UNCERTAINTY, CONFIDENCE AND SUBOPTIMALITY IN CHOICE

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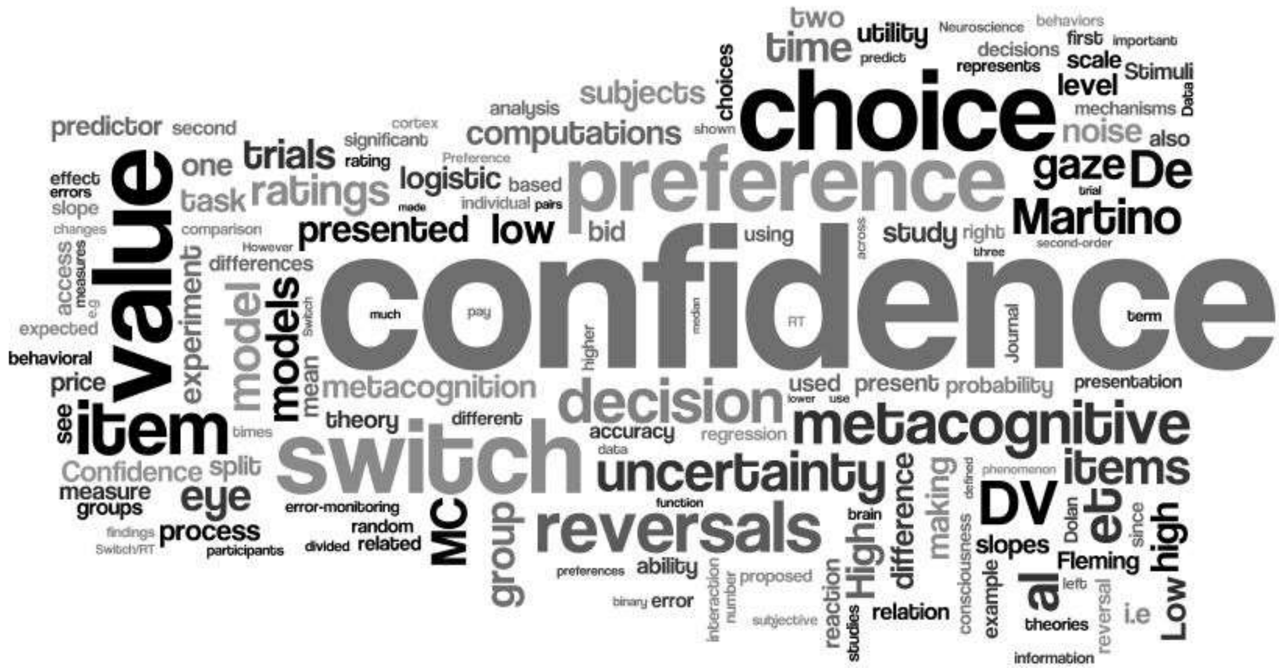

Visual abstract

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1. ABSTRACT

People are not always certain about the choices they make, not even when it comes to simple choices like choosing between a bag of crisps and a chocolate bar. The fact that choices are not always consistent is probably due to the uncertainty inherent to our interactions with the world around us. Moreover, having a sense of confidence in our choices is directly related to the capacity of accessing this uncertainty metacognitively.

A novel behavioral measure related to switching eye gaze between items was found to be a good predictor of uncertainty for subjects performing a two alternative forced choice task. This new measure was shown to be associated with subjective reports of confidence which can differentiate between levels of choice accuracy. Confidence ratings, but not switches in eye gaze, were found to be a reliable predictor of preference reversals. This finding is interpreted as suggesting that metacognition, represented by confidence, plays a key role in monitoring errors in decision making.

