context (both congruent or incongruent with the object, i.e., Identical Target-
9 Sample pair-types). The Different Target-Sample pair-types allowed us to test our main
10 hypothesis of opposing effects of prediction validity depending on signal reliability on the
11 perceived sharpness of the objects. The Identical Target-Sample pair-types were included to
12 also assess potential differences in perceived sharpness during the matching of identical
13 Sample and Target stimuli.

14 An experimental session contained 160 trials divided into two blocks of 80 trials: the
15 80 trials where the object had low reliability always appeared first and were followed by the
16 80 trials where the object had high reliability. Within each block, we had 20 objects \times 2
17 conditions of semantic context congruence for the Sample object (congruent vs. incongruent
18 context) \times 2 types of Target-Sample pairs (identical Target-Sample pair-types vs. different
19 Target-Sample pair-types). The experiment lasted approximately 30-40 minutes, depending on
20 the speed at which participants adjusted the blur of the Sample object, and contained a break
21 every 40 trials. For each trial, we recorded the blur level attributed to the Sample object to
22 match the Target object (Matched Blur Level, MBL).



1 Fig 1. Illustration of the experimental conditions and the display. A. Example of stimuli presented in
2 each experimental condition. For each trial, the Sample and Target objects were the same but appeared
3 either at a low blur level where the object was fairly sharp (high reliability condition) or at a high blur
4 level making the object identity ambiguous (low reliability condition). The scene context could be either
5 congruent with the object (correct/valid predictions) or incongruent with the object (incorrect/invalid
6 predictions). Furthermore, the scene contexts of the Target and the Sample could be either identical or
7 different. B. Illustration of the display in a trial with an incongruent Target and a congruent Sample
8 (different Target-Sample pair-type). Two blurred objects appeared simultaneously, the Target on the
9 left and the Sample on the right. Participants were asked to adjust the Sample object's blur level until
10 they judged both objects as equally blurred.

11

12 **3. Data analysis**

13 We measured the level of blur that participants attributed to the Sample to judge the
14 Target and the Sample as equally blurred (Matched Blur Level, MBL). Data were analysed
15 using R software (R Core Team, 2019) and *lme4* package (Bates, Mächler, et al., 2015) to
16 perform a linear mixed-effects analysis of the effect of signal Reliability (high vs. low), Target-
17 Sample pair-type (identical vs. different), and Congruence between the Sample object and its
18 context (congruent vs. incongruent) in a $2 \times 2 \times 2$ within-subject design. The signal Reliability,
19 the Target-Sample pair-type, the congruence of the Sample and their interaction terms were
20 introduced into the model as fixed effects. The intercepts for subjects, as well as the random
21 slopes per participant for the effect of signal Reliability, Target-Sample pair-type, Sample
22 congruence and their interactions were specified as random effects.

23 We conducted the minimum number of analyses needed to test our hypotheses to avoid
24 increasing the risk of Type-1 error. According to opposing process theory (Press et al., 2020),
25 enhanced perception of expected relative to unexpected objects should occur when the stimuli
26 are ambiguous and the visual signal is unreliable while enhanced perception of unexpected

1 relative to expected objects should occur when the signal is more reliable. We therefore
2 expected that in the low reliability condition, congruent objects would be subjectively
3 perceived as sharper than incongruent objects at objectively equal blur levels. Therefore, for
4 Target-Sample (T/S) pairs of different contexts in the low reliability condition, the MBL of
5 Sample objects in the T-incongruent/S-congruent condition should be higher than the MBL of
6 Sample objects in the T-congruent/S-incongruent condition. On the other hand, we expected
7 that in the high reliability condition, incongruent objects would be subjectively perceived as
8 sharper than congruent objects at an objectively equal blur level. Therefore, for Target-Sample
9 pairs of different contexts in the high reliability condition, the MBL of Sample objects in the
10 T-congruent/S-incongruent condition should be higher than the MBL of Sample objects in the
11 T-incongruent/S-congruent condition. To address this main hypothesis, we therefore tested the
12 interaction between the Congruence of Sample objects and the signal Reliability for Different
13 pair-types, as well as the difference between the MBL of congruent and incongruent Sample
14 objects in each signal Reliability conditions (i.e., two non-orthogonal a priori tests).

