

The roles of predictive information in absolute evaluative processing

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**The roles of predictive information in
absolute evaluative processing**

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Abstract

Predictive processing is fundamental to many aspects of the human mind, including perception and decision-making. The previous researches show that animals and humans share similar preference toward the information that provides reliable prediction for the future outcome, mainly future rewards, even though obtaining predictive information does not change the value of upcoming rewards. It remains to be elucidated, however, in which way predictive information impacts on absolute evaluative processing, particularly in tasks that employ bivalent stimulus sets. Various accounts, including framing, proactive interference, and cognitive control, appear to imply contradictory proposals on the relation between prediction and preference formation.

To disambiguate whether predictive cues produce congruent biases versus opponent mechanisms in evaluative processing, we conducted two experiments in which participants were asked to rate individual food images. The image database included appetitive and aversive items. In each trial, a cue predicted, with varying degrees of reliability, the valence of the impending food image. In both experiments, we found that the ratings exhibited congruent biases as a function of the reliability of the predictive cue, with the highest evaluations following the most reliable positive-valence predictions. Eye prepositioning further showed a selective spatial bias suggestive of response preparation in line with the predictions. The response times also exhibited a pattern of results consistent with selective preparation, producing slow responses following invalid predictions. The data suggested an active form of evaluative processing, implementing a confirmation bias that aims to accommodate the prediction.

In addition, the several extended analyses show other characteristic of the predictive information in this particular experimental paradigm. Pupil dilation analysis during the cue exposure suggests that pupillary responses do not work as a function of explicit features of the predictive cues such as cue reliability, cue valence and cue color. However, the intrinsic arousal level that is induced by the predictions from predictive cues is the major factor that involves the pupil dilation. The history analysis of evaluation score shows that there is no significant effect of confounds by predictive information and the exposure of images in the past on the evaluation process of current images. And lastly, the median split analysis shows interesting evidences on the underlying mechanism behind human evaluation processing. Regardless of cueing condition, outcome valence and other experimental conditions, people have tendency to give more extreme rating when they decide to response fast by their own wills. These interesting results inspire promising future works that provide further investigation of the underlying mechanism of evaluation processing.

In conclusion, this thesis provides the solid evidences of how the predictive information affects the absolute evaluation in various cue reliability and cue valence for both positive and negative outcomes. The results suggested that confirmation bias from predictive cue works actively as the amplifier of subjective value of the congruent outcomes while also being the reducer of the incongruent outcome. Other extra analyses show the robustness of experimental paradigm, potential physiological indicator for measuring intrinsic arousal value of predictive information by using pupil dilation and also the interesting underlying mechanism of evaluation processing in relationship between response speeds with the polarization of the rating score. These data not only answer the main questions that we have on the role of predictive information in absolute evaluation but also open up the new chapter of future research that might provide other insight mechanisms of human evaluation processing.

Ethics statement

The protocols for the present study were designed in accordance with the Declaration of Helsinki, and were approved by the Human Ethics Committee of the Faculty of Arts and Science, Kyushu University (issue number 201711). Informed consent was obtained in writing from each subject.

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Chapter 1: General Introduction

One of the powerful motivator in the daily life is the desire to know what will happen in the future. The information that can lead to the prediction towards future outcome always fascinates people including cognitive neuroscientists and psychologists to investigate how the brain reacts to this kind of information. In broader perspective, the predictive processing is a big part of our brain engine because the predictive processing in general can refer to any type of processing towards the future state; not only the information processing but also the internal body states up until the state of surrounding environments. The difference between sensory inputs with the predictions from top-down brain process create errors and the brain adapts to minimize these errors in cortical processing (Clark, 2013). Because the prediction processing works as a bridging process over the different points of time, from the information in present and the past towards cognitive outcomes in the future, predictive processing is unarguable main cognitive function that makes our brain so efficient (Bubic, Von Cramon, & Schubotz, 2010).

The predictive information is one kind of specific predictive processing inside the brain which is triggered by information that provides the hints about the outcomes, events or experiences in the future. In daily life situations, people generally seek for this kind of information because the accurate predictors accommodate us in planning and preparing how to deal with that upcoming future. Although gaining information will not affect the amount of upcoming outcome, the study by Iigaya et al. (Iigaya, Story, Kurth-Nelson, Dolan, & Dayan, 2016) also shows that humans still have preference to gain more information about upcoming outcome in general. Not only in human but also animal studies that conducted in monkeys (Blanchard, Hayden, & Bromberg-Martin, 2015) and pigeons (McDevitt, Dunn, Spetch, & Ludvig, 2016; Zentall, 2016) show that these animals have the same seeking behaviors for the

information when the information is related to rewards in near future. In pigeons' studies, the results even showed that pigeons prefer to select sub-optimal choices that provide certain information more than the optimal choice that come after uncertain information.

Moreover, the monkeys studies by Bromberg-Martin and Hikosaka (Bromberg-Martin & Hikosaka, 2009, 2011) also showed the neural bias in macaque monkeys in the preference test between two choices that provided different predictions of the upcoming rewards. Even though the choice selection does not change the amount of upcoming rewards, monkeys still preferred to select the choice that provided certain information about the upcoming rewards more than the choice that provided uncertain information. In addition, the activation of dopamine neurons in lateral habenula immediately after the exposure to the certain information of either big or small rewards have similar characteristics with the dopamine activation when either big or small rewards are given after uncertain information. These studies suggest that reward seeking mechanism and information seeking mechanism might be the same mechanism when the information provides prediction to rewards. Also the preferences toward this predictive information are embedded in neuronal level, not only in the higher cognitive process.

Although previous researches established the roles of predictive information in the relative evaluation processing between different choices, there is still unclear about how predictive information affects the absolute evaluation. In the other words, animals and humans have preference towards the certain predictive information but how subjective value of the outcome change by predictive information is still underdetermined. The previous researches on the predictive processing gave two major suggestions on the role of prediction on the evaluation process; either prediction produces congruent bias in the evaluation process (Cunningham, Van Bavel, & Johnsen, 2008; Jin, Zhang, & Chen, 2017; Levin, Johnson, Russo, & Deldin, 1985; Tversky & Kahneman, 1981; Wilson, Lisle, Kraft, & Wetzell, 1989) or the prediction leads to the active inhibition that reduces the subjective value of the outcome

(Aydogan et al., 2018; Cheng, Wu, & Lin, 2014; Geers & Lassiter, 1999; Stamos, Goddyn, Andronikidis, & Dewitte, 2018). In this sense, other empirical studies that are designed specifically to investigate the role of predictive information on the subjective evaluation are needed.

In the previous studies, there are reports about the related factors that might correspond to the effectiveness of the predictive information. In utility of anticipation researches (Loewenstein, 1987), the longer duration of anticipation towards future rewards also works as the enhancement over time on the subjective value of the outcome while the coexist mechanism, called temporal discounting, also reduces the subjective value of the outcome as a function overtime. Even though the boost by anticipation might overcome the discounting effect at first but, for long term, the temporal discounting will counter and suppress the subjective value of outcome instead (Iigaya et al., 2016). Therefore, there is a possibility that effectiveness of predictive information on evaluation processing can be influenced by the anticipation duration between the exposure to predictive information and outcome.

Other interesting factors are the valence of the outcome. While most of prediction errors, information errors, utility of anticipation studies based on the rewards (Bromberg-Martin & Hikosaka, 2009, 2011; Iigaya et al., 2016; Schultz, 2013; Schultz, Dayan, & Montague, 1997), the opposite prediction for negative outcomes is barely investigated. Many previous studies show the asymmetrical effect between positive and negative outcomes, events or experiences on many cognitive processes such as behavioural outcomes according to threaten justice (Barclay & Kiefer, 2014) and satisfaction level of products (Mittal, Ross Jr, & Baldasare, 1998; Rychalski & Hudson, 2017). Also, there are clear evidences that people tend to have bias towards positive information (Peeters, 1971; Unkelbach, Fiedler, Bayer, Stegmüller, & Danner, 2008) but the negative information have stronger impact in general for psychological phenomena (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). To provide the whole

pictures of how predictive information affects the underlying brain mechanism during the subjective evaluation process, it is essential to use bivalent stimuli set as the outcome of our experimental paradigm.

To create novel contribution in this kind of study, the series of experiments in the current thesis are mainly designed for evaluation of single stimulus and supporting bivalent stimuli set. By adapting from choice selection paradigm, which is highly regarded as a paradigm that can use for direct comparison between animal and human study, to single image evaluation task, we can observe how predictive information influence in the subjective value of the outcome through the changes of evaluation score. Moreover the observation of how the predictive information affects the absolute evaluation of both positive and negative outcome in single experiment can provide the further understanding of how predictive information operate in each stimuli valence. By combining this two major adaptation in the behavior paradigm, the results of this study should be able to identify the overall mechanism of the predictive information in subjective evaluation.

In Chapter 2, the main body of this thesis will be explained and described in details of our finding by combining series of two experiments together. The first experiment is designed for overall observation in the role of predictive information on single image evaluation task by using bivalent food images set as stimuli that displayed after predictive cue. In this experiment, the design is not only made for investigating the effect of predictive cue on the rating score but also investigating the factors from literature that might influence the effectiveness of predictive cue including cue reliability level (100% certain cue or 50% uncertain cue), cue valence (either positive or negative) and delay time (either 1s or 9s delay time). Gaze data of participants is captured using desktop eye-tracker, Eye tribe, to provide the other physiological indicators of bias that create by predictive information.

In the second experiment, we manipulated the cue reliability level to 75% for providing the surprise effect as a feature of predictive information when the prediction is correct most of the time but not always. Also we introduced neutral cue which is just random cues with no valence for investigating the difference between 50% uncertain cue and neutral cue. In addition, the directional gaze bias that was found in the first experiment was investigated further by introducing the different direction of evaluation bar to different group of subjects. According to this design, the results of gaze distribution analysis for the second experiment could show that whether directional gaze bias is followed the direction of score on the evaluation bar, or, it works as function of other cognitive bias in general. This main chapter had been published in the Scientific Reports in the title of “Active Confirmation Bias in the Evaluative Processing of Food Images” (Ounjai, Kobayashi, Takahashi, Matsuda, & Lauwereyns, 2018).

In chapter 3, other interesting investigations were done on results from both experiments which provided some more insights of the predictive information and some interesting suggestions on the underlying mechanisms of subjective evaluation process. Results of pupil dilation analysis show how pupil reacts to the predictive cue and stimuli in each experimental condition. History analysis on the evaluation score provided supporting evidence on the robustness of the paradigm by countering the concern of the experimental design that whether the information in the previous trial is still maintained and contaminated the rating of current trial, or not. Lastly, median split analysis of both experiments had been done to observe the relationship of reaction time in evaluation process for each experimental condition. This analysis provides further interesting data that suggests underlying mechanism behind evaluation process when participants decided to response fast or slow by their own will. According to results of median split analysis, the consistency of cueing effect obtained in this paradigm is shown as a bias by predictive cues expressed in different response speed.

The last chapter of this thesis provided the general discussion on the findings about the roles of predictive information in absolute evaluation process. The limitations and concerns of experimental conditions, measuring methods and the stimuli set are mentioned with suggested solutions for future experiments. Finally, the most promising future works that inspired by the findings in this study are mentioned with my own predictions on those future works and how those future studies might provide interesting insight of evaluative decision-making process in general.

Chapter 2: Active Confirmation Bias in the Evaluative Processing of Food Images

Introduction

In contemporary psychology, neuroscience, and philosophy of mind, the most comprehensive accounts of brain and mind suggest that predictive processing is central to many, if not all, forms of cognition (Clark, 2013, 2015; Friston, 2010; Hohwy, 2013; Lauwereyns, 2010). Also with respect to evaluative processing, it has been shown that contextual information can elicit expectations that modulate the liking of stimuli as diverse as visual art (Kirk, Skov, Hulme, Christensen, & Zeki, 2009), music (Aydogan et al., 2018), coffee (Fenko, de Vries, & van Rompay, 2018), soda (Schmidt, Skvortsova, Kullen, Weber, & Plassmann, 2017), and wine (Plassmann, O'Doherty, Shiv, & Rangel, 2008). The effects of prior expectations appear to have a fundamental impact on the perceptual processes underlying the evaluation, in ways that are difficult to accommodate with normative theories about rational decision-making (Kahneman, 2003).

Instead of rational decision-making, evaluative processing often involves complex or seemingly inscrutable processes we usually call “subjective,” with the implication that they are idiosyncratic and cannot be disputed (as according to the Latin maxim, *De gustibus non est disputandum*; “In matters of taste, there can be no disputes”). However, in reality we frequently do debate evaluative processing in virtually all aspects of human society, from commerce to health and well-being, from bioethics to politics. The phenomena of evaluative processing warrant scientific investigation, particularly with a view to understanding how, and when, biases distort the evaluation of objects and events that afford no easy objective metric (Kroger & Margulis, 2017; Lauwereyns, 2010; Stauffer & Buckley, 2005; Ziegert & Hanges, 2005).

The issue is to chart the extent to which evaluative processing is pervious to external influences. The present study aims to contribute to this task.

More specifically, we focus on the direction of influences from prior expectations when both the predictions and the outcomes are bivalent. We chose food images as a relevant category for evaluative processing with bivalent items (Armell, Beaumel, & Rangel, 2008; Lim, O'Doherty, & Rangel, 2011; Sokol-Hessner, Hutcherson, Hare, & Rangel, 2012) that elicit a complex integration of visual and non-visual features (e.g., flavor, caloric value, nutritive attributes) (Bailey & Muldrow, 2018; Bielser, Crézé, Murray, & Toepel, 2016; Kühn et al., 2016; Suzuki, Cross, & O'Doherty, 2017). Previous research in our lab had further shown that the rating of individual food items provides a suitable opportunity to investigate the cognitive mechanisms underlying evaluation (Wolf et al., 2018). Here, we examine how explicit, supraliminal positive or negative predictions impact on the evaluation of appetitive or aversive food images.

Previous research on framing effects might be taken to suggest that bivalent predictions should lead to congruent biases in the evaluative processing, with more positive evaluations following positive predictions and vice versa (Cunningham et al., 2008; Jin et al., 2017; Levin et al., 1985; Tversky & Kahneman, 1981; Wilson et al., 1989). We term this the “congruent bias” hypothesis. The congruent biases from framing would be due to explicit expectations under voluntary control. It has further been suggested that such positive or negative expectations evolve over time, potentially becoming more polarized (Iigaya et al., 2016; Loewenstein, 1987). Other phenomena and theories can also be interpreted to imply similar congruent biases, albeit on the basis of implicit mechanisms that would be activated automatically or unconsciously by the predictive cues. These phenomena and theories include priming (Bargh, 2006; Dalenberg et al., 2014; Stöckli, Stämpfli, Messner, & Brunner, 2016), proactive interference (Wright, Kelly, & Katz, 2018), Pavlovian-instrumental transfer (Cartoni,

Balleine, & Baldassarre, 2016; Geurts, Huys, Den Ouden, & Cools, 2013), and emotional contagion (Howard & Gengler, 2001; Morales & Fitzsimons, 2007).

In contrast, predictive cues could lead to the activation of opponent mechanisms, aiming to operate explicitly against external influences. We term this the “opponent mechanism” hypothesis. For instance, proactive control would function as an endogenously activated mechanism in opposition to biasing information (Amodio & Swencionis, 2018; van Wouwe, Band, & Ridderinkhof, 2009). Previous research has identified a number of conditions in which the evaluative processing counteracted the biasing influences (Aydogan et al., 2018; Cheng et al., 2014; Geers & Lassiter, 1999; Stamos et al., 2018). Here, the opponent mechanism hypothesis implies a deliberate effort to inhibit responses in line with the prediction. Such active inhibition, however, may produce opposite effects, promoting responses that run counter to the cueing, analogous to phenomena such as inhibition of return (Klein, 2000) and negative priming (Frings, Schneider, & Fox, 2015). Thus, the evaluation of appetitive food images would be higher following negative predictions than following positive predictions. Conversely, aversive food images, when occurring in contrast to the prediction, would be evaluated more negatively than aversive food images that appear in agreement with the prediction.

Counteractive evaluative processing might also occur as a function of more implicit opponent mechanisms, consistent with the notion of prediction errors in the neuroscience literature on dopaminergic mechanisms (e.g., an unexpected reward leads to stronger dopaminergic activation than an expected reward; such activation is thought to reflect learning and adaptive evaluative processing) (Berridge, 2007; O’doherly, 2012; Schultz, 2013; Schultz et al., 1997). Here, the conjecture would be that the predictive context amplifies the evaluative processing of unexpected outcomes.

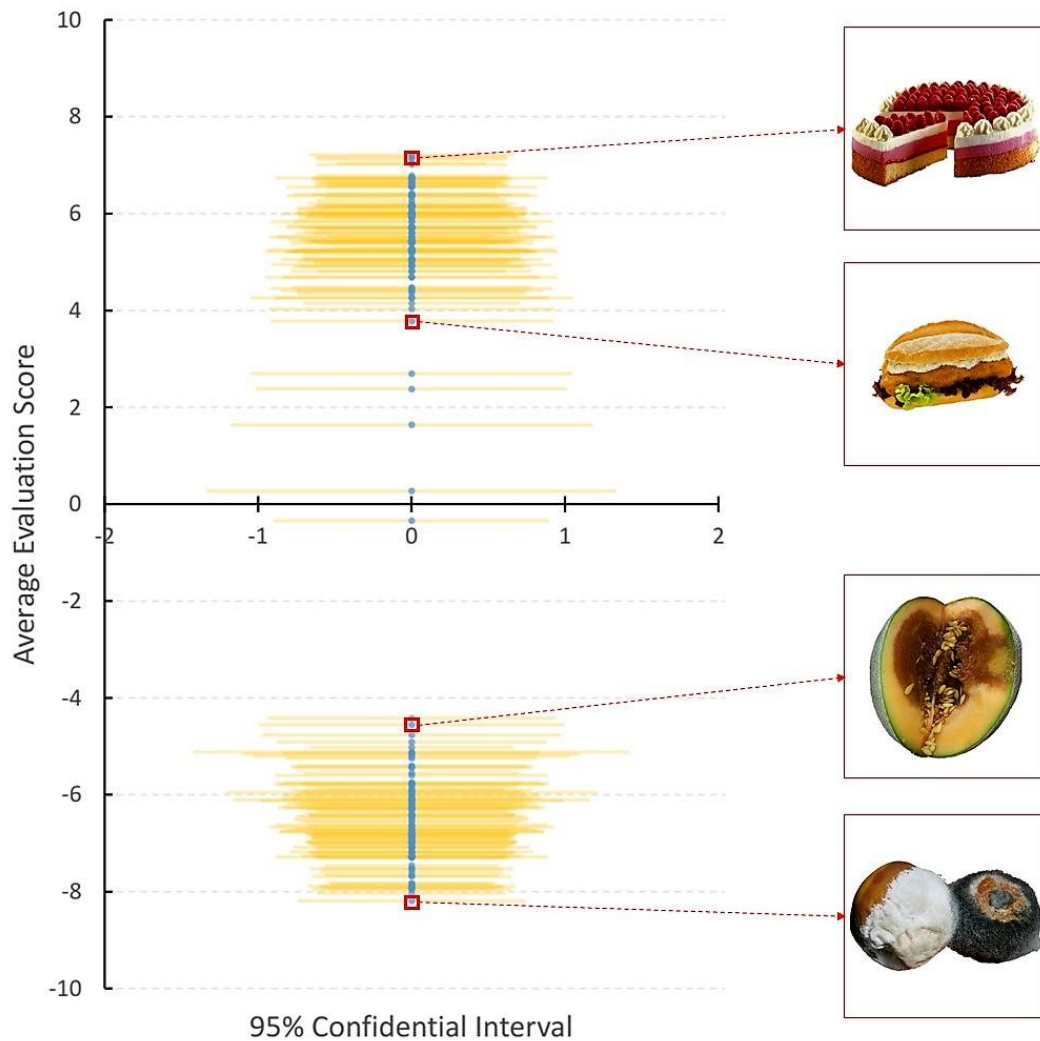


Figure 1. Distribution of the bivalent stimulus set. The blue points and yellow lines reflect the average evaluation scores (blue, vertical axis) and the associated 95% confidence intervals (yellow, horizontal axis) of the 200 images in the database, collapsed across all conditions and all subjects in the present study. Four representative images are shown in inset figures on the right.