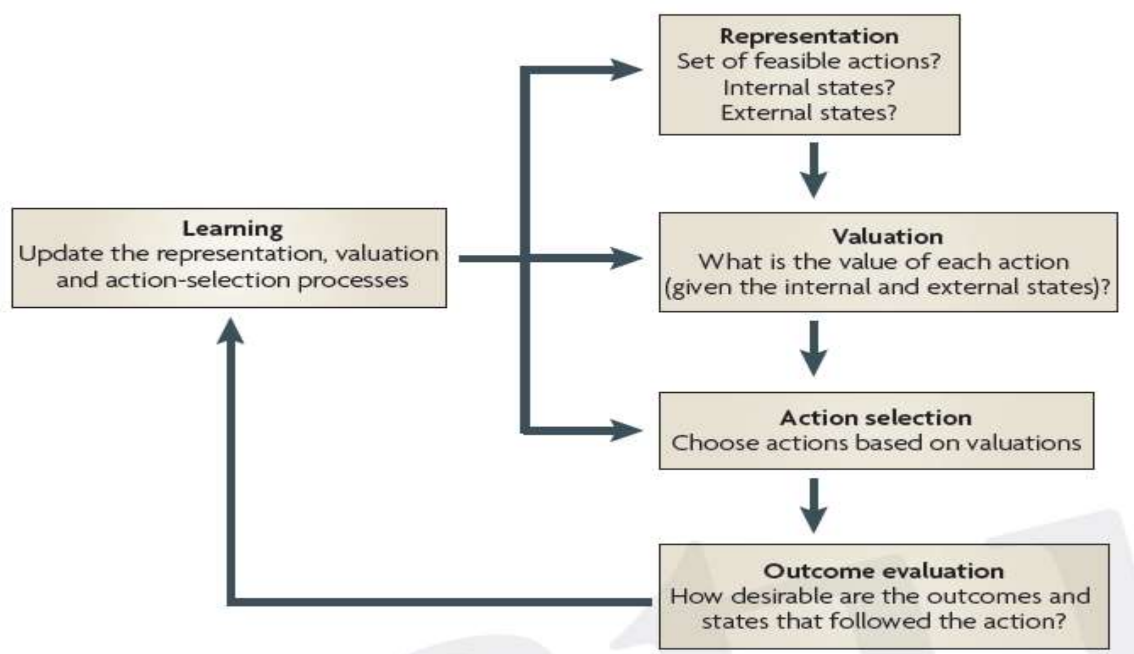
2. INTRODUCTION

2.1 VALUE

Choice permeates everything people do on a daily basis. While many of our choices are perceptual decisions (e.g. deciding if an object is green or blue), a number of decisions that really matter for our life are based on value (e.g. deciding which job to accept) and thus always have an affective valence associated with them. However, perceptual decisions are not completely divorced from a sense of value but differ from other kinds of value-based decisions to the extent in which they depend on the internal state of the decision maker.

Values are important determinants in decision making since they provide the basis through which decisions are made. However essential, value is only one part of the decision making process as demonstrated in the next figure:

FIGURE 1. Proposed framework of a decision making process (adapted from Rangel, Camerer & Montague, 2008)



Decision making involves the steps shown in this figure: representation, valuation, action selection, outcome evaluation and learning. Each computational step is important in achieving optimal and adaptive actions. Adequate representation of the problem involves integration of information across the sensory modalities and internal representation of the current state of the decision maker. This introspective ability is also important for value computations since it provides a preliminary basis for error-monitoring of the value computation itself. In other words, when an agent computes value, the computation of value is necessarily accompanied by some degree of noise (i.e. a probability for error, uncertainty or loss of information) given by the fact that the nervous system is a highly complex system (Glimcher, 2008). Firing rates of neurons for example have been proposed to behave under the restriction of latent probability distributions (Hoyer & Hyvärinen, 2003). Risk signals are even represented (on a more abstract level) in the brain in areas such as the striatum and the orbitofrontal cortex (OFC) (Schultz et al., 2008). Moreover, noise in value computations is not only due to complexity of the brain but to the uncertainty that is inherent to the structure of the world itself. Applying concepts of probability distributions to perceptual decisions is quite well established (Körding & Wolpert, 2006). Both motor control behaviors (Wolpert & Landy, 2012) and decisions involving ambiguous perceptual stimuli (Yuille & Kersten, 2006) or integration across sensory modalities (Ernst & Banks, 2002) have been modeled under Bayesian probabilistic assumptions. The scientific community is arriving at an ever higher consensus in this regards, permitting claims as bold as stating that the whole brain is in fact a machine computing Bayesian probabilities (Knill & Pouget, 2004).