15 Furthermore, if expectations based on congruent or incongruent contextual information
16 influence the perceived sharpness of objects (through the relative enhancement of either
17 expected or unexpected features), such perceptual effects should also occur during the
18 matching of identical Target-Sample pairs (i.e., both congruent or incongruent stimuli).
19 However, they should equally affect the Target and Sample objects (Firestone & Scholl, 2014).
20 Therefore, the perceived difference in blur between the Target and Sample objects in the
21 Identical pair-types (and hence the difference in MBL between T-congruent/S-congruent and
22 T-incongruent/S-incongruent conditions) in both objects' Reliability conditions should be
23 reduced (or even absent) relative to Different pair-type trials. To address this hypothesis, we
24 thus also tested the three-way interaction between the object's Reliability, the Target-Sample
25 pair-type and the Congruence of the Sample.

1 We used the method proposed by Bates, Kliegl, et al. (2015) to build parsimonious
2 mixed models limiting convergence problems. Visual inspection of the residual plots did not
3 reveal any obvious deviations from homoscedasticity or normality. The p-values were obtained
4 by Satterthwaite approximation with the *lmerTest* package (Kuznetsova et al., 2017). The
5 significance threshold was set at .025 (.05/2 = .025) after Bonferroni correction for the two
6 non-orthogonal tests performed (the Sample congruence effect in the low and high reliability
7 conditions for the different Target-Sample pair-types). Effect sizes were estimated using
8 Cohen's d_z (Lakens, 2013).

10 4. Results

11 Mean MBLs for each experimental condition are shown in Fig. 2. Given that the blur
12 level of the Target object could be of 5 or 18 in the high and low reliability conditions,
13 respectively, a mean MBL above (below) these values in each signal Reliability condition
14 would indicate an overestimation (underestimation) of the Sample's blur relative to the Target.

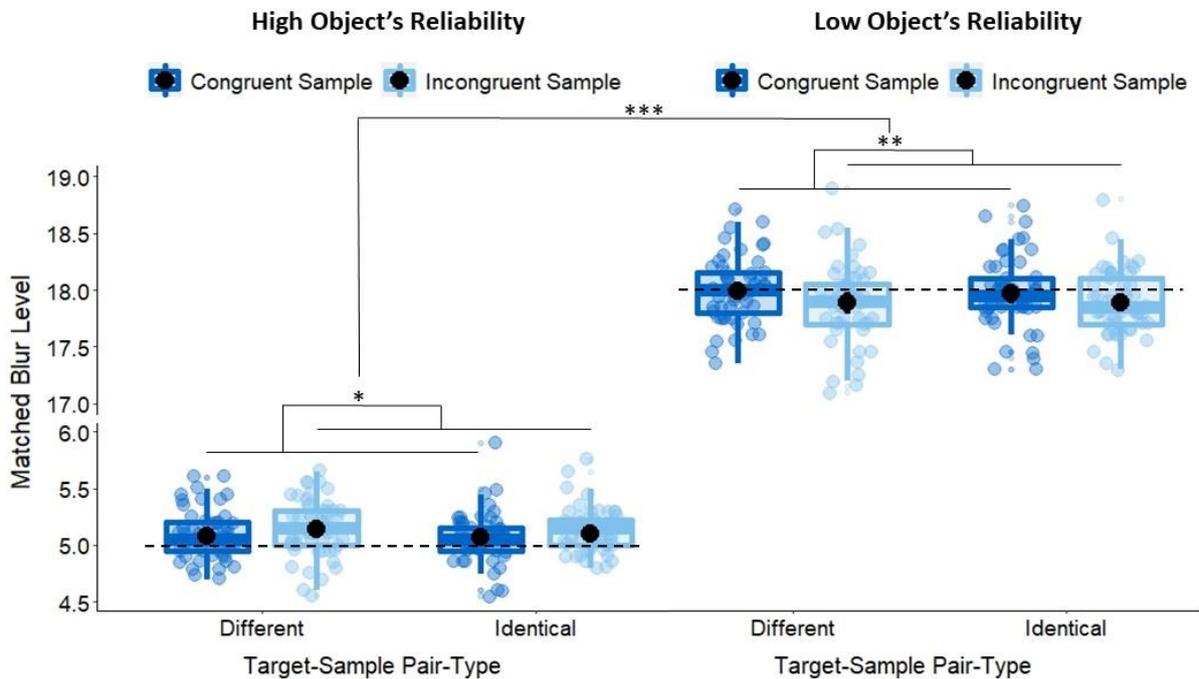
15 Results revealed first a main effect of signal Reliability, $t(51.99) = 375.66, p < .001, d_z$
16 $= 51.601$, indicating that the MBL was higher in the low reliability condition ($M = 17.93, SE =$
17 0.13) than in the high reliability condition ($M = 5.10, SE = 0.10$). This was to be expected given
18 that the blur level of the Target was higher in the low than high reliability condition. There was
19 neither a significant main effect of Sample congruence, $t(8368) = 1.26, p = .208, d_z = 0.173$,
20 nor a significant main effect of Target-Sample pair-type, $t(8368) = 1.13, p = .259, d_z = 0.155$.