Rationale of the present study

The present study was explicitly designed to pitch the congruent bias hypothesis against the opponent mechanism hypothesis. We conducted two experiments in which subjects received a predictive visual cue in advance of a single food image in each trial. The subjects were asked to rate the food image on a scale from -10, for most aversive, to +10, for most appetitive. The database of food images included a balanced variety of images to cover the

entire range on the bipolar scale (see Figure 1). The predictive cue indicated, with varying degrees of reliability, whether the impending food image would be aversive or appetitive. In Experiment 1, the predictive cue was either perfectly reliable or random (see Figure 2). Thus, in Experiment 1, random cues effectively offered only a positive or negative framing. After the presentation of the food image, the subjects could manipulate a joystick to record their evaluation (see Figure 3). In Experiment 2, the predictive cue was either 75% reliable or explicitly neutral. In both experiments we recorded manual responses and eye positions.

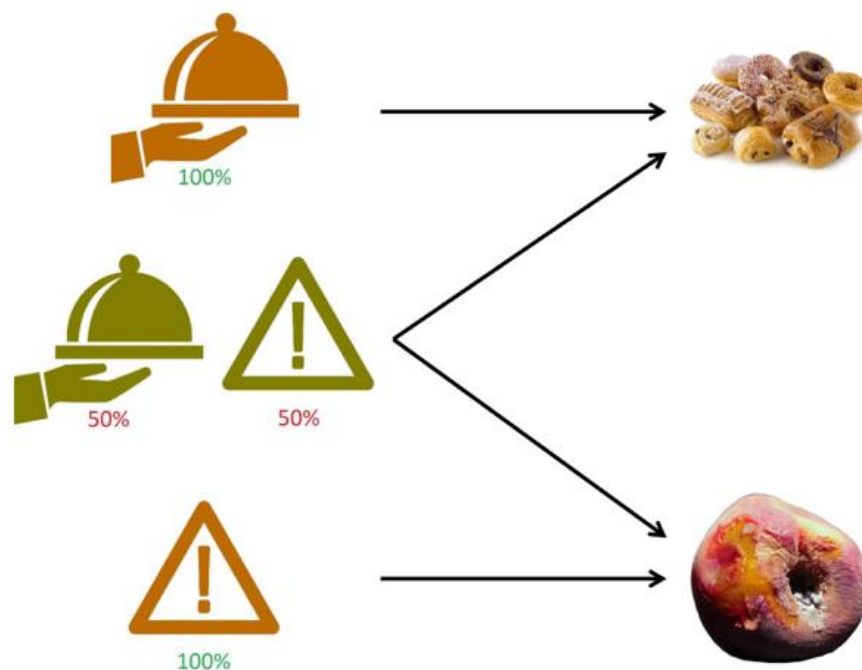


Figure 2. Schematic representation of the predictive cues in Experiment 1, associated with different outcome types. The color indicates the level of reliability (orange, 100%; green, 50%) whereas the icon indicates the valence (tray, positive; hazard, negative). For 50% reliable cues, the predicted valence reflects merely framing.

According to the congruent bias hypothesis as a function of framing, the evaluations for appetitive items would be the highest for perfectly reliable predictions, and higher following positive framing than following negative framing. For aversive items, the evaluations would be the lowest for perfectly reliable predictions, and lower following negative framing than

following positive framing. Given that framing would depend on voluntary control, the size of the framing effects should depend on the reliability of the predictive cues. Framing is also hypothesized to lead to response preparation (i.e., anticipatory eye positioning toward the expected response side), and likewise influence response time, with faster responses when the valence of the target matches with the prediction than when there is a mismatch between prediction and outcome. Theories and phenomena that predict congruent biases on the basis of implicit mechanisms do not predict any influence of the cue's predictive validity, nor do they predict any active response preparation (i.e., no prediction of effects on response time or eye prepositioning).

According to the opponent mechanism hypothesis, the evaluations for appetitive items would be higher following negative framing than following positive framing, and again higher following positive framing than following perfectly reliable predictions. That is, when unexpected or running against the prediction, a positive item would elicit the largest counteractive amplification and therefore receive the most favorable evaluation. Analogously, the evaluations for aversive items would be lower following positive framing than following negative framing, and again lower following negative framing than following perfectly reliable predictions. That is, when unexpected or running against the prediction, a negative item would elicit the strongest amplification and therefore receive the lowest evaluation.

The opponent mechanism hypothesis, as a function of cognitive control, would imply counteractive response preparation (i.e., eye prepositioning toward the direction opposite to the prediction, and slowing of responses that match with the prediction). Opponent mechanisms on the basis of implicit processes (i.e., prediction error) should not affect eye prepositioning or response time.

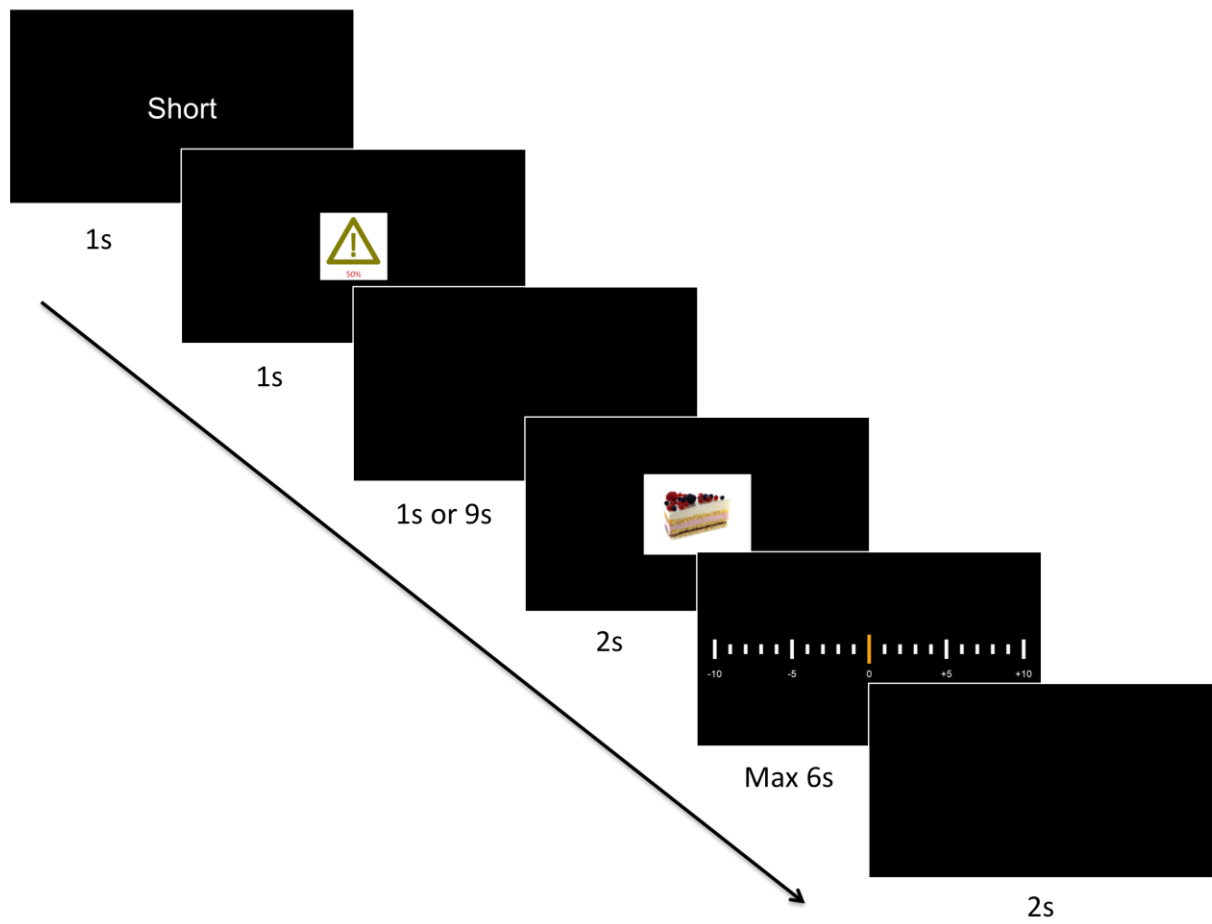


Figure 3. Trial structure in Experiment 1. Each trial starts with a word cue, presented for 1 s, indicating whether it will be either a short- or long-delay trial. The predictive cue is shown for 1 s, followed by a blank screen for either 1 s (short delay) or 9 s (long delay). The target image is shown for 2 s at the center of the screen, followed by the evaluation bar. Participants have maximally 6 s to respond by bending the joystick. The response is followed by a 2 s inter-trial interval.

Methodology

Subjects

In Experiment 1, there were 42 subjects. All were Kyushu University students (26 males, 16 females) with a mean age of 22.45 ± 3.63 years. In Experiment 2, there were 66 subjects. All were Kyushu University students (38 males, 28 females) with a mean age of 23.94 ± 4.54 years. There were 3 left-handed subjects in Experiment 1, and 2 in Experiment 2; however, these subjects also used their right hand to manipulate the joystick.

In both experiments, all subjects had normal or corrected-to-normal vision. Each person was given 1000 yen as a compensation for the participation, which lasted less than 1 hour. All subjects gave informed consent, and reported that they were in healthy condition before and after the experiment.

Apparatus and stimuli

The visual stimuli were presented in a dimly lit room on a 23.8-inch full high definition flat-panel-monitor, with a display resolution of 1920×1080 pixels. The subjects were seated approximately 62 cm from the monitor. To minimize head movement a chin-rest with a forehead-support was used. The evaluation responses were recorded using a joystick (Logitech, Switzerland; model no. 963290-0403). Eye positions were recorded using Eye Tribe, an eye-tracking device at 60 Hz sampling rate (The Eye Tribe Aps, Denmark); a system with sufficient reliability for present purposes (Dalmaijer, 2014; Ooms, Dupont, Lapon, & Popelka, 2015; Wolf et al., 2018; Zommara, Takahashi, Ounjai, & Lauwereyns, 2018).

In order to start the eye tracking, the subject was asked to follow a dot on the screen for a 16-point calibration. After the calibration, the gaze coordinates were calculated through Eye Tribe with an average error of less than 0.5° visual angle on the 23.8-inch display. To prevent

heat buildup a small universal serial bus (USB) fan was used. All events and recordings were controlled through code written in Psychopy version 1.84.2 (Peirce, 2007, 2009) including the PyTribe library.

All visual stimuli were presented as inset images on a white background in the middle of the otherwise black screen. The size of the inset image was fixed at 380×380 pixels for the predictive cues, and at 600×600 pixels for the food images. The predictive cues were icons: a tray for positive; a hazard sign for negative; and a checkerboard for neutral. Different colors were used (counterbalanced across subjects) to indicate the reliability of the cues in Experiment 1. Food images were drawn from the FoodCast research image database (FRIDa) (Foroni, Pergola, Argiris, & Rumiati, 2013) and supplemented with non-copyrighted images to construct a set of 200 food images with a balanced range of appetitive and aversive stimuli. If necessary, images were resized to fit in the frame of 600×600 pixels. The images were classified into 100 appetitive and 100 aversive stimuli based on the categorization by FRIDa and ratings by lab members. The categorizations proved valid for all 200 images based on the average responses of all subjects in Experiments 1 and 2: Each stimulus in the category of aversive food images received on average a negative rating, whereas each stimulus in the category of appetitive food images received on average a positive rating.

Experimental procedures

Experiment 1.

Participants were asked to evaluate 180 naturalistic food images in 3 consecutive blocks of 60 trials with breaks of not more than 5 minutes between the blocks. At the start of each trial, the word “short” or “long” was presented for 1s in the middle of the screen to indicate the delay time between the predictive cue and the target image, either 1s or 9s. Next the predictive cue

was shown at the center of the screen for 1s, followed by the blank screen for the delay period. Then the target image was shown for 2s, and in turn replaced by the response screen. The subject had maximally 6s to evaluate the food image by bending the joystick to move the cursor on the evaluation bar from -10 to 10. The bending angle was used to indicate the evaluation score. After the response was made, there was a blank screen for 2s as inter-trial interval (ITI).

Different icons were used for the predictive cues to indicate the outcome, either appetitive or aversive, whereas the color indicated the reliability level of the cue, either 100% or 50% reliability. The color assignment was counterbalanced across subjects. The reliability of the predictive cue was further indicated numerically in percentage, presented in small print beneath the icon.

The subjects were instructed to give their evaluation for each food image, focusing on the appeal of the image, not their general preference of the pictured food item. The evaluations had to be given on a continuous rating scale from -10 to 10, with a value of -10 for a maximally disgusting food image, a value of +10 for a maximally attractive food image, and a value of 0 for a food image that was neither likeable nor disgusting. The subjects were instructed to start bending the joystick for evaluation only after the evaluation bar appeared on the screen.

It was explained to the subjects that the cues predicted whether the upcoming food image would be likeable or dislikeable, with different levels of certainty, either 100% certain or 50%.

Before the experimental session, the subjects were given the opportunity to practice controlling the joystick for up to 30 times. The experiment included 180 trials, consisting of 15 repetitions of each of the 12 conditions, with 3 levels Cue Type (Certain, Valid, Invalid), 2 levels of Outcome Type (Positive, Negative), and 2 levels of Delay Time (1s, 9s). No food

image was presented more than once. The 180 trials were presented in pseudorandom order to ensure that each block of 60 trials contained 5 repetitions of each condition.

Experiment 2.

Participants were asked to evaluate 200 naturalistic food images in 4 consecutive blocks of 50 trials with breaks of not more than 5 minutes between the blocks. The procedures were the same as in Experiment 1 except for the following. The delay time between the predictive cue and the food image was fixed at 2s; and no word cue was given to indicate the delay time at the beginning of the trial. The cue reliability for the positive and negative cues was fixed at 75%, and a third type of cue was included (a neutral cue, represented by a checkerboard as icon).

The evaluation bar assignment was changed for 2 groups of subjects, with either a conventional alignment (negative – left; positive – right) or the opposite alignment. Here, subjects were asked to confirm their evaluation by clicking the trigger on the joystick.

The experiment included 200 trials, divided into 6 conditions, with 3 levels Cue Type (Valid 75%, Neutral, Invalid 25%) and 2 levels of Outcome Type (Positive, Negative). The Valid 75% conditions consisted of 60 repetitions, whereas the Invalid 25% and the Neutral conditions each consisted of 20 repetitions (see details in Appendix A2). No food image was presented more than once. The 200 trials were presented in pseudorandom order to ensure that each block of 50 trials contained the same distribution of trials per condition.

Results

Experiment 1

In Experiment 1, in addition to the variations of cue types and food images, we manipulated the delay between the predictive cue and the target food image to examine whether the prior expectations strengthen over time (Iigaya et al., 2016; Loewenstein, 1987). If so, any influences from the predictive cues on the evaluative processing of the food images should be larger after long delays than after short delays.

For each subject, the data could be classified into 12 conditions by the type of outcome, the delay time and the type of predictive cue. There were two types of outcome, either positive or negative, and two levels of delay time, either 1s or 9s between predictive cue and target image. For the predictive cues, there were three types defined by the relationship between the predictive information and the actual outcome; a cue with 100% reliability was labeled as “Certain”; a cue with 50% reliability followed by the predicted outcome was labeled as “Valid 50%”; and a cue with 50% reliability followed by the opposite outcome was labeled as “Invalid 50%”.

Evaluation scores.

In order to facilitate the comparison across conditions, for negative outcomes the sign of the given evaluation score was inversed. Figure 4 presents the average evaluation scores in each condition for Experiment 1. Regardless of outcome type and delay time, the evaluation scores appeared to be the highest for the Certain condition, and the lowest for the Invalid 50% condition. Negative outcomes appeared to be rated more extremely than positive outcomes. For statistical analysis of the average evaluation scores, we employed a three-factor analysis of

variance (ANOVA) with repeated measures, in which the factors Outcome Type, Delay Time, and Cue Type were all within subjects.