Since every computation carried out by the central nervous system is plagued by noise, corrective mechanisms are fundamental for correcting errors at each level of the decision making process. Action and outcome feedback loops are improved through learning. The discrepancy between predicted outcomes and actual outcomes are gradually corrected for, reducing prediction errors.

Different kinds of prediction errors are accounted for in the brain such as prediction errors regarding states (situations) and prediction errors regarding expected rewards (Gläscher, Daw, Dayan & O'Doherty, 2010). When it comes to correcting both external and internal state representations, such as those regarding subjective value computations, metacognition possibly represents a special set of mechanisms for error-monitoring (Yeung & Summerfield, 2012). If it is the case that metacognitive mechanisms (e.g. confidence in a decision) can correct errors in decision making, this opens the door for a whole new line of research in explaining these types of errors.

2.2 THEORIES OF VALUE, PREFERENCE, CHOICE AND VIOLATIONS OF RATIONALITY

Before addressing the potential function of metacognition as an error-monitoring and error-correcting mechanism, it is important to present some normative theories that define errors when making choices (in regards to their rationality assumptions). The literature concerned with the study of value in decision making is robust with findings that express the sub-optimal nature of value computations that consequently influence choices and preferences. Sub-optimality and irrationality in decision making are closely related and are characterized by normative accounts of decision making such as Von Neumann's and Morgenstern's (1953) formulation of expected utility theory. They proposed four axioms on which to base expected utility theory that provided theorists with a mathematically tractable and consistent set of predictions in relation to decisions:

1) Completeness: For every A and B either $A \succcurlyeq B\ or\ B\ \preccurlyeq A$.
2) Transitivity: For every A, B and C with $A\ \succcurlyeq B$ and $B\ \succcurlyeq C$ we must have $A\ \succcurlyeq C$.
3) Independence: Let A, B, and C be three lotteries with $A\ \succcurlyeq B$, and let $t\ \in (0,1]$; then $tA + (1-t)C\ \succcurlyeq tB + (1-t)C$.
4) Continuity: Let A, B and C be lotteries with $A\ \succcurlyeq B\ \succcurlyeq C$; then there exists a probability p such that B is equally good as $pA\ + (1-p)C$.

The operators used here $\succcurlyeq$ and $\preccurlyeq$ represents preferring one option as much as or more (or less) than the other option. This theory rests upon the assumption of an ideal decision maker that should be able to use logical rules to maximize her or his utility. Though this theory is normative and only provides insight into how an actor should act (i.e. describe the best possible course of action), violations of the axioms are an interesting starting point for a whole agenda of research in decision making. Certain violations of these axioms include, but are not restricted to, loss aversion, hyperbolic temporal discounting, preference reversals, loss aversion and many more. Behavioral scientists on the other hand have embarked on the path of describing the behavioral principles that guide these violations of rationality as in Kahneman and Tversky's (1979) prospect theory. The dialectics between normative and descriptive theories of behavior are fruitful given that improvement in normative theories can be led by findings through empirical research. In this regards, Rabin (2000) expands on expected utility theory in proving that loss aversion cannot be explained by expected utility theory and that reference-dependence must be incorporated into the theory (Koszegi & Rabin, 2006).