21 Concerning our main hypothesis, results revealed a significant interaction between
22 Sample congruence and signal Reliability for the different Target-Sample pair-types, $t(4132)$
23 $= 3.27, p = .001, d_z = 0.449$. More precisely, in the low reliability condition of different Target-
24 Sample pair-types, we observed a significant effect of Sample congruence, $t(2066) = 2.54, p =$
25 $.011, d_z = 0.349$, where participants attributed a higher blur level to congruent Sample objects

1 than incongruent Sample objects (congruent Sample: $M = 17.99$, $SE = 0.14$; incongruent
2 Sample: $M = 17.89$, $SE = 0.14$). On the contrary, in the high reliability condition of different
3 Target-Sample pair-types, participants tended to attribute a higher blur level to incongruent
4 Sample objects than congruent Sample objects but this difference was not significant after
5 Bonferroni correction, $t(2066) = -2.07$, $p = .039$, $d_z = 0.284$ (congruent Sample: $M = 5.08$, SE
6 $= 0.10$; incongruent Sample: $M = 5.14$, $SE = 0.10$).

7 Concerning our second hypothesis, the three-way interaction between Sample
8 congruence, Target-Sample pair-type and signal Reliability was not significant, $t(8368) = 0.74$,
9 $p = .462$, $d_z = 0.102$, indicating that the interaction between Sample congruence and signal
10 Reliability did not significantly differ in the identical relative to the different Target-Sample
11 pair-types. This pattern of results therefore rather suggests a two-way interaction between the
12 Sample congruence and the signal Reliability irrespective of the Target-Sample pair-type
13 which was indeed significant, $t(8368) = 4.02$, $p < .001$, $d_z = 0.552$. We tested the effect of
14 Sample congruence a posteriori for each of the signal Reliability conditions. In the low
15 reliability condition, we found a significant effect of Sample congruence, $t(4186) = 3.26$, $p =$
16 $.001$, $d_z = 0.448$, where participants attributed a higher blur level to congruent Sample objects
17 than incongruent Sample objects (congruent Sample: $M = 17.98$, $SE = 0.13$; incongruent
18 Sample: $M = 17.89$, $SE = 0.13$), suggesting perceptual enhancement of expected relative to
19 unexpected objects. On the contrary, in the high reliability condition, participants attributed a
20 higher blur level to incongruent Sample objects than congruent Sample objects and this time
21 the difference was significant, $t(4186) = -2.34$, $p = .019$, $d_z = 0.321$ (congruent Sample: $M =$
22 5.07 , $SE = 0.10$; incongruent Sample: $M = 5.12$, $SE = 0.10$), suggesting perceptual enhancement
23 of unexpected relative to expected objects.

1 There was no other significant interaction (interaction between Target-Sample pair-type
 2 and signal Reliability: $t(8368) = -0.47, p = .637, d_z = 0.065$, interaction between Target-Sample
 3 pair-type and Sample congruence: $t(8368) = -0.08, p = .937, d_z = 0.036$).



4
 5 Fig 2. Mean Matched Blur Level (MBL) for each condition. Mean MBL for congruent and incongruent
 6 Samples under different and identical Target-Sample pair-types conditions for high (left) and low (right)
 7 reliability. A high blur level corresponds to a very blurred object, while a low blur level corresponds to
 8 a relatively sharp object. The y-axis is discontinued for illustrative purposes. Black dots and error bars
 9 indicate mean and standard error over all individuals and trials, respectively. The dashed lines
 10 correspond to the perfect matches for each condition. Colour dots correspond to individual observations.