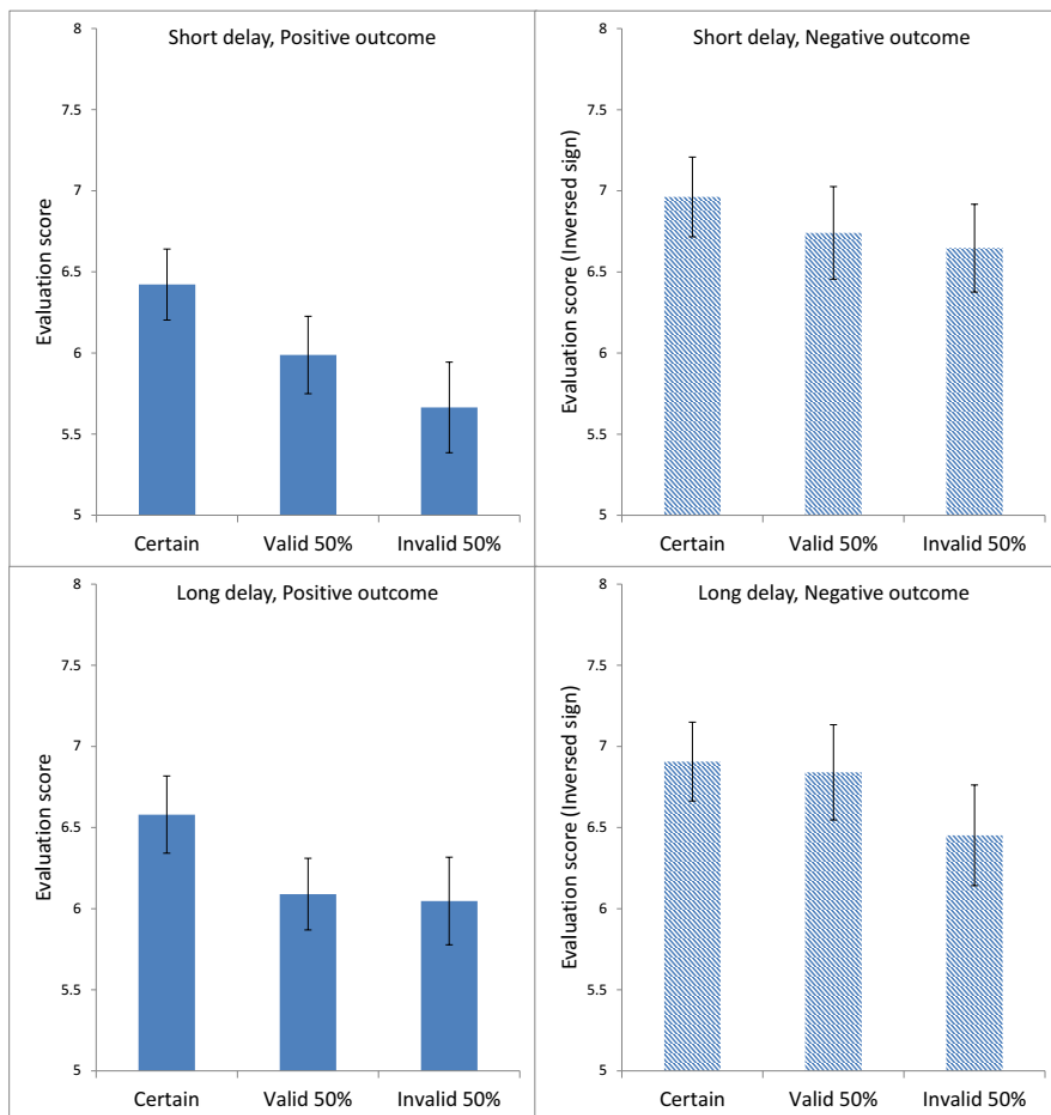


Figure 4. Average ratings in each condition in Experiment 1. Each panel shows data for Certain, Valid 50%, and Invalid 50% conditions. The top two panels are from the short-delay conditions; the bottom two panels from the long-delay conditions. The left two panels present the positive-outcome conditions; the right two panels, the negative-outcome conditions. The signs were inversed for the ratings in the negative outcome conditions in order to facilitate comparison with the positive outcome conditions. The error bars show the standard error of the mean in each condition.

The ANOVA produced a significant main effect of Cue Type, $F(2,82) = 6.560$, $MSE = 1.716$, $\eta_p^2 = 0.138$, $p < 0.005$, as well as a significant main effect of Outcome Type, $F(1,41) =$

4.906, $MSE = 10.073$, $\eta_p^2 = 0.107$, $p < 0.05$. There was no significant effect of Delay Time, $F(1,41) = 1.068$, $MSE = 0.792$, $p = 0.307$. Post-hoc pairwise comparisons using the Bonferroni test indicated that the average evaluation scores in the Certain condition were significantly higher than in the Valid 50% condition at $p < 0.05$, and also significantly higher than in the Invalid 50 % condition at $p < 0.05$. The difference between the Valid 50% and the Invalid 50% condition was not significant, $p = 0.274$.

There was a significant interaction between Delay Time and Outcome Type, $F(1,41) = 4.385$, $MSE = 0.503$, $\eta_p^2 = 0.097$, $p < 0.05$. Post-hoc comparisons using the Bonferroni test showed, for short-delay trials, significantly more extreme evaluation scores for negative outcomes than for positive outcomes at $p < 0.05$, whereas in long-delay trials there was no significant difference between positive and negative outcomes, $p = 0.653$. There were no other significant interactions (all F values less than 2).

Manual response times

Response times were measured from the onset of the screen with the evaluation bar until a bend was detected in the joystick. By this definition, all trials in which the subject started bending the joystick before the onset of the screen with the evaluation bar were excluded from the analysis. For this reason, a total of 9.93% of all trials was rejected for the response time analysis. Two subjects started bending the joystick prematurely in every trial in some conditions; the data from these two subjects were excluded from the ANOVA analysis on response time.

Figure 5 presents the subjects' average response times in Experiment 1, using the same format as for the evaluation scores in Figure 4. Visual inspection suggested that the response

times tended to be the fastest in the Certain condition and the slowest in the Invalid 50% condition.

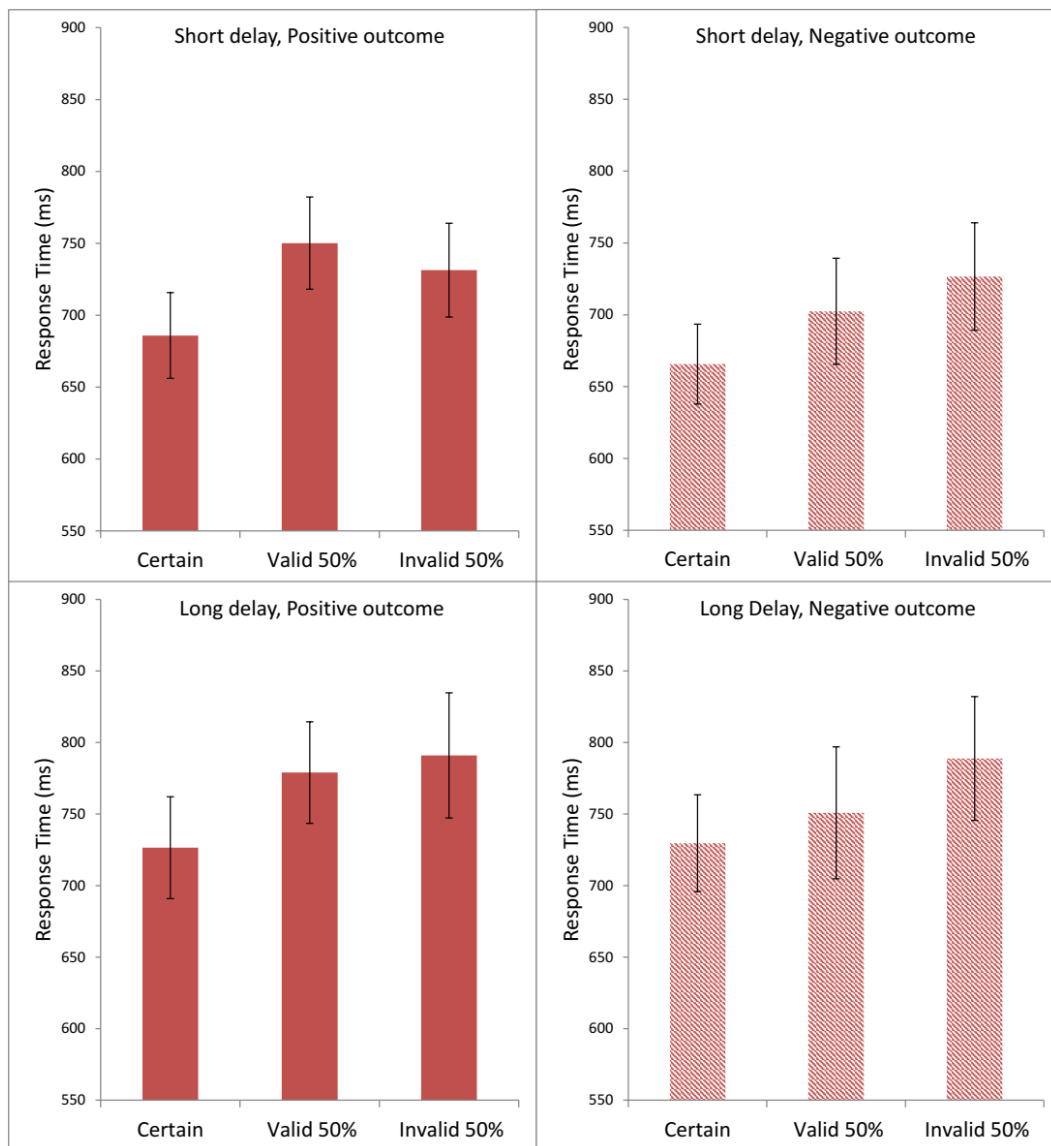


Figure 5. Average response times (ms) in each condition in Experiment 1. Each panel shows data for Certain, Valid 50%, and Invalid 50% conditions. The top two panels are from the short-delay conditions; the bottom two panels from the long-delay conditions. The left two panels present the positive-outcome conditions; the right two panels, the negative-outcome conditions. The error bars show the standard error of the mean in each condition.

Preliminary normality tests (Shapiro-Wilk) showed significant deviations from normality in the response times. For this reason, the subsequent statistical analysis of response times was conducted on a simple inverse transformation ($1/RT$) (Whelan, 2008), which yielded

normal distributions. Statistical analysis, with a three-factor repeated measures ANOVA, completely within subjects, produced a significant main effect of Cue Type, $F(2,78) = 9.163$, $MSE = 0.045$, $\eta_p^2 = 0.190$, $p < 0.001$, and also of Delay Time, $F(1,39) = 34.061$, $MSE = 0.039$, $\eta_p^2 = 0.466$, $p < 0.001$. Outcome Type did not have a significant effect on the response time $F(1,39) < 1$. Post-hoc comparisons using the Bonferroni test indicated that the average response time in the Certain condition was significantly faster than in the Valid 50% condition at $p < 0.01$, and also significantly faster than in the Invalid 50% condition at $p < 0.01$. The difference between the Valid 50% and the Invalid 50% condition was not significant, $p = 0.802$.

There were no significant interactions (all F values less than 1.5).

Gaze distribution data

In order to examine whether the predictive cues elicited an anticipatory response bias, we analyzed the average gaze positioning during the delay period. A response bias should lead the subjects' gaze positions to deviate toward the direction associated with the predicted outcome (in Experiment 1: negative – left, positive – right). This analysis of gaze positioning is focused on the blank screen period before target onset; at this time, before the outcome is known, the cue conditions can only be separated between 100% reliable and 50% reliable. In this analysis, then, the data were classified into eight conditions according to Delay Time (1s or 9s), Cue Valence (either positive or negative) and Cue Reliability (50% or 100%). For each subject in each condition, the average horizontal eye position was calculated during the delay relative to the blank screen.

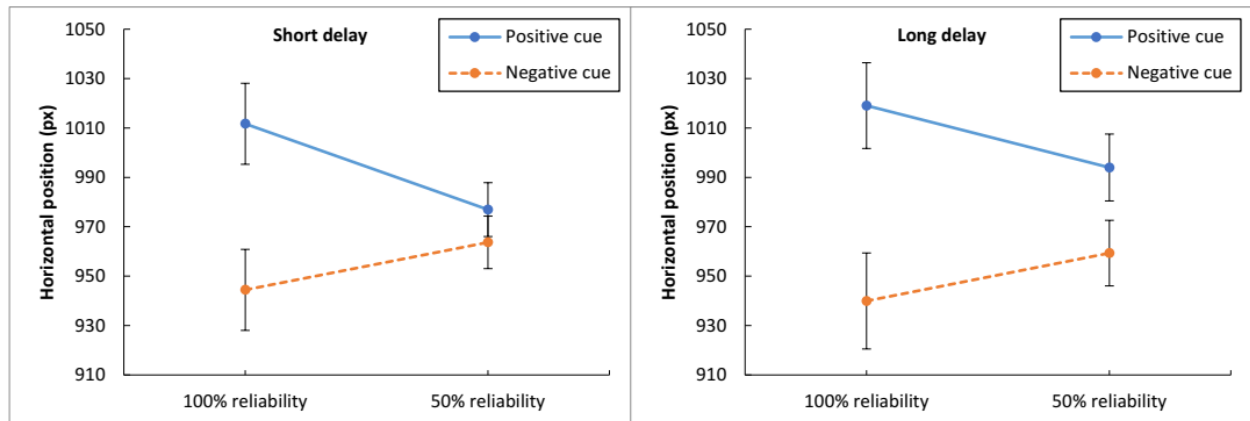


Figure 6. Average horizontal eye positions during the delay period in Experiment 1, as a function of delay duration, cue reliability, and cue valence. The Y-axis represents the horizontal position on the screen (the screen width is set to 1920 pixels). The left panel shows the data for the short-delay trials; the right panel, for the long-delay trials. The conditions with positive cues are shown in blue; with negative cues, in orange. The error bars represent the standard error of the mean.

Figure 6 presents the average horizontal eye positions during the delay as a function of condition in Experiment 1. For both delay durations, the average horizontal eye positions appeared to be shifted to the left or right depending on the cue valence, with more pronounced biases for 100% reliable cues and for longer delays.

A three-factor repeated measures ANOVA indicated that Cue Valence produced a statistically significant effect on the average horizontal eye positions, $F(1, 41) = 6.937$, $MSE = 28559.298$, $\eta_p^2 = 0.145$, $p < 0.05$. Delay Time, $F(1, 41) < 1$, and Cue Reliability, $F(1, 41) = 3.297$, $MSE = 714.375$, $p = 0.077$, did not produce a significant effect on the gaze positioning.

There was a significant interaction between Cue Valence and Delay Time, $F(1, 41) = 6.402$, $MSE = 906.995$, $\eta_p^2 = 0.135$, $p < 0.05$, and also between Cue Valence and Cue Reliability, $F(1, 41) = 7.213$, $MSE = 7051.153$, $\eta_p^2 = 0.150$, $p = 0.010$. There were no other interaction effects (the remaining F values < 1). Overall, the gaze positioning showed significant response biases associating positive cues with the rightward direction, negative cues

with the leftward direction. These biases were particularly pronounced for long delays and 100% reliable cues.

Experiment 2

In Experiment 2, we investigated further the effect of the reliability level of the predictive cues, as well as the response bias observed in the gaze positioning. One concern with the response bias was that in the previous experiment, we employed only one fixed scheme of mapping between spatial position and response (negative – left; positive – right). To ensure that the response bias followed from the prediction rather than any inherent spatial bias, we counterbalanced the mapping between spatial position and response across subjects in Experiment 2. Thus, we divided the subjects into two groups; one group was always presented with the default evaluation bar (as in Experiment 1; negative – left; positive – right); and the other group was always presented with a flipped evaluation bar (positive – left; negative – right).

With respect to cue reliability, instead of using certain versus random cues, in Experiment 2 we set a fixed reliability of 75% for both positive and negative cues, and further included a neutral cue type (a checkerboard, without positive or negative framing). Finally, in Experiment 2 the delay time was fixed at 2s.

Thus, there were 12 conditions, with one between-subjects factor, Evaluation Bar (default versus flipped), and two within-subjects factors, Outcome Type (positive or negative) and Cue Type. For the Cue Type, there were three types defined by the relationship between the predictive information and the actual outcome; cues followed by the predicted outcome were labeled as “Valid 75%”; cues followed by an outcome opposite to the prediction were labeled as “Invalid 25%”; and cues that did not predict an outcome were labeled as “Neutral”.

Evaluation scores

As before, for negative outcomes the sign of the given evaluation score was inversed. Figure 7 presents the average evaluation scores in each condition for Experiment 2. The predictions appeared to affect the evaluation scores for positive outcomes, but not for negative outcomes. For positive outcomes, the effects of the predictions again suggested spill-over rather than updating. For statistical analysis of the average evaluation scores, we employed a three-factor analysis of variance (ANOVA) with repeated measures, in which the factors Outcome Type and Cue Type were within subjects, whereas the factor Evaluation Bar was between subjects.

The ANOVA produced a statistically significant main effect of Outcome Type, $F(1,64) = 10.071$, $MSE = 6.654$, $\eta_p^2 = 0.136$, $p < 0.005$. The main effect of Cue Type was not statistically significant, $F(2,128) = 2.934$, $MSE = 0.815$, $p = 0.057$, nor was that of the between-subjects factor Evaluation Bar, $F < 1$.

There was a statistically significant interaction between Cue Type and Outcome Type in the average evaluation scores, $F(2,128) = 7.120$, $MSE = 0.403$, $\eta_p^2 = 0.100$, $p < 0.005$. Post-hoc pairwise comparisons, with the Bonferroni test, showed that for negative outcomes, there were no significant effects of cue type, whereas for positive outcomes, the average evaluation scores in the Valid 75% condition were significantly higher than those in the Invalid 25% condition at $p < 0.05$, and significantly higher than those in the Neutral condition at $p < 0.001$.

There were no two-way or three-way interactions with the between-subjects factor Evaluation Bar (all F values < 1).

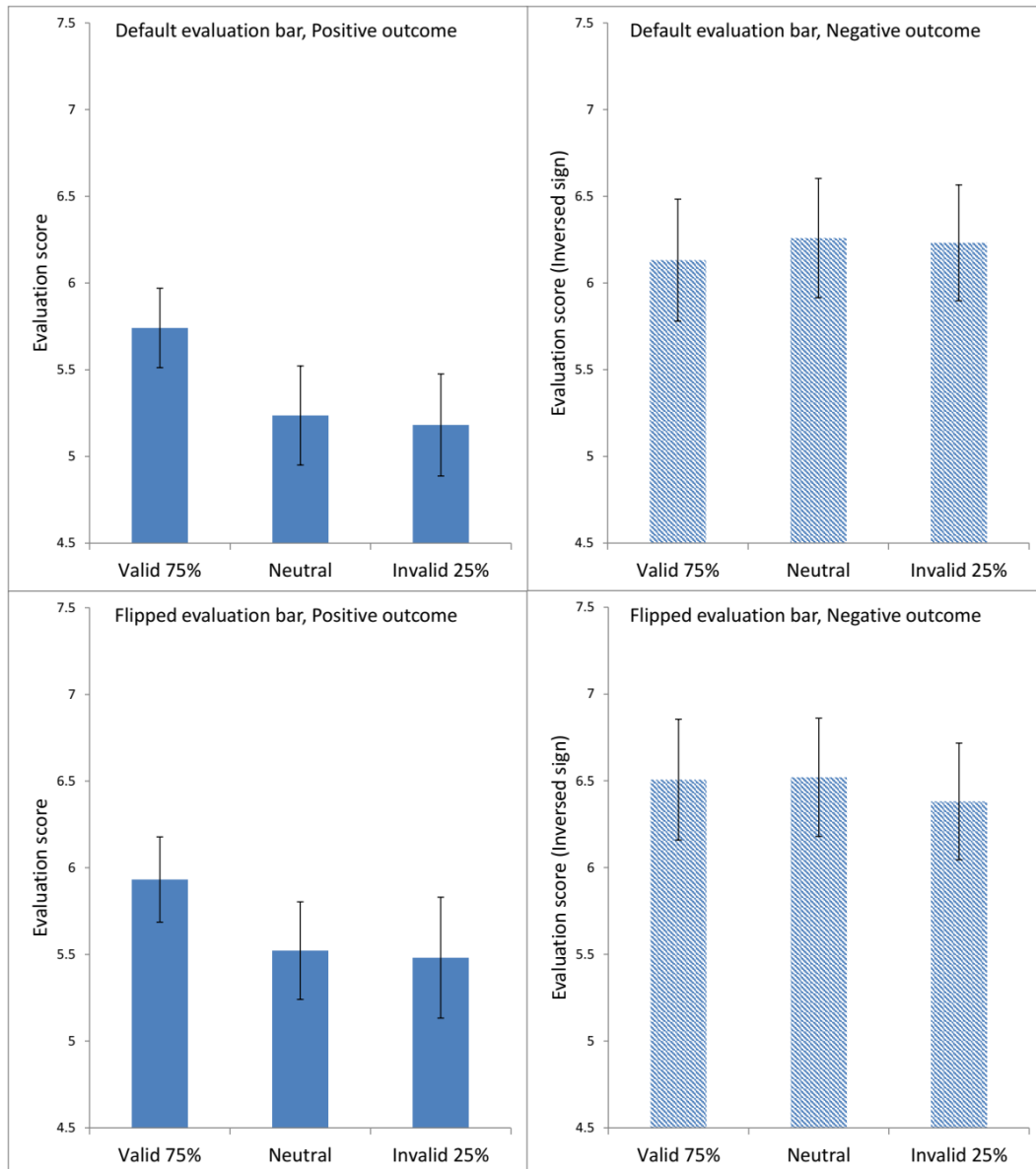


Figure 7. Average ratings in each condition in Experiment 2. Each panel shows data for Valid 75%, Neutral, and Invalid 25% conditions. The top two panels show data from participants who used the Default Evaluation Bar; the bottom two panels are from participants who used the Flipped Evaluation Bar. The left two panels present the positive-outcome conditions; the right two panels, the negative-outcome conditions. The signs were inversed for the ratings in the negative outcome conditions in order to facilitate comparison with the positive outcome conditions. The error bars show the standard error of the mean in each condition.