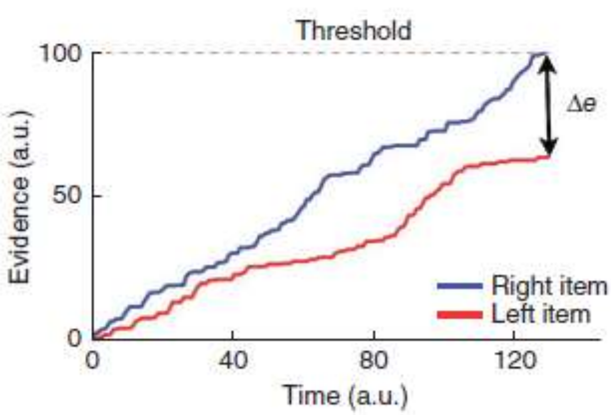
However, both normative and descriptive theories are deterministic with respect to the formulation of utility (that roughly equate to value in the economic jargons). Some attempts have been recently made to account for noise and uncertainty at the least in the measurement of utility (Hey, 2005). Camerer and Ho (1994) model an error term as a constant probability for preference reversals reflecting the possibility of errors just as pure trembles in the decision process. Two particularly appealing theories of decision making that explicitly model the error term as noise in the decision process itself; stochastic expected utility theory (Blavatskyy, 2007) and random utility discrete choice models (McFadden, 1980; McFadden & Train, 2000). Stated broadly these models can be represented in the form $U(L) = \mu_L + \xi_L$. Subjects are expected to maximize stochastic expected utility (U) of lotteries (L) (i.e. options) and random errors (ξ) (usually modeled as logistic distributions) are additive on the utility scale. Expansions on these models have been developed such as McFadden & Train's (2000) approximate maximization of utility through a mixed multinomial logit model that explicitly represents the noise associated with the attributes of each individual option. The variance in the error term has also been related to effects of complexity in choice set design (De Shazo & Fermo, 2002). However, these models are problematic for two reasons: firstly, they focus only on the noise produced by errors in the experimental measurement while overlooking the noise inherent in the computational process itself (Faisal, Selen & Wolpert, 2008; Glimcher, 2005); secondly, they ignore the causes underlying the error term (i.e. fluctuations in uncertainty).

Further along the path of behavioral scientists' view of choices and preferences are the theories that propose the exact mechanisms of deliberation involved in computing a decision, namely preference or value. These theories are of special interest here since they provide the basis for modeling the stochastic dynamics of value computations which are neglected in the static and deterministic theories mentioned previously. Many models in this spirit are based on the assumption that the process of making a decision involves accumulation of evidence in favor of each individual option. Busemeyer & Townsend (1993) proposed a model called Decision Field Theory and more recently

Krajbich et al. (2010) proposed a similar model called the attentional drift diffusion model. Both models share a lot in common but essentially differ in the predictions concerning attention weights. The former theory establishes attention weights (measured through eye gaze fixations for example) while the latter assumes an even distribution of attention across options. The models provide a basis for analyzing the difference between online and offline accounts of valuation. Some authors propose that value is actually constructed through the process of its elicitation (Lichtenstein & Slovic, 2006).

Most evidence accumulation models assume either sequential or parallel processing that accumulates up to a certain threshold which is the time when the decision is made. The threshold is an important parameter since it determines speed-accuracy tradeoff. A related alternative for modeling deliberation is the race model that was proposed by Vickers (1970) for perceptual decisions and adapted by De Martino et al. (2013) for the analysis of confidence and metacognitive ability in value-based decision making. The race model is slightly different than other models with respect to the establishment of decision thresholds; whereas other models establish two thresholds (one for each option in a binary choice task), the Vickers race model establishes one threshold for the difference in value between both options.

Figure 2. Depiction of the race model (De Martino, Fleming, Garrett & Dolan, 2013).