11 * $p < .05$. ** $p < .01$. *** $p < .001$

12
 13 For completeness, we repeated the same statistical analyses, this time adding the
 14 random effects of stimuli. Thus, intercepts for stimuli, as well as the random slopes per stimuli
 15 for the effect of signal Reliability, Target-Sample pair-type, Sample congruence and their
 16 interactions were specified as random effects in our mixed effect model. Again, visual

1 inspection of the residual plots did not reveal any obvious deviations from homoscedasticity or
2 normality.

3 After including the random effects of the stimuli, results revealed no significant
4 interaction between Sample congruence and signal Reliability for the different Target-Sample
5 pair-types, $t(18.99) = 1.70, p = .106, d_z = 0.234$. Furthermore, the three-way interaction between
6 signal Reliability, Target-Sample pair-type and Sample congruence was not significant,
7 $t(19.02) = 0.34, p = .738, d_z = 0.047$ and there was also no interaction between signal Reliability
8 and Sample congruence, $t(19.26) = 1.74, p = .098, d_z = 0.239$.

9

10 **5. Discussion**

11 The present study investigated the effect of predictions validity, based on contextual
12 information, on the subjective perception of objects depending on the reliability of the visual
13 signal. To this end, participants performed a perceptual matching task consisting in adjusting
14 the blur level of an object (Sample) embedded in a congruent or incongruent scene context
15 (leading to valid or invalid predictions about the object, respectively) to match the blur level of
16 the same object (Target) embedded in a congruent or incongruent context. To address the effect
17 of signal reliability, the objects could appear at a low (i.e., high signal reliability) or high blur
18 level (i.e., low signal reliability). Based on the opposing process theory (Press et al., 2020)
19 postulating that expected stimuli are perceptually enhanced relative to unexpected stimuli
20 when the visual signal is noisy while they should be relatively perceptually dampened when
21 the visual signal is more reliable, we expected that at an objectively equal blur level, congruent
22 objects would be subjectively perceived as sharper than incongruent ones when the blur level
23 was high and that incongruent objects would be perceived as sharper than congruent ones when
24 the blur level was low. However, we expected the perceived difference in blur between the
25 Target and Sample objects in both signal Reliability conditions to be reduced when object pairs

1 had an identical than a different context (Firestone & Scholl, 2014).

2 Contrary to this assumption, results revealed no significant difference between
3 perceptual effects of expectations observed in the Different and Identical pair-type conditions.
4 This suggests that even when identical, the Target and Sample objects were however perceived
5 as different. The significant two-way interaction between Sample congruence and signal
6 Reliability as well as pairwise post-hoc tests however suggested that the effect of Sample
7 Congruence reversed according to signal Reliability (i.e., congruent Sample objects were
8 perceived as sharper than incongruent ones when signal reliability was low, while the opposite
9 was found when signal reliability was high) irrespective of the pair-type condition - and hence
10 of the congruence of the Target object.

11 Following Firestone & Scholl's rationale, if "perceptual" effects can still be found when
12 stimuli are identical, such effects may rather reflect the influence of non-perceptual judgements
13 or response biases. In the context of our experiment, objects that make more sense in congruent
14 contexts may for example be more readily judged as sharp or "clear" than objects in
15 incongruent contexts without it being associated with perceptual effects. Such non-perceptual
16 judgements could therefore bias perceptual matching. However, the fact that the effect of
17 Sample congruence was reversed as a function of signal reliability irrespective of the pair-type
18 condition (i.e., crossed interaction between Sample congruence and signal Reliability) makes
19 this interpretation unlikely. Indeed, if our effects were driven by a systematic response bias for
20 example consisting in judging congruent objects as clearer than incongruent ones (and
21 therefore in systematically attributing more blur to congruent than incongruent Sample
22 objects), such a bias should be present in both reliability conditions. However, there is little
23 chance that response biases were also reversed as a function of signal reliability (i.e., that
24 congruent objects were judged as clearer than incongruent ones when signal reliability was
25 low, but were judged as less clear when signal reliability was high) without it being influenced

1 by perceptual effects.