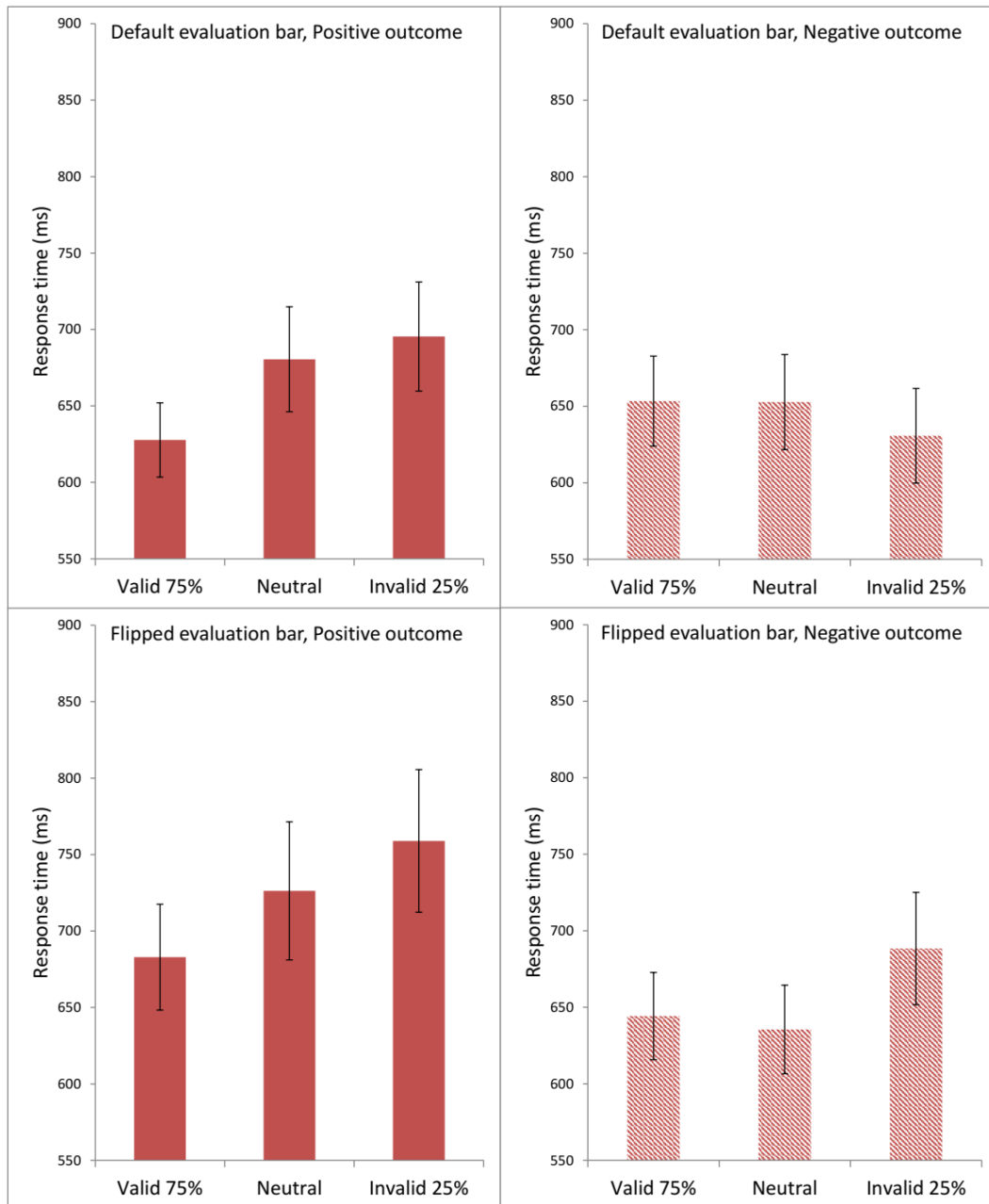


Figure 8. Average response times (ms) in each condition in Experiment 2. Each panel shows data for Valid 75%, Neutral, and Invalid 25% conditions. The top two panels show data from participants who used the Default Evaluation Bar; the bottom two panels are from participants who used the Flipped Evaluation Bar. The left two panels present the positive-outcome conditions; the right two panels, the negative-outcome conditions. The error bars show the standard error of the mean in each condition.

Manual response times

In order to prevent a loss of data due to premature bending of the joystick, in Experiment 2 the response method was modified by requiring the subjects to press the button

on the joystick with their index finger for confirmation. Thus, response time was defined as the time between the onset of the response screen and the button press on the joystick. Figure 8 presents the average response times in each condition in Experiment 2, using the same format as Figure 7. Overall the Valid 75% conditions appeared to produce the fastest response times, particularly for positive outcomes.

As in Experiment 1, preliminary normality tests (Shapiro-Wilk) showed significant deviations from normality in the response times; the subsequent statistical analysis was conducted on the inverse response times, which yielded normal distributions. A three-factor repeated measures ANOVA produced a significant main effect of Outcome Type, $F(1,64) = 4.531$, $MSE = 0.118$, $\eta_p^2 = 0.066$, $p < 0.05$. The factor Cue Type did not produce a significant main effect, $F(2,128) = 2.605$, $MSE = 0.033$, $p = 0.078$, nor did the between-subjects factor Evaluation Bar, $F < 1$. There was a statistically significant interaction between Cue Type and Outcome Type, $F(2,128) = 3.905$, $MSE = 0.030$, $\eta_p^2 = 0.058$, $p < 0.05$. Post-hoc pairwise comparisons using the Bonferroni test showed that, for positive outcomes, there was a significant difference between the Valid 75% condition and the Invalid 25% condition at $p < 0.01$, but not between the Valid 75% and the Neutral conditions, $p = 0.056$, nor between the Neutral and the Invalid 25% conditions, $p = 0.530$. Conversely, for negative outcomes, there were no significant differences as a function of Cue Type (all p values above 0.7).

There was no significant interaction between Cue Type and the between-subjects factor Evaluation Bar, $F(2,128) = 2.771$, $MSE = 0.033$, $p = 0.066$, nor between Outcome Type and Evaluation Bar, $F < 1$. The three-way interaction was also not significant, $F(2,128) = 1.796$, $MSE = 0.030$, $p = 0.170$.

Gaze distribution data

As in Experiment 1, we analyzed the gaze positioning during the delay period in Experiment 2 to examine whether the predictive cues elicited a response bias. In this analysis, focused on the blank screen period before target onset (i.e., when the outcome is not yet known), the data were classified into six conditions by the between-subjects factor Evaluation Bar (default or flipped) and the within-subjects factor Cue Type (either positive, neutral, or negative). For each subject in each condition, the average horizontal eye position was calculated during the delay relative to the blank screen.

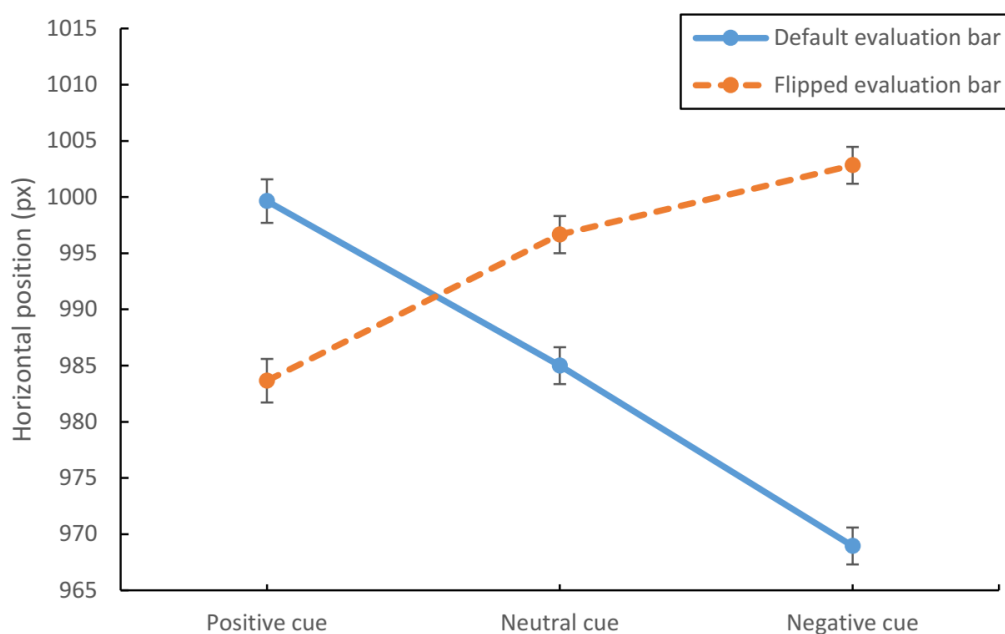


Figure 9. Average horizontal eye positions during the delay period in Experiment 2, as a function of the type of cue and evaluation bar. The Y-axis represents the horizontal position on the screen (the screen width is set to 1920 pixels). The data with the Default Evaluation Bar are shown in blue; with the Flipped Evaluation Bar, in orange. The error bars represent the standard error of the mean.

Figure 9 presents the average horizontal eye positions during the delay as a function of condition in Experiment 2. The data appeared symmetrical for the two groups of subjects, suggesting that the gaze positioning flipped as a function of evaluation bar alignment,

implementing response biases (toward the negative or positive pole depending on the prediction).

In the subsequent ANOVA, in order to facilitate the comparison with different evaluation bar alignments, we used the inverse of the horizontal eye position data in the flipped evaluation bar condition; that is, we subtracted the given horizontal eye positions from the maximal horizontal pixel value (1920). This procedure aligns the horizontal eye position data of the two groups in the same direction, so that any response biases yield similar numerical values across the evaluation bar conditions.

A repeated measures ANOVA confirmed that the within-subjects factor Cue Type had a statistically significant impact on the gaze positioning during the blank screen period, $F(2,128) = 40.023$, $MSE = 257.261$, $\eta_p^2 = 0.385$, $p < 0.001$. Post-hoc pairwise comparisons using the Bonferroni test showed that there were statistically significant differences in the average horizontal eye positions at $p < 0.001$ for all pairwise comparisons among the three cue types. The horizontal eye positions leaned most toward the positive pole following positive cues ($M = 967.992$, $SD = 7.872$), and most toward the negative pole following negative cues ($M = 943.061$, $SD = 6.667$), implying more central positioning after neutral cues ($M = 954.169$, $SD = 6.726$).

Also the between-subjects factor Evaluation Bar produced a significant effect on the average horizontal eye positions, $F(1,64) = 18.088$, $MSE = 9495.071$, $\eta_p^2 = 0.220$, $p < 0.001$. However, there was no interaction between Cue Type and Evaluation Bar, $F(2,128) = 2.493$, $MSE = 257.261$, $p = 0.087$.

Discussion

Two experiments were conducted to examine the effects of predictive cues on the evaluation of single food images. The experiments pitched the congruent bias hypothesis, as a function of framing (Cunningham et al., 2008; Iigaya et al., 2016; Jin et al., 2017; Levin et al., 1985; Loewenstein, 1987; Tversky & Kahneman, 1981; Wilson et al., 1989) or more implicit processes (e.g., priming or emotional contagion) (Bargh, 2006; Cartoni et al., 2016; Dalenberg et al., 2014; Geurts et al., 2013; Howard & Gengler, 2001; Morales & Fitzsimons, 2007; Stöckli et al., 2016; Wright et al., 2018), against the opponent mechanism hypothesis, derived from the concepts of proactive control (Amodio & Swencionis, 2018; Cheng et al., 2014; Geers & Lassiter, 1999; Stamos et al., 2018; van Wouwe et al., 2009) and prediction error (Berridge, 2007; O'doherty, 2012; Schultz, 2013; Schultz et al., 1997). In Experiment 1, we found that the evaluation scores were influenced by the predictive cues, such that 100% reliable cues produced more extreme scores than 50% reliable cues, both for aversive and for appetitive food images, suggesting the operation of a congruent bias. The response times showed slower responses following 50% reliable cues than following 100% reliable cues, further implicating a selective response preparation in line with the predictions. Gaze prepositioning during the delay period, after prediction but before the food image, also suggested a response bias in accordance with the predictions.

Experiment 2 provided corroborating evidence, again showing that the evaluation scores were influenced by the predictive cues, with 75% reliable cues leading to more extreme scores for correct predictions than for incorrect predictions, suggesting congruent bias effects, particularly in the case of appetitive food images. Once again, the response times showed slower responses following incorrect predictions than following correct predictions, indicating that prior expectation guided the selective response preparation. Gaze prepositioning during

the delay period also exhibited a response bias in accordance with the predictions, regardless of the spatial alignment of positive versus negative poles.

Positive predictive cues elicited an anticipatory process that set up a congruent response bias, leading to gaze prepositioning in the spatial direction associated with the positive pole of the evaluation bar. This response bias caused appetitive images to be evaluated more positively while (in case of erroneous prediction) causing aversive images to be evaluated less negatively. Conversely, the opposite processes occurred for negative predictions. Crucially, these anticipatory processes and response biases reflected active inferences (Friston, 2010; Hohwy, 2013), depending on the perceived reliability of the predictive cues, with stronger effects for more reliable cues.

Taken together, both experiments provided solid evidence in favor of the congruent bias hypothesis. As a corollary, the data charted how external influences from prior (“objective”) information can have a significant impact on subsequent (“subjective”) evaluative processing, underscoring the potential importance of this line of research for other domains of value-based decision-making (e.g., in politics and bioethics).

Congruent Bias as an Active Process toward Confirmation

Several elements in the data suggested a role for active, deliberative processing in response to the predictive information rather than merely effects from automatic associations. The effects of cue reliability on evaluation scores suggested voluntary control of expectation. In Experiment 1, the congruent bias was large following cues with 100% reliability, but there was no significant difference between the 50% Valid and 50% Invalid condition. In Experiment 2, the 75% reliable cues did have an impact on the evaluation scores, particularly for positive outcomes (with more extreme scores in the 75% Valid condition than in the 25% Invalid

condition). The pattern of data suggested that the subjects set their expectations based on the perceived reliability of the predictive cues – strongly for highly reliable cues, somewhat for reasonably reliable cues, and not so much for unreliable cues. Most likely, this was due to actively controlled usage of the predictive cues.

Here, it should be noted that the active processing of predictive information does not necessarily preclude the existence of concurrent, more implicit types of interference. A useful approach in this regard, compatible with the concept of framing (Cunningham et al., 2008; Iigaya et al., 2016; Jin et al., 2017; Levin et al., 1985; Loewenstein, 1987; Tversky & Kahneman, 1981; Wilson et al., 1989), may be that of the somatic marker hypothesis (Bechara, Damasio, & Damasio, 2000; Damasio, 1996; Verweij, Senior, Domínguez, Juan, & Turner, 2015). Applying this hypothesis to the current data, we might suggest that the covert action of “marker” signals underpinned the introduction of a congruent bias in the selection of an aversive or appetitive mode of processing. Importantly, this hypothesis contends that it is erroneous to limit human decision-making to mechanisms of either conditioning alone or cognition alone. Thus, while the concurrent operation of conditioning cannot – should not – be excluded, the relevant point here is that the cue reliability determined the degree of impact from predictive information. This finding implicates cognitive control and active processing.

Apart from the dependence of evaluative processing on the reliability of the predictions, two further aspects of the data suggest that the impact of external influences was mediated via active, cognitive control. Notably, the gaze prepositioning indicated a selective preparation aligned with the expected direction of response. This gaze prepositioning was likewise sensitive to the cue reliability, with more pronounced prepositioning for more reliable predictive cues. Also, the response times indicated that the evaluative processing was more effortful following incorrect predictions than following correct predictions, again suggesting

an active form of inference relative to the earlier prediction. Once more, the effects on response times depended on the reliability of the predictive cues.

The effortful, slower evaluative processing following incorrect predictions produced less extreme scores than the faster evaluative processing following correct predictions. For instance, an appetitive food image presented after a positive cue tended to quickly receive a highly positive evaluation, whereas an appetitive food image presented after a negative cue tended to receive a less positive evaluation after a longer deliberation, as if the subject tried to accommodate the prediction (finding something negative in the image, or trying to attenuate the discrepancy between prediction and outcome by reducing the evaluation). This may be thought of as an active attempt to assimilate a surprising stimulus to a prior expectation (Davidenko et al., 2018). Interestingly, there appeared to be an asymmetry, particularly in Experiment 2, with 75% reliable cues showing influences from prediction on the evaluation of appetitive images, but not on the evaluation of aversive images. This suggests that, relatively speaking, the evaluative processing of appetitive images is more vulnerable to external influences. Negative predictions tend to distort the reception of appetitive images, whereas aversive images appear to be more immune to positive framing.

In conclusion, the predictions produced a congruent response bias that can best be characterized as an active confirmation bias. Depending on the perceived reliability, positive predictive cues elicited an active positive anticipation of the food images, whereas negative cues elicited an active – and relatively stronger – negative anticipation. Correct predictions produced quick and amplified evaluation scores. Erroneous predictions produced slow and less extreme evaluation scores in an apparent effort to accommodate the prediction.