These dynamic models have great explanatory power since they can represent key aspects of the decision deliberation process such as: the difference in value (DV) between both items, the relation of reaction time with choice difficulty and provide a measure (Δe) of confidence (i.e. one dimension of metacognitive ability). In other words, Low Δe values represent a "read-out" of low confidence ratings and high Δe values represent a "read-out" of high confidence ratings. Differences in metacognitive ability are parameterized by a sensitivity term σ_{conf}. In the study conducted by De Martino et al. (2013), values are not conceptualized as fixed entities but as distributions of values. Values are sampled throughout the deliberation process and compared between options giving rise to a joint probability distribution of the differences between both values.

After having presented a perspective on value in the light of probability distributions, certain questions arise pertaining to why this should be so. The noise present in value computations potentially reflects a special kind of structured interaction of agents with the world they live in. Second-order mechanisms that control for and evaluate this noise have great adaptive value for agents since probabilistic interactions necessarily imply the possibility of sub-optimal behaviors arising. These second-order mechanisms can be generically labeled under the term of *metacognition* though the exact definition of this label is problematic (Koriat, 2005). Confidence thus represents an important instance of the set that comprises metacognitive processes and has the potential for being a candidate mechanism for correcting violations of rationality assumptions (e.g. correcting for preference reversals).

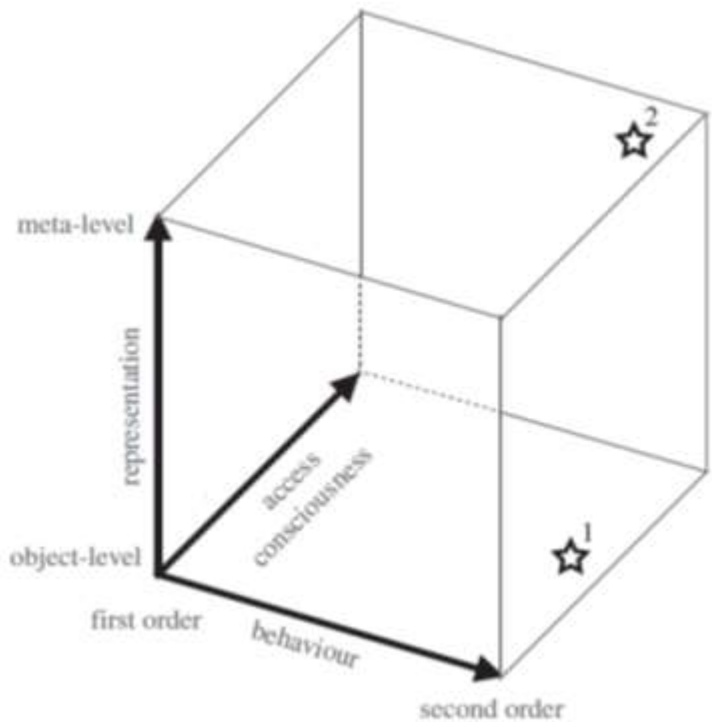
2.3 CONFIDENCE AS A METACOGNITIVE MECHANISM

Uncertainty is inherent to our interactions with the world. Actions as trivial as crossing a road can involve a certain degree of uncertainty, which can in turn determine the outcome of a decision. Crossing the road at a certain point in time depends on the *estimate* of the velocity of incoming traffic for example. Other decisions are much more subjective, as in choosing between a chocolate bar and peanuts, but still have a degree of uncertainty associated with them. The cognitive mechanisms dealing with uncertainty in decision making are not well understood.

The complement of uncertainty is the confidence in a decision (e.g. rating how confident you are in choosing a chocolate bar over a bag of peanuts). Confidence can be conceptualized in different ways and several theories have been proposed in explaining its mechanism and function. If confidence is defined in relation to uncertainty, then confidence is the degree of certainty a decision maker has in being correct about a choice. Analogous to the relation between confidence and uncertainty is stating them in terms of signal and noise respectively. The signal-to-noise ratio is present on all levels of computations done by the brain and the nervous system (Faisal, Selen & Wolpert, 2008).