2 If results in the identical pair-types cannot be attributed to a response bias, how to
3 explain that the pattern of results in this condition was similar to the different pair-type
4 condition? Results of a recent study by Dubova & Goldstone (2022) may provide an interesting
5 lead to answer that question. These authors challenged the assumption that perceptual effects
6 induced by prior knowledge should equally affect all items in the visual field by arguing that
7 during perceptual matching tasks such as ours, the Target and Sample stimuli (even if identical)
8 can hardly be perceived similarly at the same time. In their study, these authors recorded
9 participants' eye movements during a perceptual (colour) matching task such as ours and
10 observed that participants fixated more often on the Sample which was being adjusted than on
11 the Target which therefore mostly appeared peripherally throughout the task. In the theoretical
12 context of the present study, such behaviour could have a critical impact on matching
13 performance and may explain the observed differences even in the Identical pair-type trials.
14 Indeed, our Target and Sample objects had a relatively small size (2.4° of visual angle) and
15 were each surrounded by a large context. When participants fixated one of the objects, the other
16 appeared with an eccentricity of 16.3° degrees and the inner border of its context was at 14.3° .
17 If participants adopted a similar strategy as in Dubova & Goldstone (2022) consisting in
18 fixating on the Sample object most of the time, this implies that the Target object was perceived
19 with a poorer spatial resolution inherent to peripheral vision. More detrimental, the context of
20 the Target object may also have appeared blurry and therefore less informative or more
21 ambiguous with respect to its congruence with the Target object. Perceptual effects induced by
22 context-based expectations could thus have affected the Target less strongly than the Sample.
23 Our pattern of results does suggest that participants' performance (i.e., matched blur level)
24 varied according to the congruence of the Sample object but not the congruence of the Target
25 object. Another possible explanation for the similar pattern of results in the Identical and

1 Different Target-Sample pair-types may come from the design of our experiment in which the
2 Target's blur level was kept constant throughout the high and low reliability blocks (blur levels
3 of 5 and 18, respectively) while the Sample's blur varied from trial to trial. This could have led
4 participants to create an accurate estimate of the Target blur level in each condition, which
5 became less prone to effects induced by contextual information relative to the Sample's, thus
6 eliminating the Target congruence effect.

7 On the other hand, the observed effect of the Sample's congruence which was reversed
8 as a function of signal reliability (irrespective of the Target-Sample pair-type) is in line with
9 our hypotheses. In the low reliability condition, participants attributed a higher blur level to
10 expected Sample objects than to unexpected Sample objects. This indicates that at a physically
11 equal blur level between the Sample and Target objects, expected objects subjectively appeared
12 as sharper than unexpected ones. This is also in line with previous works showing (1) increased
13 perceived sharpness of blurred stimuli which can be related to prior knowledge relative to
14 meaningless/unpredictable stimuli (Lupyan, 2017; Perez et al., 2020; Rossel et al., 2022) and
15 (2) that this effect is stronger as the reliability of the visual signal decreases (Rossel et al.,
16 2022). Results of the present study therefore allow us to extend these previous findings by
17 showing that blurred expected stimuli are also perceived as sharper than unexpected ones.

18 This pattern of results was reversed in the high reliability condition. Participants
19 attributed a higher blur level to the Sample objects with an incongruent scene context than to
20 the Sample objects with a congruent scene context, indicating that at a physically equal blur
21 level between the Sample and Target objects, unexpected objects subjectively appeared as
22 sharper than expected ones. This pattern of results therefore supports the idea of opposed
23 perceptual effects of expectations as a function of signal reliability, in line with the opposing
24 process theory. Interestingly, it can however be noted that these perceptual effects mostly
25 seemed to affect unexpected rather than expected stimuli. Indeed, as can be seen in Fig. 2, the

1 MBL for expected Sample objects was very close to a “perfect match” suggesting an accurate
2 estimation of their blur irrespective of the Signal reliability. On the contrary, the blur of
3 incongruent Sample objects tended to be underestimated when signal reliability was high -
4 which would suggest that the object is perceived as sharper than it actually is, while it was
5 overestimated when signal reliability was low - which would suggest that the object is
6 perceived as blurrier than it actually is. The relatively enhanced (dampened) perception of
7 expected than unexpected stimuli when signal reliability is low (high) put forward by the
8 opposing process theory may therefore actually stem from these effects on unexpected stimuli.