Chapter 3: Further investigation in the absolute evaluation process

Introduction

Along the process of current study, there are other additional analysis methods that had been done for observing other aspects of predictive cue in this absolute evaluation process. The results of these analyses which will show in this chapter, on one hand, had been done as exploratory process within the capacity of current equipment and experimental setup but, in the other hand, show more insightful about the underlying mechanism of evaluation process in general. Some results are also useful as additional supplements for showing the robustness of the experimental task while some also open the new possibility of future works in our laboratory pipeline.

This chapter starts with the investigation of the effect of predictive cue on the pupil dilation. As the potential physiological data that can be measured by Eye tribe with the adequate quality of data for research in comparison to other eye-trackers in market (Dalmaijer, 2014), the pupil dilation in many moments of experimental paradigm was investigated. According to previous studies, pupillary responses can be used as a physiological measurement for the affective process of visual (Bradley, Miccoli, Escrig, & Lang, 2008; Hess & Polt, 1960; Kuchinke, Trapp, Jacobs, & Leder, 2009) and auditory stimulation (Partala & Surakka, 2003). The pupil dilation analysis was used in wide range of cognitive psychology study such as indicating attention shifts (Wierda, van Rijn, Taatgen, & Martens, 2012), preconscious state of decision making and online measurement for the noradrenergic system's locus coeruleus as summarized in (Laeng, Sirois, & Gredebäck, 2012).

According to these literatures, there is feasibility that different features of predictive cues can trigger the different pattern of pupillary responses and might show underlying

mechanism behind predictive processing of our brain. In this thesis, the pupil dilation analysis was done solely on the data of experiment 1 because, even though the results of the pupil dilation analysis are interesting, the results suggest that other experiments that specifically design to support the investigation of this finding are required. The conclusion of pupil dilation results also leads to the design decision of experiment 2 that is not focused on the investigation many aspects of eye behaviours but shift to mainly investigate the gaze distribution instead.

Other concern in our paradigm is the sequential effects of the experiments that whether evaluation process of given trial was influenced by the stimuli or cue in the previous trial or not. There are evidences in the previous studies shows that sequential effect can be confounds in absolute judgement of physical properties of stimuli (Holland & Lockhead, 1968) or subjective decision of some stimuli set such as attractiveness of face (Kondo, Takahashi, & Watanabe, 2012) and TV performance (Page & Page, 2010). In order to validate the confound of sequential effects in current experimental paradigm, the history analysis of evaluation score has been done in both experiment to observe the influence of outcome valence and cue validity in previous trial on the evaluation score of current trial conditions.

Finally, the analysis on evaluation score of both experiments by split the response of each individual into two groups using the median of response time as the criteria show interesting relationship between reaction time and evaluation score. Moreover, this analysis was done for investigating the consistency of predictive cue effect on evaluation score in both slow and fast response condition. According to the results, it shows the possibility that people use different decision process when people voluntary decide to give response fast or slow by themselves. The conclusion of this analysis open up the new feasible research line that will conduct in near future for observing this mechanism.

Method

Pupil dilation analysis

From the task design of experiment 1, the valence of predictive cues has been embedded by the cue shape and the cue reliability level has been notified by cue color. In experiment 1, cue color had been counter-balanced between group; green color mean 100% reliability level and orange color mean 50% reliability level for one group of subjects while the meaning of color is switched in the another group of subjects. According to counter-balancing procedure, the effect of cue valence, cue reliability and cue color on pupil dilation can be investigated in the population analysis. The analysis also has been done separately for 1s and 9s delay conditions because participants exposed to the blank screen in the different duration which affect the pupil size of participants because of the adaptation to dark environment.

In the pupil dilation analysis, the baseline data is calculated by averaging pupil size during inter-trial-interval of the previous trial which is mean that the first trial of each block will be excluded from the analysis. As minimum requirement, the valid trial for this analysis should have at least 100ms long of captured data during ITI period for calculating baseline. Trials that had measurement issues and did not reach the minimum requirement were rejected from the analysis. Data of each trial across the whole population that pass rejection criteria will be categorized by cue valence, cue color and cue reliability level. The average changes of pupil size in comparison to the baseline for each individual in each specific trial are presented separately in each experimental conditions. Note that, the pupil size is shown in arbitrary unit provide by Eye tribe SDK.

The results are shown in two different periods of time; during blank screen after the predictive cue and during the stimuli exposure. For the pupil dilation results during blank screen, the results of 1s and 9s delay are separated into two graphs because of the different duration of delay time. The pupillary responses in each delay time condition are presented in

two separate graphs; either summarize by cue reliability level regardless of cue color or by cue color regardless of cue reliability level. For the pupil dilation during stimuli exposure, the result of pupil dilation is categorized only by the delay time and outcome valence since the dilation should affect only by the stimuli condition, not cue condition.

History analysis

To observe the influence of sequential effect on this experimental design, the behavior data has been categorized by outcome valence and cue validity of current and previous trial in both experiments. Since the delay time have no significant effect on evaluation score according to results in chapter 2, delay time condition had been excluded for this analysis. Similar to pupil dilation analysis, the first trial of each block is rejected due to the fact that there is no trial before. In total we will have the 36 conditions for each experiment as combination of 2 possible outcome types with 3 possible cue validities for each outcome type in current trial and previous trial. Evaluation score of each combination of experimental conditions are averaged across entire population.

For experiment 1, the pseudo-random order causes the missing data for 8 out of 42 subjects that did not encounter with all 36 combinations of experimental condition, so, we simply reject data from those 8 subjects for our factorial ANOVA. However, in experiment 2, picture set for each block of each participant were randomly generate from the pool of entire image sets. This procedure of experiment 2 created much higher chance that each participant did not encounter will all 36 combinations in history analysis. To prevent high rejection rate in factorial ANOVA due to missing data, the missing data is estimated by using the average evaluation score of that specific condition. Using this method, we can keep the variance of

entire population to be approximately the same with the raw data but still be able to perform factorial ANOVA to the entire population.

Median split analysis

To observe the underlying mechanism of evaluation process in the self-determined fast and slow response condition, the evaluation scores of each subject are separated by the median of reaction time of each individual in each experimental condition. Then the evaluation scores of the fast and slow response in each experimental condition had been averaged separately by response speed. Paired T-test on average evaluation score between the fast and slow response group has been applied to each specific condition for both experiments. The results can explain how the self-determined fast and slow rating speed affect the evaluation score in each specific condition.

Result

Pupil dilation analysis

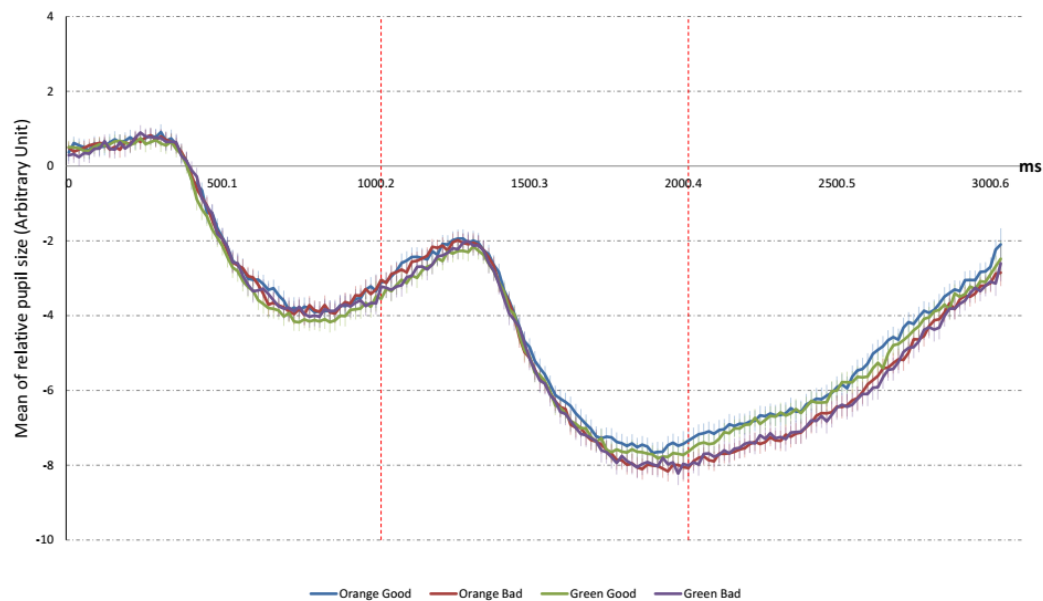


Figure 10. The changes of pupil size over time in experiment 1 for each cue valence and cue color on 1s delay condition. This graph represents pupil dilation starting from the moment of time cue exposure until the end of delay time; each graph represents average pupil size in each cue valence and cue color with error bars that represent 95% confidential interval. The first vertical red line indicates the moment that time cues offset and predictive cues onset while the second vertical red line indicates the moment when predictive cues offset and the screen black out.

Figure 10 and 11 present the changes of pupil size according to the cue valence and cue color during experiment 1 in 1s and 9s delay condition respectively. Regardless of cue color and delay condition, the results show more constriction of pupil when expose to negative cue comparing to positive cue. The difference of pupil size last until around 500ms after cue offset. Then, the pupil dilates overtime due to the exposure to blank screen in dark experimental environment.

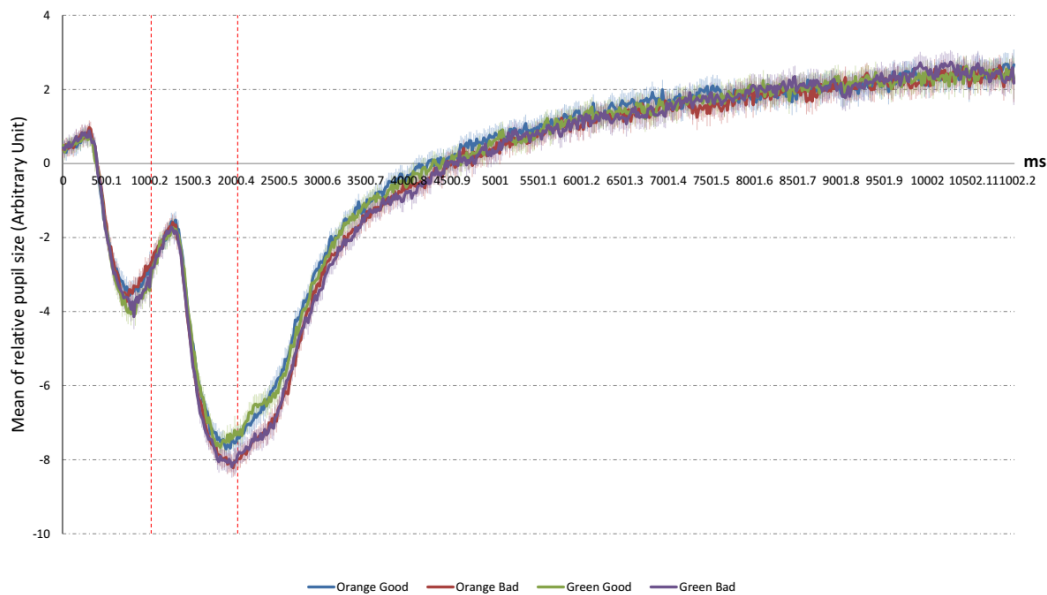


Figure 11. The changes of pupil size over time in experiment 1 for each cue valence and cue color on 9s delay condition. This graph represents pupil dilation starting from the moment of time cue exposure until the end of delay time; each graph represents average pupil size in each cue valence and cue color with error bars that represent 95% confidential interval. The first vertical red line indicates the moment that time cues offset and predictive cues onset while the second vertical red line indicates the moment when predictive cues offset and the screen black out.

While Figure 10 and 11 show the categorization of data by cue color the Figure 12 and 13 is categorized by cue reliability level regardless of cue color instead. Again regardless of cue reliability level and delay condition, the average pupil size is smaller when expose to negative cue comparing to positive cue. The grouping patterns of pupillary responses by cue valence also last until around 500ms after cue offset similar to Figure 10 and 11.

Note that, the longer exposure to the blank screen in dark environment in 9s delay condition cause the average pupil size become bigger than baseline while the 1s delay time is not long enough for the eye to readjust and widen pupil until the average size go over baseline. This fact causes the average pupil size at the starting of stimuli exposure period become difference for 1s delay condition comparing to 9s delay condition.

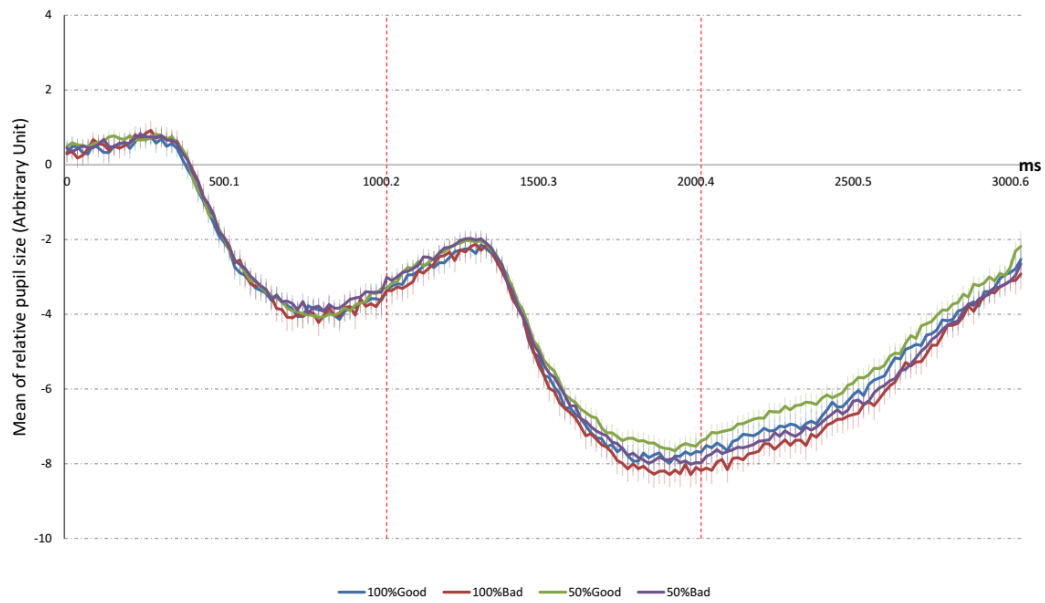


Figure 12. The change of pupil size over time in experiment 1 for each cue valence and cue reliability on 1s delay condition. This graph represents pupil dilation starting from the moment of time cue exposure until the end of delay time; each graph represents average pupil size in each cue valence and cue reliability level with error bars that represent 95% confidential interval. The first vertical red line indicates the moment that time cues offset and predictive cues onset while the second vertical red line indicates the moment when predictive cues offset and the screen black out.

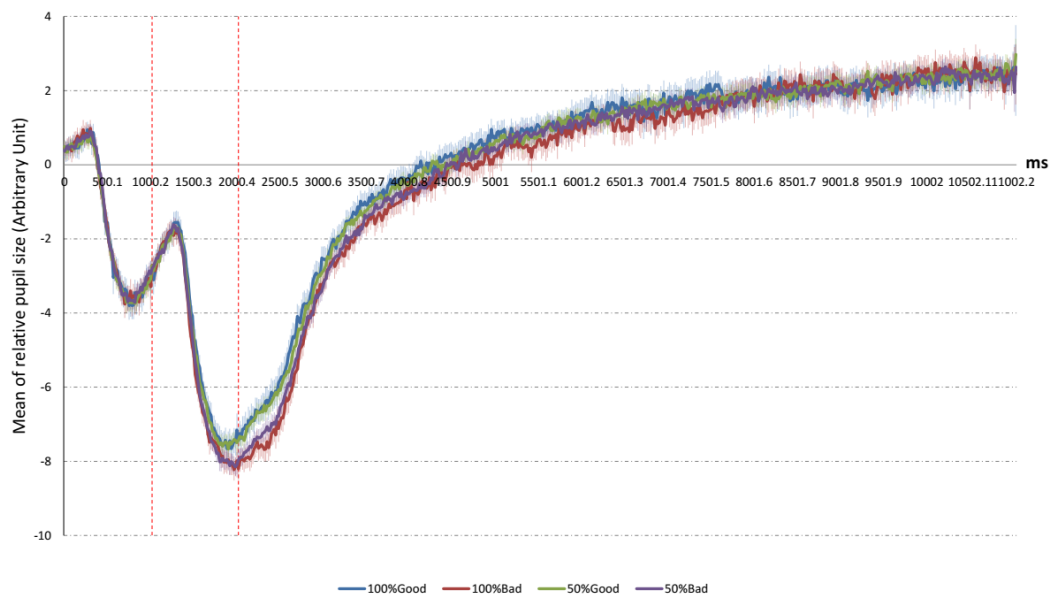


Figure 13. the change of pupil size over time in experiment 1 for each cue valence and cue reliability on 9s delay condition. This graph represents pupil dilation starting from the moment of time cue exposure until the end of delay time; each graph represents average pupil size in each cue valence and cue reliability level with error bars that represent 95% confidential interval. The first vertical red line indicates the moment that time cues offset and predictive cues onset while the second vertical red line indicates the moment when predictive cues offset and the screen black out.