Distinguishing between different levels of confidence has received increased attention recently. However, there seems to be a well-established consensus that confidence represents a second-order cognitive process in relation to a given choice. This entails that confidence be considered a metacognitive process. In this respect, Fleming, Dolan & Frith (2012) distinguish at least three defining orthogonal axes of metacognitive processes (which encompasses confidence): the behavioral, representational and access consciousness levels (see Figure 3).

FIGURE 3. Three levels of metacognition (adapted from Fleming, Dolan & Frith, 2012)



Exemplifying two independent measures of confidence will clarify the distinctions made in this figure:

1) Second-order behaviors ("behaviors about behaviors") are usually the type of behaviors researched in animal studies as in the amount of time an animal is willing to wait for a reward after having made a decision regarding the desired option (Kepecs & Mainen, 2012; Smith et al., 1995; see Tolman, 1927, for a first approximation to this level of consciousness).
2) Second-order representations ("cognition about cognition") such as confidence ratings for a given choice also require accurate access to this information which could reflect the individual differences in metacognitive ability (De Martino, Fleming, Garrett & Dolan,

2013; Fleming et al., 2010 for a neuroanatomical substrate underlying these differences; Timmermans, Schilbach, Pasquali & Cleeremans, 2012).

De Martino et al. (2013) have shown that subjective confidence in value comparison plays a key role in the construction of a value estimate. They proposed a computational model in which confidence in the choice dynamically arises during value comparison (see race model mentioned previously). They hypothesized that the encoding of both value and confidence occurs in the vmPFC (ventromedial prefrontal cortex). Subsequently, metacognitive processes in the rRLPFC (right rostrolateral prefrontal cortex) facilitated subjective reports of confidence which could represent a parallel process to value computation or, alternatively, modulate choice accuracy (De Martino, Fleming, Garrett & Dolan, 2013). This is consistent with studies showing metacognitive access in the perceptual domain (Yokoyama et al., 2010; Fleming et al., 2012). This finding provides an understanding of how people can access knowledge of what they want to a certain degree with certain variation across individuals.

As mentioned earlier, metacognitive mechanisms such as confidence can serve as error-monitoring functions. A possible implication of this is that error-monitoring is dependent on the level of access consciousness (metacognitive ability) of subjects but not on lower level orders of metacognition. In other words, people enjoy privileged access to the noise present in value computations through a specific type of metacognition; access consciousness. A suitable experimental setup can directly test this hypothesis. To achieve this, two objectives are required: 1) to establish a low level behavioral process akin to confidence ratings in the decision process, 2) to independently test the hypothesis that access consciousness serves as an error-monitoring mechanism whereas second-order metacognitive behaviors (behaviors about behaviors) do not. This research agenda would directly contribute to the debate pertaining to what degree of metacognition can be seen in animals and how this differs from how metacognition is defined in humans (Fleming, Dolan & Frith, 2013). Choosing a suitable decision error becomes fundamental. The phenomenon of preference reversals (see below for a definition) is ideal because it enables testing of the second objective; specifically, what is the predictive power of both measures of uncertainty for preference reversals.

2.4 PREFERENCE REVERSALS AND THEIR RELATION TO METACOGNITIVE ACCESS

Preference reversals describe the fact that people often choose often inconsistently (e.g. sometimes they choose A over B and sometimes B over A). The reversals can be manipulated in a context sensitive way and the manipulations reveal different violations of rationality axioms. Preference reversals are an interesting bias since they violate key axioms of economic choice (such as independence or transitivity) and the principle of procedure invariance (Slovic, 1995). They were originally observed as the incompatibility between choosing a *P* bet (high probability of winning a small prize) over a *$* bet (low probability of winning a large prize) while at the same time putting a higher value on the *$* bet (Lichtenstein & Slovic, 1971). The phenomenon can be elicited in diverse ways. For example, subtle changes of choice, as in varying the set of options, have been shown to have a great impact on the preference ordering and thus the relative ordinal ranking of the gambles offered (Soltani, De Martino & Camerer, 2012). Revisions of the basic axioms of expected utility theory have hence been under close scrutiny. Suggestions such as modifying the independence axiom in favor of maintaining the transitivity axiom have been put forth (Holt, 1986). An initial concern for economists regarding these studies was that the original psychological experiments were not financially motivated and did not elicit participants' preferences truthfully. Grether & Plott (1979) applied an incentive compatible mechanism (a Becker-DeGroot-Marschak auction; Becker, DeGroot & Marschak, 1964) in their studies in response to these concerns, only to find that the phenomenon of preference reversals was still present.