9 These findings raise the question of the neural mechanisms underpinning the selective
10 perceptual enhancement of stimuli depending on predictions’ accuracy and signal reliability.
11 The opposing process theory (Press et al., 2020) proposes that predictions about sensory inputs
12 are signalled via descending connections between adjacent areas along the cortical hierarchy.
13 These prediction signals would “preactivate” the neural representation of expected stimulus
14 features in lower-level areas by enhancing the response of neurons tuned to these features while
15 inhibiting the response of neurons tuned to unexpected ones. If sensory inputs closely match
16 predictions, no further process is required which speeds up stimulus processing and
17 recognition. If sensory inputs however clearly and strongly diverge from expectations, neural
18 representations in low-level areas should be dominated by the response of neurons tuned away
19 from expected features. The gain of these neurons’ response would subsequently increase while
20 the gain of neurons tuned to expected features would decrease. This would favour the
21 processing of unexpected and hence potentially informative content used to update predictions.
22 However, if sensory inputs are noisy, their neural representation should be too. The response
23 of neurons tuned to unexpected features may therefore not differ enough from the response of
24 neurons tuned to expected ones to trigger the dampening mechanism. In which case, enhanced
25 response of neurons tuned to expected features would still predominate. In this context, signal

1 reliability is thus estimated as the variance of the distribution of neural responses to the stimulus
2 (the larger the variance, the less reliable the signal, Ernst & Banks, 2002). Such “sensory”
3 estimation of signal reliability may also be combined to top-down expectations based on prior
4 experience (e.g., knowing that sensory inputs are likely to be (un)reliable, Yon & Frith, 2021).
5 An important implication of these assumptions is therefore that the selective enhancement of
6 responses to expected/unexpected features not only occur alternatively depending on signal
7 reliability, but also over the time course of visual processing - the relative enhancement of
8 responses to expected features preceding that of unexpected features. Although the design of
9 the present study does not allow to empirically address this assumption, further studies
10 addressing the subjective perception of expected and unexpected stimuli while varying the
11 exposure duration of stimuli could be considered to explicitly test this hypothesis (e.g., Yon &
12 Press, 2017).

13 It should however be noted that the supplementary analyses including the random
14 effects of the stimuli in our models showed no significant interaction between the Sample
15 congruence and the signal Reliability. This indicates that these results, which were significant
16 in the main analyses not including the stimuli variability, cannot be extended to all visual
17 stimuli but rather restrict to the stimuli used for the present experiment. Indeed, the stimulus
18 variability included in the supplementary analyses hides the global fixed effects tested as these
19 fixed effects were not large enough relative to the variability of the stimuli to reach the
20 significant threshold. The fact that we cannot generalise our results to all stimuli is not
21 necessarily problematic as our stimuli were not very ecological and specifically built to address
22 our hypotheses. Therefore, it would however be interesting to replicate this study with more
23 ecological stimuli (e.g., photographs of real scenes containing expected or unexpected objects,
24 see e.g., Öhlschläger & Vö, 2017) to determine whether such findings can be generalised to
25 every visual stimulus.

1 Investigating the perceptual effects of expectations as a function of signal reliability
2 under more ecological conditions may also have important implications to better understand
3 the determinants of subjective perception of expected/unexpected visual stimuli in various
4 contexts and populations and how this may in turn influence behaviour. For example, in daily
5 situations such as driving in which expectations and anticipation are crucial and information
6 across the visual field becomes noisier with speed, the present findings may suggest that an
7 unexpected stimulus in the periphery could be perceived as less clearly and possibly ignored,
8 undetected and/or misunderstood relative to an expected stimulus. Answering these questions
9 also has societal and clinical implications as it would for example allow to better identify the
10 extent to which sensory deficits related to visual pathologies or ageing can be compensated for
11 or on the contrary amplified by these predictive mechanisms when processing expected relative
12 to unexpected stimuli. For example, in a widespread visual pathology such as cataract which
13 can induce colour-faded or blurry vision making sensory inputs less reliable, perception of
14 unexpected stimuli is likely to be more affected than that of expected stimuli.

15

16 **6. Conclusions**

17 In conclusion, our results suggest that expectations based on scene contextual
18 information differentially affect the subjective perception of expected and unexpected objects
19 and that these effects are also modulated by the reliability of visual signals. Visual perception
20 is dominated by what we expect when the environment is uncertain but tends to be biased
21 toward what surprises us as sensory inputs become more reliable. The present findings
22 therefore provide empirical support for the recently developed opposing process theory which
23 may help to reconcile a priori contradictory findings in the literature on how expectations shape
24 perception.

25

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4

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