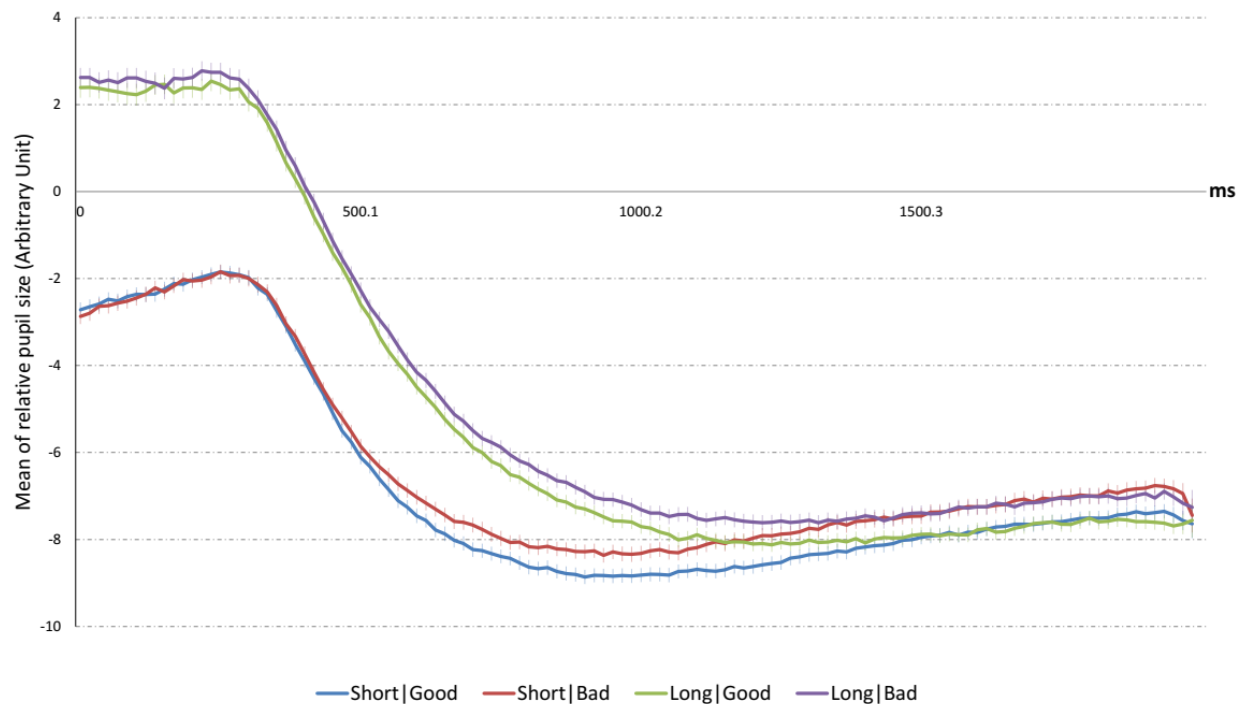


Figure 14. the change of pupil size over time in experiment 1 for each outcome valence and delay time condition during 2s stimuli exposure period. Each graph represents average pupil size in each outcome valence and delay time with error bar that represent 95% confidential interval.

In Figure 14, the pupil dilation during 2s exposure time of stimuli is shown for each outcome valence and delay time condition. At the moment of cue onset until around 500ms after that, the pupil size is group by the time delay condition which is caused by the different exposure duration to the dark environment during delay time. from 500ms until 1500ms after stimuli onset, pupil start to readjust the size which is formulated the grouping pattern by stimuli valence. This grouping last consistently until the stimuli offset. Unlike the pupil dilation pattern during the cue exposure, the pupil become more constrict when participants expose to the appetitive food comparing to when participant expose to aversive food. In other words, the pupil dilation become more constrict when expose bad cue valence and good outcome valence in comparison to the exposure to good cue valence and bad outcome valence

History analysis of evaluation score

Figure 15 visualizes the average evaluation score of experiment 1 in each combination of cue validity and outcome valence in current trial and previous trial. Each grid filled by color which represent average evaluation score of that specific condition according to the color chart on the right hand side. This 2D histogram shows the vertical recurrent color pattern but no horizontal recurrent color pattern is observed. This vertical recurrent color pattern suggests that only experimental conditions of current trial affect the average evaluation score.

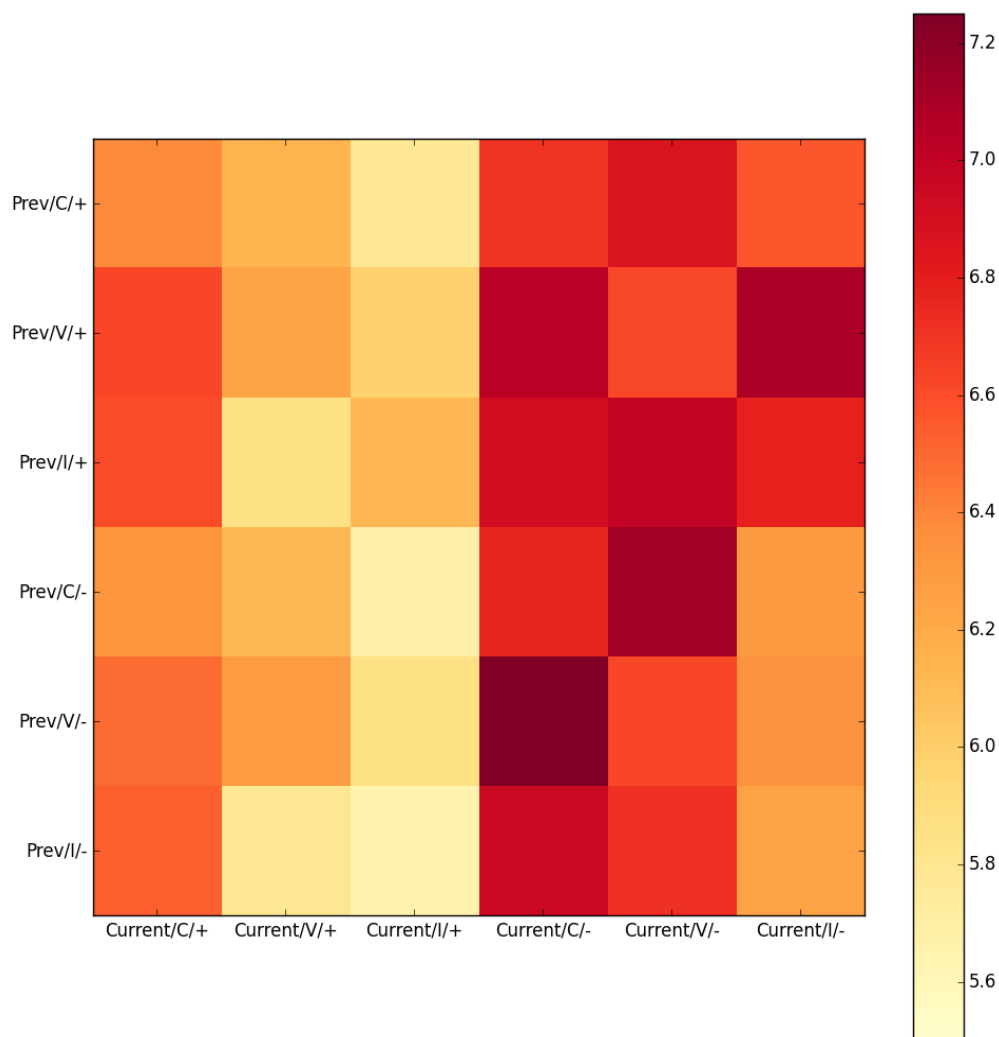


Figure 15. The 2D histogram visualizes the average evaluation score of experiment 1 arranging by previous trial conditions and current trial conditions. C, V, I are acronyms of Certain, Valid 50% and Invalid 50% cue condition respectively while Prev and Current refer to previous trial and current trial. The color represents average evaluation score of that specific condition which can be translate through the color chart on the right hand side.

By rejecting 8 subjects that have missing data out of the analysis of experiment 1, the factorial ANOVA produced a significant main effect of cue type of current trial on average evaluation score, $F(2,66) = 9.029$, $MSE = 46.131$, $\eta_p^2 = 0.215$, $p < 0.001$. Post-hoc pairwise comparison using Bonferroni test shows that the average evaluation scores in the certain condition of current trial were significantly higher than the valid 50% condition of current trial at $p < 0.05$ and also significantly higher than the invalid 50% condition of current trial at $p < 0.05$. The different between Valid 50% of current trial and the Invalid 50% of the current trial was not significant, $p = 0.423$.

There were no significant interactions (all F values less than 2).

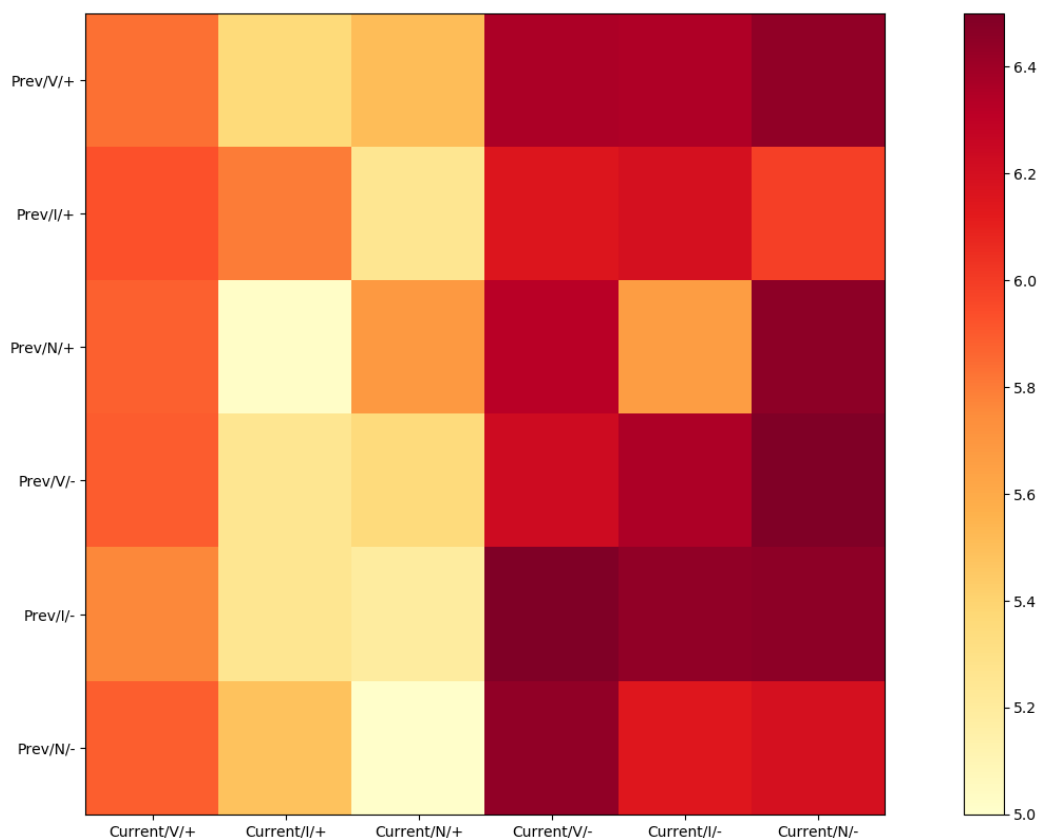


Figure 16. The 2D histogram visualizes the average evaluation score of experiment 2 arranging by previous trial conditions and current trial conditions. V, I, N are acronyms of Valid 75%, Invalid 25% and Neutral cue condition respectively while Prev and Current refer to previous trial and current trial. The color represents average evaluation score of that specific condition which can be translate through the color chart on the right hand side.

With the similar arrangement as Figure 15, Figure 16 visualizes the average evaluation score of experiment 2 under each combination of cue validity and outcome valence. As a reminder, the cue validity of experiment 1 and experiment 2 are different; in experiment 2, there is no certain cue, cue reliability level is 75% and the neutral cue is introduced as new cueing condition. Unlike Figure 15 that have visually clear recurrent vertical pattern, the left half of the histogram have lower average evaluation score comparing to the right half of the histogram in Figure 16 which suggests that outcome valence of the current trial should have an influence on the evaluation score

As mentioned in the methodology of history analysis, the missing data is around 4.43% of the whole data point but splash all over the population. To conduct factorial ANOVA, the missing data have to be estimated. Data estimation had been conducted by using the mean of evaluation score of that specific condition for filling the missing data without too much change on the variance of the whole population.

The factorial ANOVA produce a significant main effect of outcome type of current trial on average evaluation score, $F(1,65) = 10.148$, $MSE = 343.450$, $\eta_p^2 = 0.135$, $p = 0.002$. Cue type of current trial, Outcome type of previous trial and Cue type of previous trial did not have significant effect (all F values less than 2)

There were significant interactions between Cue type and Outcome type of the current trial, $F(2,130) = 5.177$, $MSE = 13.227$, $\eta_p^2 = 0.074$, $p = 0.007$. Post-hoc pairwise comparisons with the Bonferroni test showed that, for negative outcomes, there were no significant effects of cue type, whereas for positive outcomes, the average evaluation scores in the Valid 75% condition were significantly higher than those in the Invalid 25% condition at $p < 0.05$, and significantly higher than those in the Neutral condition at $p < 0.05$.

Median split analysis

To provide further understanding on the underlying mechanism of evaluation process in absolute evaluation task, the relationship between reaction time and evaluation score is investigated through this median split analysis. For the experiment 1, the result in Figure 17 was arranged in the same arrangement with behaviour results in Chapter 2. However, since the evaluation bar condition in experiment 2 did not have significant effect on average evaluation score, the median split analysis of experiment 2 had been done by ignore the evaluation bar type.

As shown in Figure 17, the average evaluation score of the fast response group in experiment 1 are rated more extreme comparing to the slow response group for every experimental conditions. By performing factorial ANOVA on average evaluation score, similar to the analysis of evaluation score in Chapter 2, with response speed either faster or slower than their own median of reaction time as additional factors (from now those two conditions will be mentioned as “fast response” and “slow response”), the result again provide the significant effect of outcome $F(1,39) = 4.499$, $MSE = 89.673$, $\eta_p^2 = 0.103$, $p < 0.05$ and significant effect of cue types $F(2,78) = 7.030$, $MSE = 26.448$, $\eta_p^2 = 0.153$, $p < 0.005$ on average evaluation score which is identical with the findings in Chapter 2. Note that the reason why F value, MSE and η_p^2 is not identical with the results in Chapter 2 cause by the rejection of 2 subjects who have no valid reaction time data in some specific condition as mentioned in Chapter 2. Since those two participants have no valid reaction time data in some conditions so their evaluation score have to be rejected in the factorial ANOVA for median split data of experiment 1. Additionally, response speed also has significant effect on the average evaluation score; the fast response also lead to more extreme evaluation score in comparison with slow response $F(1,39) = 176.075$, $MSE = 262.342$, $\eta_p^2 = 0.819$, $p < 0.001$.

The interaction between delay condition and outcome types, again, had been observed with the same characteristics as been described in Chapter 2. However, there are three way interaction between response speed, delay time and cue types at $F(2,78) = 3.777$, $MSE = 3.188$, $\eta_p^2 = 0.088$, $p < 0.05$.

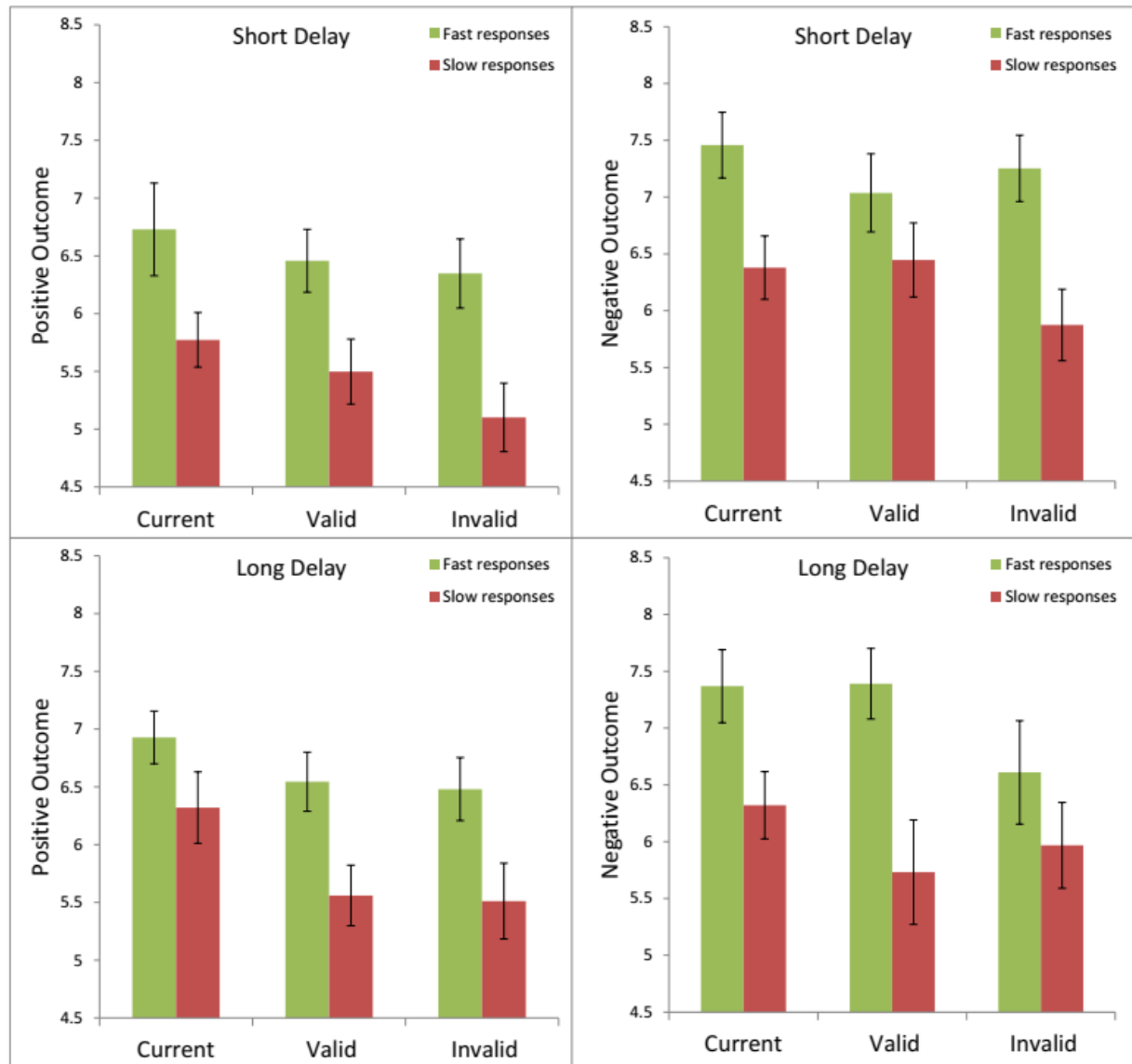


Figure 17. The average rating in each condition in experiment 1 split into two groups by median of reaction time. The green color indicates the average rating score in each condition when participants rated images faster than their own median of reaction time in that condition. The red color represents the average score of each condition when the response is slower than median of reaction time. The error bars indicate standard errors.

To observe the characteristics of this three-way interaction, the median split data of experiment 1 is split by response speed, delay time and cue type conditions then performed the Post-hoc comparison using Bonferroni test. The results show that, under short delay condition with any cueing condition (either certain cue, valid cue or invalid cue), the average evaluation score of the of fast-response trials are significantly more extreme comparing to slow-response trials at $p < 0.001$. Also under short delay condition with fast response trials, the average evaluation score of certain cue condition is significantly higher than valid cue condition at $p = 0.001$ and higher than invalid cue condition at $p = 0.007$, while, the average evaluation score of certain cue condition is significantly higher than invalid cue condition at $p = 0.006$ and the average evaluation score of valid cue condition is significantly higher than invalid cue condition at $p = 0.021$ in short delay condition with slow response trials. Moreover, only under invalid cue condition, the average evaluation score of fast response trials are significantly more extreme than average evaluation score of slow response trials in both short and long delay conditions at $p < 0.001$ and $p = 0.001$ respectively, while, the average evaluation score of long delay trials is rated significantly more extreme in comparison to the average evaluation score of short delay trials only in the slow response trials.

Similar to the result of median split analysis in experiment 1, the median split analysis on experiment 2 data show same extreme rating in fast response trials in comparison to slow response trials in all other experimental conditions as shown in Figure 18. Using factorial ANOVA with response speed as additional factor, the results show the significant effect of outcome type and significant interaction between outcome type and cue type that is identical with results in the analysis of evaluation score of experiment 2 in Chapter 2. Additionally, the response speed have significant effect on the average evaluation score; the fast response trials will be rated significantly more extreme in comparison to slow response trials $F(1,64) = 243.820$, $MSE = 288.839$, $\eta_p^2 = 0.792$, $p < 0.001$.

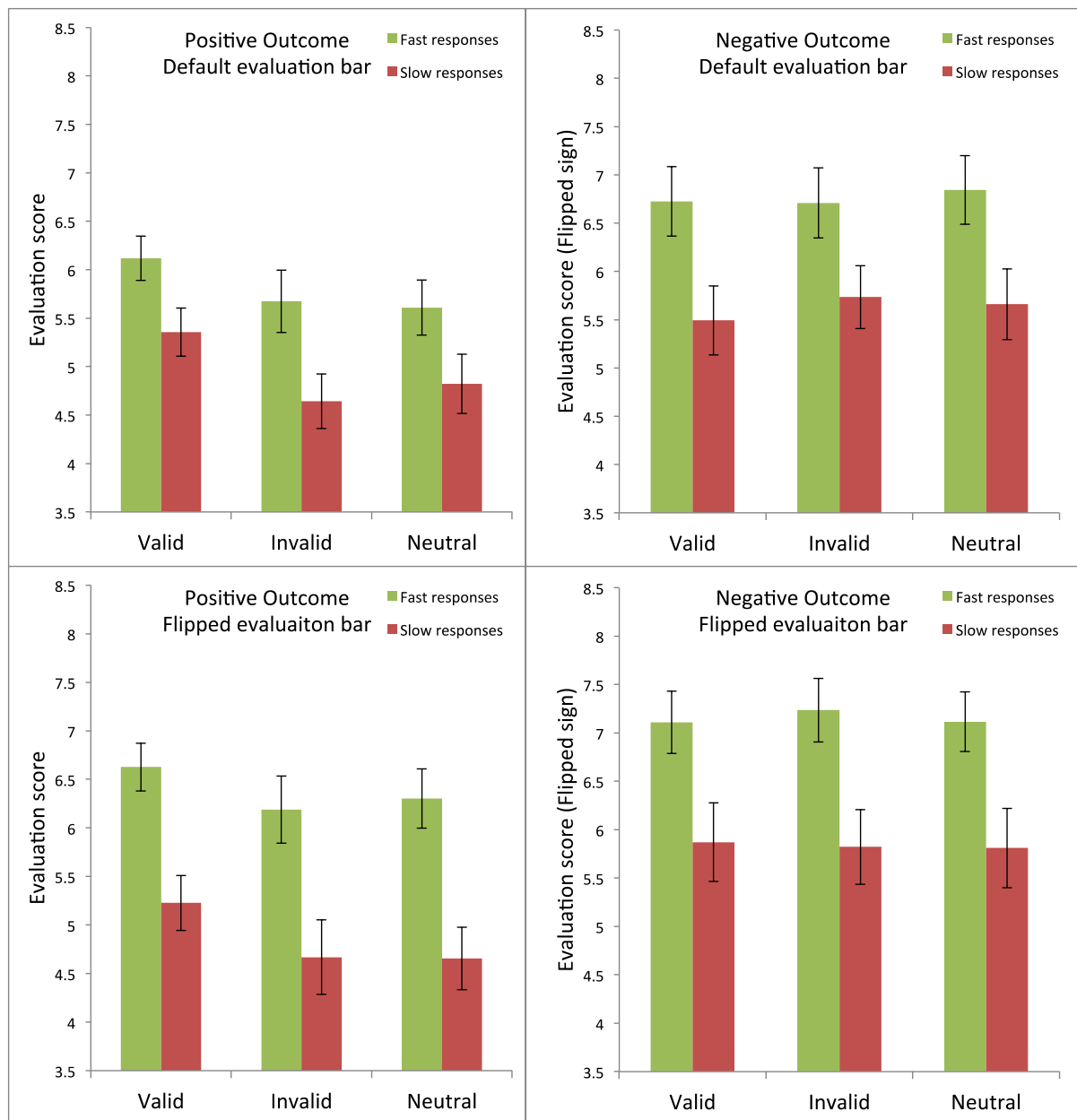


Figure 18. The average rating in each condition in experiment 2 split into two groups by median of reaction time. The green color indicates the average rating score in each condition when participants rated images faster than their own median of reaction time in that condition. The red color represents the average score of each condition when the response is slower than median of reaction time. The error bars indicate standard errors.

The significant interaction between response speed and evaluation bar is observed $F(1,64) = 7.520$, $MSE = 8.909$, $\eta_p^2 = 0.105$, $p = 0.008$. The post-hoc comparison using Bonferroni test shows that fast response trials is rated significantly more extreme in comparison to slow response trials for both evaluation bar types at $p < 0.001$, however, there is no

significant different of the average evaluation score of default evaluation bar group in comparison to flipped evaluation bar group in any response speed; $p = 0.147$ for fast response trials and $p = 0.872$ for slow response trials.

In summary, the results of median split analysis in both experiments show same tendency that faster response lead to more extreme evaluation score. This phenomenon is very consistent across different arrangements of evaluation bar and did not affect by cue reliability level either 100% certain, 75% valid/invalid and 50% valid/invalid cueing conditions in both positive and negative valence of outcome.

Discussion

Pupil dilation analysis

According to the results of pupil dilation on the experiment 1 data, it seems like there is a conflict in the results. In Figure 10 to 13, it clearly shows that the only factor that affects the pupil size is the cue valence, not cue reliability nor cue color. The negative cues also induce more constriction of the pupil in comparison to positive cues which can be observed since 500ms after cue onset and the differentiation between two cue valence can be observed until around 500ms after cue offset. However, during stimuli exposure in Figure 14, the results show that pupil constriction also works as function of the valence of the stimuli but the appetitive food images induce more constriction in comparison to the aversive food images. This contradiction of opposite effect on pupil dilation during cue exposure and stimuli exposure cannot be explained by the direction of valence.

However the previous study by Bradley and colleagues (Bradley et al., 2008) showed that pupillary changes response differently for pleasant and unpleasant stimulus according to arousal level of the stimuli; for both pleasant and unpleasant stimuli, the higher arousal level induce more dilation of pupil but the different of pupillary changes between low and high arousal in pleasant stimuli is much larger than pupillary changes between low and high arousal in unpleasant stimuli. Also the pleasant stimuli induce higher peak of dilation and lower peak of constriction in comparison to the unpleasant stimuli.

In context of our study, the negative cue is implicitly lower arousal level in comparison to positive cue because negative cue induces expectation towards aversive food images that participants prepare to avoid the outcomes while the positive cue induces the expectation towards the appetitive food images which is more interesting experiences for participants. For stimuli, the aversive food images induce stronger emotional impact on participant in comparison to the appetitive food images. This asymmetry impact between positive and

negative information is well-known in the literature as summarize in (Baumeister et al., 2001). According to previous studies, the aversive food images can be considered as high arousal, unpleasant stimuli and appetitive food images can be considered as low arousal, pleasant stimuli. Then the pupil dilation data during stimuli exposure of the experiment 1 completely repeat the findings by Bradly et al.

Therefore, this results show that we can observe the intrinsic arousal level that embedded in the expectation creating by the valence of predictive cues. It still has some issues with the control of experiment in the luminance of stimuli. To avoid the confound in pupillary response, it is better to repeat this result by using black and white stimuli which can be easier for luminance control of the stimulus. However, the appetitive and aversive feeling of food is mainly formed by the color of food and color adjustment of same food images have high impacts on the direction of valence in food contexts as shown in previous researches (Garber Jr, Hyatt, & Starr Jr, 2000; Genschow, Reutner, & Wänke, 2012; Spence, Levitan, Shankar, & Zampini, 2010). In summary, it has a big trade off that we might lose the sensation of stimuli set for getting better luminance control which have to be done specifically for the pupil dilation analysis. This trade off leads to the decision to remove the investigation of pupillary response from the objective of experiment 2. So the design of experiment 2 was not created to support the further analysis on pupil dilation and put it as another feasible future experiment.

History analysis on the evaluation score

The 2D histograms of average evaluation score categorizing by the experimental condition of previous and current trial in both experiment 1 and 2 suggest that the average evaluation score is mainly influent by the current trial condition, either cue type of current trial for experiment 1 or outcome type of current trial in experiment 2. While there is no statistical

interaction found in the results of factorial ANOVA in experiment 1, the significant interaction between cue type and outcome type of current trial is found in experiment 2 which is the same pair of interaction effect with the results from ANOVA on average evaluation score of experiment 2 (see the details of results in Chapter 2).

In summary, the history analysis on the average evaluation score of both experiment 1 and 2 suggest that there is no sequential effect in the rating of the images while the main factors that affect the average evaluation score in this history analysis is remained the same with the main factors that presented in the analysis of average evaluation score in Chapter 2 for both experiment. This result supports the robustness of the paradigm in general.

Median split analysis: the gate to new question

One interesting aspect of the subjective evaluation processing is how reaction time involves in the evaluation. In this research, both experiment 1 and 2 conducts under voluntary response with more than enough time limited at 6 seconds (according to the results in chapter 2, average reaction time of both experiment in every conditions are less than 1 second). Since participants are voluntary decided to make the rating fast or slow by themselves, the results of median split analysis can explain the relationship between reaction time and evaluation score in each experimental conditions.

According to the results, participants rated both appetitive and aversive food images that came after all cue reliability levels, cue valence under all delay time conditions significantly more extreme when they made decision faster than median of response time comparing to when the decision made slowly. These phenomena can be observed in both experiments which is shown the consistency of this phenomena. Also the direction angular movement for making the response have no effect on this phenomena as seen in the results

from factorial ANOVA that there is no significant difference of average evaluation score between default evaluation bar group and flipped evaluation bar group in both fast and slow response trials condition. These results suggest the interesting concept which will be mentioned as “speed polarization” effect. Unlike speed accuracy error, there is no accuracy measurement in the absolute evaluation task but, in this specific condition, people tend to be more polarized on their rating when they quickly made decision.

At this moment, the best description of the speed polarization might come from the switching between categorical thinking and analytical thinking mode. We hypothesize that the self-determined response pace reflects the heuristic mode that people use at that moment for performing the evaluation. When they determined to give rating fast, they categorize the rating scale into couple of choices instead of perceiving the entire range of possible rating score. For example, participants might simplify the continuous rating scale from -10 to 10 in both experiment into -10 for hate, -5 for moderately dislike, 0 for neutral, 5 for like and 10 for love. This categorical thinking process broke down when participants spend more time to rethink about the food images which lead to the mode of analytical thinking for more precise adjustment of the rating score according to the details of images that retrieve from memory.

To proof the speed polarization hypothesis, the series of future works should conduct in the same stimuli set under single image evaluation paradigm but have to add the timing condition to the experiment. One feasible design is by adding time urgency condition into the same stimuli set with the hypothesis that if the speed polarization is existing, the rating score under urgency should be much more extreme in comparison of the self-paced evaluation process in general.

In conclusion, the extra analyses in chapter 3, even though had been done as exploratory analysis at first, provide supporting evidence and open the new question for future experiment.

The history analysis shows the robustness of experimental design by countering the concern about sequential effects. The interesting results from pupil dilation analysis suggest the possibility of using pupillary responses to indicate the intrinsic arousal level that is induced by given information. And the speed polarization hypothesis that is suggested by median split analysis might lead to series of future experiments that can answer underlying brain mechanism in subjective evaluation process.

Chapter 4: General Discussion

This thesis purposes the role of predictive information in the absolute evaluation process using single image paradigm where the observation has been done under various delay time, reliability of information and validity of information with bivalent stimuli. In the past, previous researches suggested the role of predictive information in two opposite directions for evaluative decision making, either the given information will enhance the subjective value of outcomes when the outcomes and information have the same direction of valence (Cunningham et al., 2008; Jin et al., 2017; Tversky & Kahneman, 1981; Wilson et al., 1989), or, the subjective value of outcomes will be reduced by the predictive information when the valence of outcome and information are opposite (Aydogan et al., 2018; Cheng et al., 2014; Geers & Lassiter, 1999). In this thesis, these two opposite hypothesis will be investigated in the series of two experiments.

There are two important points that need to be investigated further from previous studies. First, the literatures are dominant by two-alternative choice selection paradigm which allow almost identical paradigm to apply to both animal and human subjects. In this paradigm, subject have to choose between different choices with different level of informativeness; either informative choice or non-informative choice (Bromberg-Martin & Hikosaka, 2009; Iigaya et al., 2016). Even though, this task has advantages in the aspect that can be identically performed in both human and animal subjects, it still has limitation that results cannot directly show the preference of the selected choices. To observe more than just the relative evaluation between choices, this thesis purposes the series of experiment based on the single image paradigm for observing the absolute evaluation of participants that be manipulated by the predictive information. Second, most of previous researches in predictive error focused on the effect of predictive information mainly on the rewards. However, many studies also showed that

positive and negative valence of stimuli have asymmetry effect on many cognitive functions in both visual and auditory inputs. By this reasons, this thesis's interest also including the investigation of the predictive information on both positive and negative outcomes, therefore, the bivalent food stimuli set is used in this thesis.

In Chapter 2, the main investigation of the predictive information on the evaluation process is shown as series of two experiments. The first experiment mainly designed for investigating the overview questions of the role of predictive information on the absolute evaluation using bivalent food images as stimuli. The experiment was designed to observe how the related factors that have been reported in the previous researches affect the evaluation score in each outcome valence including different delay time and different reliability level of predictive information. In addition, the experiment also designs for investigating how gaze pattern changes following the given predictive cues. According to the results of the first experiment, the ratings of image are followed the congruent bias hypothesis as a function of framing by the valence of the cue, even though the reaction time indicated the updating process when the outcome go against expectation which is similar to the prediction error hypothesis. The gaze distribution data also supports the congruent bias hypothesis. The gaze prepositioning evidences which is shown in the gaze distribution analysis clearly works as a function of the predictive cue valence. This gaze prepositioning evidences is also the physiological indicator of the expectation towards future outcome that is created by predictive cue.

By the adjustment of cue reliability from 100% and 50% to 75% with neutral cue in second experiment, the results confirm the role of congruent bias on the rating of appetitive food image with, again, the reflect of updating mechanism in reaction time. Even though, the gaze prepositioning still has been observed for both positive and negative prediction similarly to the first experiment, the congruent bias on the evaluation score are absent for the negative valence in second experiment which show asymmetrical characteristic between positive and

negative information. According to the previous studies that negative information have stronger impact on the emotional state in comparison to positive information (Baumeister et al., 2001), the results of this thesis also confirm the same asymmetry characteristics in predictive information on the evaluation score; reliability level of predictive information towards negative outcome will be overshadowed by valence of information when the reliability level is decreased have less effectiveness on the negative valence. The stronger effect of outcome valence comparing to the effect by predictive cue can be observed from the results of experiment 1 that cueing effect is actually less pronounce in negative outcome condition in comparison to positive outcome condition. That is why the cueing effect is absented for negative outcome condition in experiment 2 when the power of cue is reduced according to lower cue validity comparing to experiment 1.

Both experiments show that the congruent bias functions as an active from of bias. The evidence of the gaze prepositioning shows the directional bias that create from the predictive cue according to the direction of the evaluation bar. This directional bias will enhance the subjective evaluation of the food image with the same valence and also reduce subjective evaluation when the outcome is opposite from the expectation following predictive cue. The gaze prepositioning indicates the expectation following cue valence with more pronounced effect when the cue reliability increase. The images that have the same valence with cues can be evaluated faster and also more extreme score because the outcome confirms the expectation. In the other hands, the images that come after different cue valence will be rated slower because the outcome go against the expectation and our brain have to update the new outcome valence according to the current stimulus. This updating process reduces the effect of bias by predictive cue and causes the subjective evaluation score become less extreme.

As summary of Chapter 2, the predictive information induces a congruent bias that can be categorized as a form of active confirmation bias. Depending on the reliability level of the

predictive cues, both positive and negative predictive cues can induce the anticipation towards food images from the same category, however, the negative cues have relatively stronger active anticipation. The correct predictions also create fast response and increase the evaluation scores while the wrong predictions required updating process which induces the slow response but less extreme evaluation scores.

In Chapter 3, other exploratory aspects in the experiment designs are discussed and provided interesting insights on the information processing of brain during absolute evaluation process. However, future experiments are still needed to address and test each new hypothesis specifically in order to obtain obvious answers. The analysis on pupil dilation shows that reliability level of predictive information has no effect on the pupillary responses but, interestingly, the intrinsic arousal level which is created by the preparation towards positive and negative stimuli is the main driven factor for the different constriction level in different cue valence.

The history analysis of evaluation score also supports the results in Chapter 2 by countering the argument about the influences of past experiences in previous trial condition on the evaluation process of current trial. According to the results of history analysis, factorial ANOVA shows that there is no influence of previous trial condition on the evaluation score of current trial in both experiments. This shows that the active confirmation bias that we found in the Chapter 2 is mainly driven by the valence and reliability of predictive cue during that specific trial only, no influence from any previous information.

According to the previous research in the sequential effect, there is the general design in the experimental paradigm that participants will expose to each stimulus sequentially and also each stimulus have to be the preference-induced stimuli such as face (Kondo et al., 2012) or performance in TV show (Page & Page, 2010). Therefore, the fact that there is no sequential

effect in both experiment 1 and experiment 2 seem to be irregular case since the stimuli set is food image and stimulus was shown one after another according to the trial structure. However, the series of experiments in recent research from Chang and colleagues show that other key element for inducing sequential effect in evaluation is that the evaluation have to be solely made by one's subjective feeling (Chang, Kim, & Cho, 2017). Therefore, one possible explanation for the results of history analysis is that bias by the expectation from predictive cues, showed in between each food stimulus, interrupt the formation of sequential history bias of stimuli. Since the evaluation process have been manipulated by the predictive information and not solely based on oneself subjective feeling, the sequential history bias is absent in this experiment. To provide the supporting data on this explanation, the follow-up experiment using same stimuli set without predictive information have to be done. If the sequential effect is observed in the follow-up experiment, the supporting idea that information which directly manipulate subjective evaluation might also reduce the power of sequential bias in evaluative decision making task.

This study still has several limitations that leave some more questions toward the design of future work. Firstly, the sensitivity limitation of Eye tribe is limited to the 60Hz with error at least 0.5° of visual angle, approximately 43 pixels according to our experimental setup. According to this technical limitation, it is still impossible to provide insight analysis on the spatial precision of the gaze prepositioning phenomena or to measure the different pattern of gaze movement between fast or slow evaluation. Also the design of both experiments is based on single image paradigm that participants had been forced to look at only one the predictive information per trial, which is the form of passive information gaining. Therefore, this study cannot ensure that the role of predictive information still be the same in the active information-gaining paradigm when participants can choose whether they want to gain the predictive information, or not, by their own will. In author's opinion, the active information-gaining

should enhance the active confirmation bias, which should create stronger effect of predictive cue. When participants can selectively gain the information by themselves, this selection process should create the hindsight bias which should enhance the framing effect of the cue valence, therefore, the congruent bias should become stronger. To answer this specific question, future experiments that provide the hybrid paradigm between choice selection and absolute evaluation have to be conducted. Last limitation is the bivalent stimuli set which is limited to the food images. Food images can be induced only the appetitive as positive feeling and disgust as negative feeling, which is not, covered all range of positive and negative emotions. To validate consistency of current findings across all emotions, the other stimuli sets such as moral images set with bivalent characteristic have to be tested under the same paradigm.

There are couple of open-end questions according to the finding in this thesis. First of all, even though the results in this thesis suggest that the influence of predictive information in evaluation score should be described by the congruent bias, the fact that some experimental conditions in literatures rather than our experimental design showed the opponent mechanism still exist. The existence of both categories of results suggest that there should be “the trigger”, either extrinsic or intrinsic parameters in information processing, which switch our mode of mind between congruent bias and opponent mechanism based on the perceived information. The results of this study still cannot unveil real form of “the trigger” yet. Second, there is a possibility that the active confirmation bias by predictive information can be described in the form of Bayesian Updating mechanism similar to the study by Iigaya et al., 2016. This further statistical inference analysis is not included in the current thesis yet but still be in our future work plan for deep investigation in the congruent bias by predictive information as function of cue validity and creating the general prediction of this confirmation bias.

Finally, the most promising future work in author’s opinion should be implemented based on the results of median split analysis. Although the reaction time will become faster

after correct expectation because the updating process is not required, but according to the median split analysis, the faster reaction time still lead to more extreme rating in every experimental conditions consistently across two experiments. This result strongly suggests that speed polarization might be a general underlying mechanism of evaluative decision making in human.

There is a concern in the results of median split analysis; the results might a cause of the response method using bending angle of joystick. According to this concern, participant have no choice in the fast-response trials rather than giving rating at extreme score because the limitation of angular momentum cause participant to take more time in order to stop the joystick at the middle range score. In the author's opinion, the angular momentum should not be the cause of the results in median split analysis, as the required physical movement for giving the extreme score is more than the required physical movement for giving the moderate score. Moreover other physical limitation such as unnatural movement to bend joystick toward right side using right hand still have no significant effect in reaction time and median split analysis of experiment 2 (evaluation bar type have no effect in both analysis), so, the other physical limitation should be compensated during the experiment by the familiarity of response method overtime. However, the follow-up experiment that use touch screen or voice response is required for creating the solid evidence to reject this concern.

To provide the solid evidences for supporting the speed polarization hypothesis, the series of experiments with time cueing conditions should be done in the future with the same stimuli set. By providing a trial with and without urgency, we can observe that there is the evidence of polarization on the rating scores under urgency, or not. If the polarization of the evaluation score also exist in the time urgency condition, so, the comparison between the characteristics of evaluation process while being force to response fast and voluntary deciding

to response fast should be able to provide another important insight on the evaluative decision making process of human.

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Appendix A

Appendix A1: Visualization of gaze distribution

As supporting evidences of the gaze prepositioning in this thesis, the gaze data of the participants in the experiment 1 are categorized by experimental conditions; delay time, cue valence and cue reliability. The data has been visualized separately to show overall eye gaze pattern during cue exposure and delay time period. The visualization is done by scatter plot and heat map by combining data from all subjects for each experimental condition. The results show that there is no sign of directional gaze bias at the 100ms after cue onset but the bias can be observed clearly during delay time.

Note that the central bias that is obviously seen in the Figure 19 cause by the experimental setup that participants stabilized their head on chin rest.

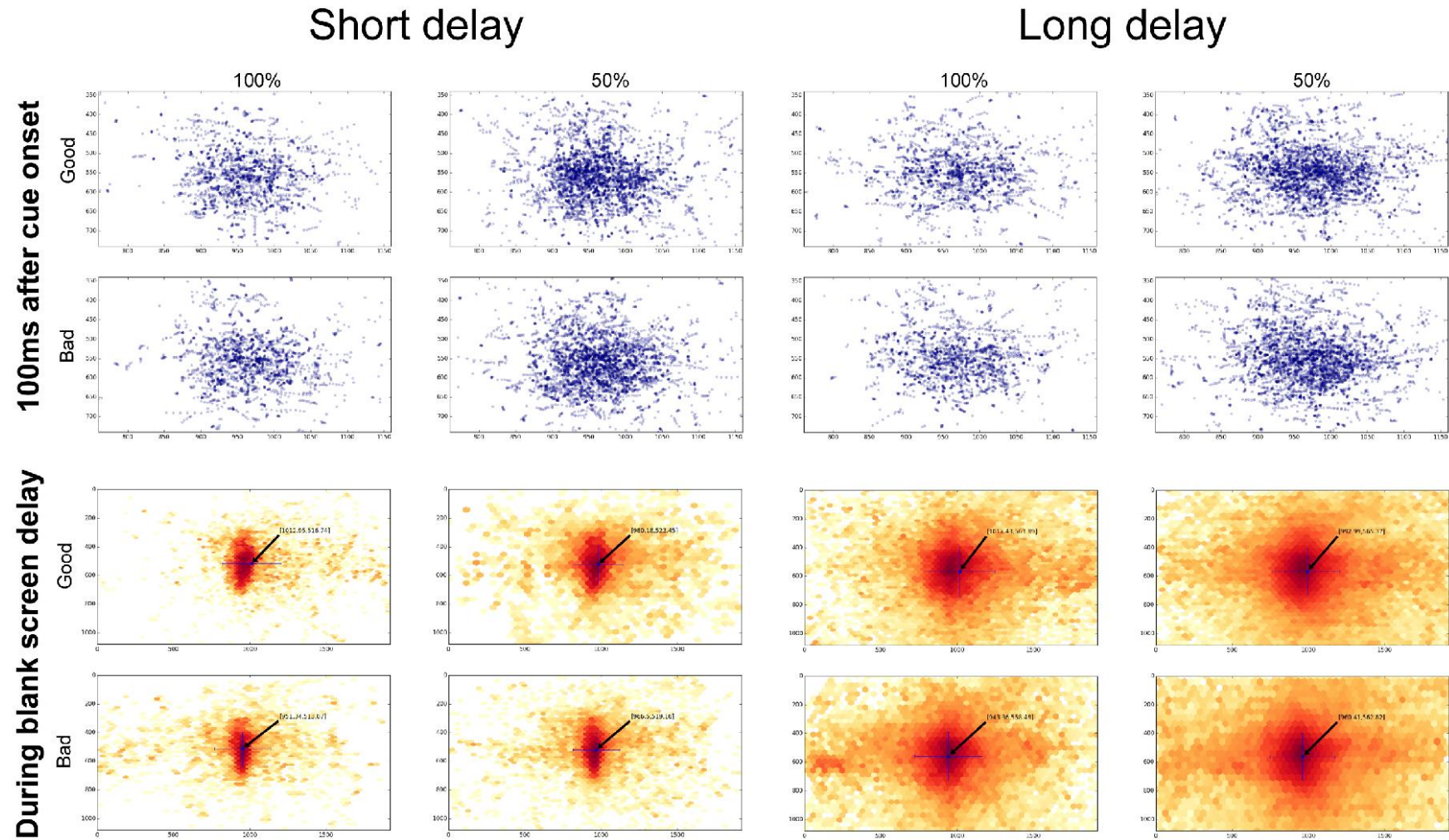


Figure 19. The scatter plots and heat maps of gaze distribution in experiment 1. The scatter plots show the gaze distribution during 100ms after cue onset while the heat map represents gaze distribution during blank screen delay. The results are arranged by delay time, cue valence and cue reliability. The arrows in heat maps indicate the average gaze position with SD as error bars.

Appendix A2: Visualization of experiment 2 paradigm

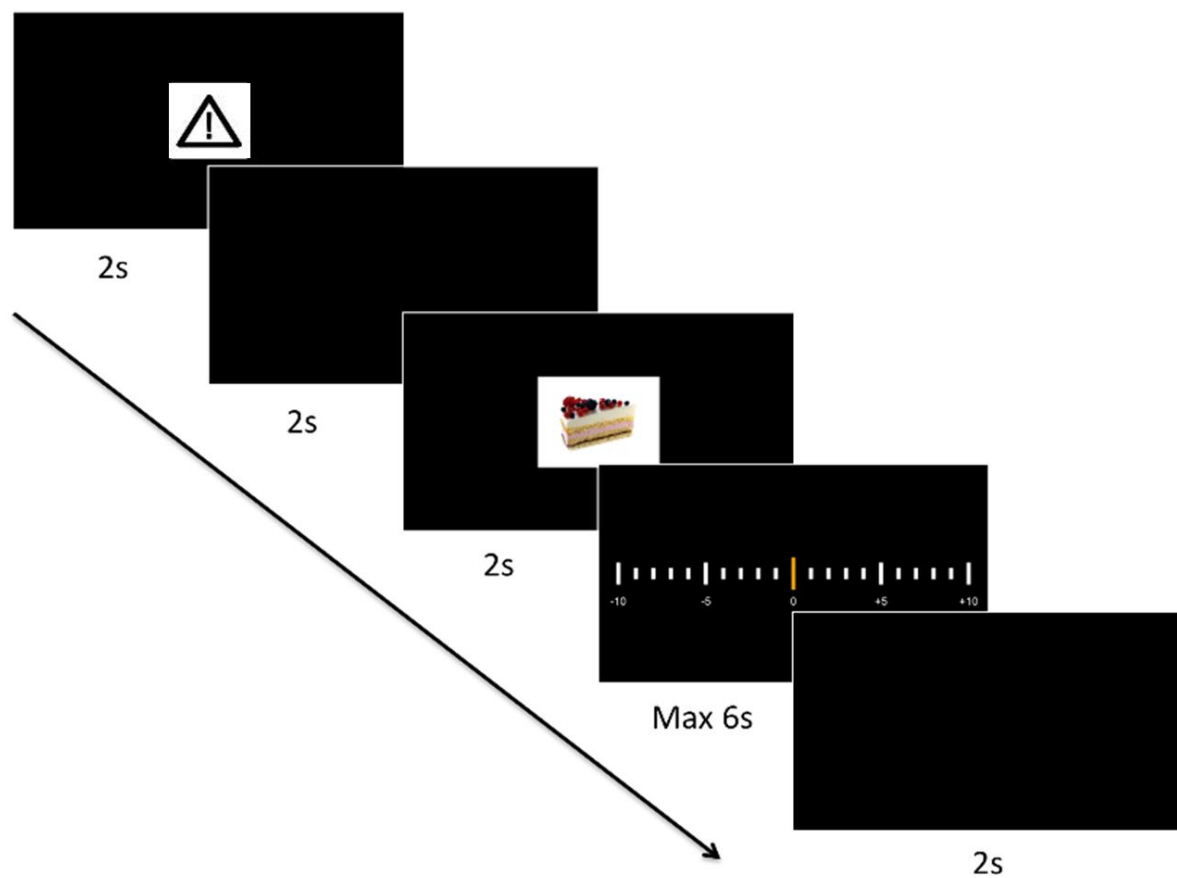


Figure 20. Trial structure in Experiment 2. Each trial starts with the predictive cue which is shown for 1 s, followed by a blank screen for 2 s. The target image is shown for 2 s at the center of the screen, followed by the evaluation bar. Participants have maximally 6 s to respond by bending the joystick. The response is followed by a 2 s inter-trial interval.

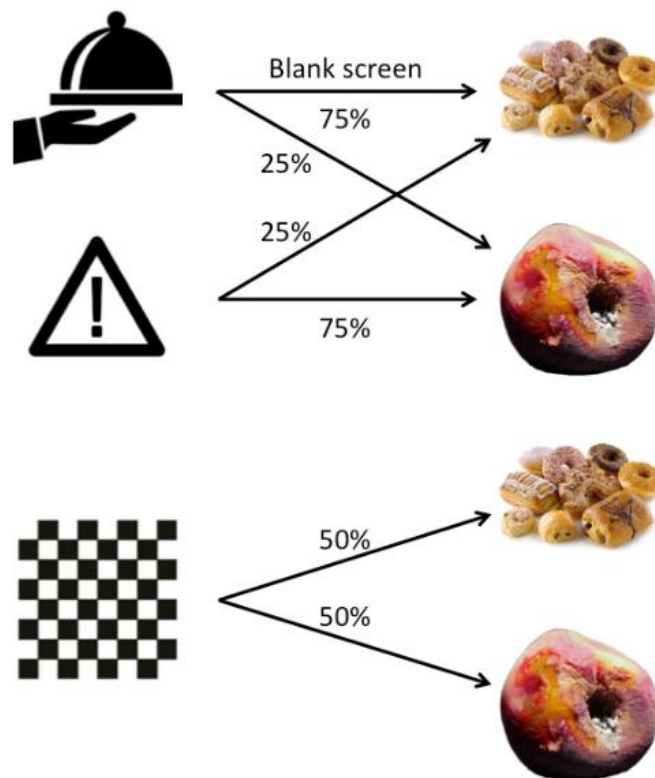


Figure 21. Schematic representation of the predictive cues in Experiment 2, associated with different outcome types. The icon indicates the valence (tray, positive; hazard, negative; checker pattern, neutral). Both positive and negative cue have 75% reliability level.

Table 1. Table shows the number of trials for each experimental condition

	75% Valid Cue	25% Invalid Cue	Neutral Cue
Positive Outcome	60 trials	20 trials	20 trials
Negative Outcome	60 trials	20 trials	20 trials

Appendix B

Appendix B1: Sample of pre-experiment questionnaire

Student ID: _____ Date: _____

Name: _____ Nationality: _____

Age: _____ Gender: Female / Male

Department / School: _____

E-mail: _____

- Hand preference:
Left _____ Right _____
- Which hand you will use during the experiment? _____ Left
Right _____
- Are you feeling healthy and well? _____ 1
2 3 4 5
Not at all Not so much Neutral Somewhat Very much
- Are you feeling hungry? _____ 1
2 3 4 5
Not at all Not so much Neutral Somewhat Very much
- Do you have sight problems? _____ Yes
No
- Are you wearing contact lenses or eyeglasses? _____ Yes
No

Appendix B2: Sample of post-experiment questionnaire

Student ID:

Date:

Name:

- Are you feeling healthy and well? 1
2 3 4 5
Not at all Not so much Neutral Somewhat Very much
- Are you feeling hungry? 1
2 3 4 5
Not at all Not so much Neutral Somewhat Very much
- Did you feel bored or sleepy during the experiment? 1
2 3 4 5
Not at all Not so much Neutral Somewhat Very much
- Please give us any comment you might have about the experiment:

Appendix B3: Sample of Informed consent (Paid)



Graduate School of Systems Life Sciences

Kyushu University

RESEARCH INFORMED CONSENT FORM

Please read this document carefully. Your signature is required for participation. To give your consent for participation in this research you should be at least 18 years old of age. The consent form is drawn up in two copies: one for you, the participant, and one for the responsible researcher.

Project Title: Modulation of subjective evaluation using predictive cues

Location: Room W2-846, West 2 building, Ito campus or
7F, West Wing building, Maidashi campus

Principal Researcher: Prof. Jan Lauwereyns

E-mail: jl@artsci.kyushu-u.ac.jp

Associate Researcher: Mr. Kajornvut Ounjai

E-mail: kajornvut.o@gmail.com

Purpose and procedure of the research

- You are asked to participate in a research study designed to investigate how predictive information will influence your evaluation.
- The experimental session consists of three blocks with short breaks in between. The duration of each block will be about 17 minutes. The total duration of the experiment is about 51 minutes.
- During this experiment, your eye movements will be captured by non-invasive sensor. You will be asked to place your chin on a chinrest in front of the computer screen.

- To reduce any interference for the eye movement data, you will be asked to avoid moving your head out of the chinrest during blocks, as well as to avoid moving your hand in between your face and the computer screen.

Possible risks

- Your participation in the experiment does not produce any risk for your health.

Compensation for your time:

- You will receive 1,000 JPY in compensation for participating in this experiment. You will be asked to fill out the details of your bank account so that the administrators can deposit the participation fee in your account.

Consent statement

1. I understand that my participation in this research is voluntary, and I have the right to withdraw at any time, without any penalty.
2. I will be assigned a code number that protects my identity.
3. I understand that my identity will not be linked with my data, and that all information I provide will remain confidential.
4. I understand the general purpose of the research and my role therein.
5. I understand that my data may be re-used in future studies.

Any technical questions about this research may be directed to the investigators listed above.

Participant's signature: _____

Date: _____

Researcher's signature: _____

Date: _____

Appendix B4: Sample of Informed consent (Optional learning experience)



Graduate School of Systems Life Sciences

Kyushu University

RESEARCH INFORMED CONSENT FORM

Please read this document carefully. Your signature is required for participation. To give your consent for participation in this research you should be at least 18 years old of age. The consent form is drawn up in two copies: one for you, the participant, and one for the responsible researcher.

Project Title: Modulation of subjective evaluation using predictive cues

Location: Room W2-846, West 2 building, Ito campus or
7F, West Wing building, Maidashi campus

Principal Researcher: Prof. Jan Lauwereyns

E-mail: jl@artsci.kyushu-u.ac.jp

Associate Researcher: Mr. Kajornvut Ounjai

E-mail: kajornvut.o@gmail.com

Purpose and procedure of the research

- You are asked to participate in a research study designed to investigate how predictive information will influence your evaluation.
- The experimental session consists of three blocks with short breaks in between. The duration of each block will be about 17 minutes. The total duration of the experiment is about 51 minutes.
- During this experiment, your eye movements will be captured by non-invasive sensor. You will be asked to place your chin on a chinrest in front of the computer screen.

- To reduce any interference for the eye movement data, you will be asked to avoid moving your head out of the chinrest during blocks, as well as to avoid moving your hand in between your face and the computer screen.

Possible risks

- Your participation in the experiment does not produce any risk for your health.

Compensation for your time:

- Please note that this research participation represents an optional learning experience; your participation is not required for any course credit. Please contact Prof. J. Lauwereyns if you have any questions in this regard.

Consent statement

1. I understand that my participation in this research is voluntary, and I have the right to withdraw at any time, without any penalty.
2. I will be assigned a code number that protects my identity.
3. I understand that my identity will not be linked with my data, and that all information I provide will remain confidential.
4. I understand the general purpose of the research and my role therein.
5. I understand that my data may be re-used in future studies.

Any technical questions about this research may be directed to the investigators listed above.

Participant's signature: _____

Date: _____

Researcher's signature: _____

Date: _____