Other ways of testing for rates of preference reversals are based on test-retest paradigms of two-alternative forced choice tasks (2AFC). Put simply, a trial with two alternatives is presented once (A and B), and then presented a second time, possibly with reverse left-right or right-left presentation (B and A). Different rates of preference reversals have been reported for a variety of related studies; 31.6% (Camerer, 1989, p. 81), 26.5% (Starmer & Sugden, 1989), 5-45% (Wu, 1994, p. 50), 25% (Hey & Orme, 1994) and 14.7% (De Martino, Fleming, Garrett & Dolan, 2013).

The question remains open as to what confidence can tell us about preference reversals and vice versa. Koriat (2013) suggests that confidence in relation to expressed preferences can serve as a diagnostic of reproducibility (likelihood of making the same choice again or switching on subsequent trials). This is certainly consistent with findings suggesting confidence is negatively related to the likelihood of preference reversals (De Martino et al., 2013). Koriat further speculates that confidence needs to be incorporated into the notion of the "underlying preferences", referring to the stability of preferences over and above random or contextual fluctuations (Simonson, 2008).

Referring to the framework on metacognition established by Fleming et al. (2012), it is important to establish if second-order behavioral measures of confidence. It is not known if the metacognitive components of these lower level computational processes have an effect on preference reversals or not. Furthermore, there have been no studies addressing the distinction between access consciousness and second-order behaviors for preference reversals. That is, does a specific type of metacognition (i.e. access consciousness reflected in confidence judgments) predict preference reversals more accurately? This represents an intriguing issue; the extent to which these metacognitive measures of confidence predict preference reversals as a group. Lower level measures of uncertainty could potentially predict preference reversals to some extent but not any better than the subsequent higher level confidence reports. For example, Tolman (1927) argues that shifts in differential responsiveness (from lesser to greater responsiveness) represents the most basic level of consciousness (i.e. metacognition in the framework used here). It is assumed that with higher level computations, these shifts in responsiveness can only become more sophisticated. This could also imply that people with better metacognitive abilities will be able to better predict preference reversals since these people have privileged access to the noise present in the probability distributions of value computations.

The experiment presented in this thesis (based on the study conducted by De Martino et al., 2013) will be used to address these questions. This study is ideal since it has duplication of trials (which is necessary for the study of preference reversals) and makes a clear distinction of individuals with better and worse metacognitive ability. This study is expanded upon through the additional use of eye tracking equipment which will provide the necessary second-order behavioral measures of confidence. The difference in time spent fixating on one item in relation to the other is a good predictor of choice (first order behavior) (Orquin, & Loose, 2013) and the number of changes in fixations between items (switching fixations between items) is proposed as a second-order behavioral measure of confidence consistent with previous animal studies proposing a similar notion (Smith et al., 2010; Tolman, 1927). Additionally, studies concerning computations based on fixation times have proposed that it is the relative value in a choice that is computed (instead of the absolute value for each item) and that differential fixations to attributes of a choice can partially explain preference reversals (Kim, Seligman & Kable, 2012; Lim, O'Doherty & Rangel, 2011).

3. METHOD

3.1 OVERVIEW

In the study I describe in this thesis, we tested how people compute value and its related uncertainty through three different measures; bids through an incentive-compatible auction, subjective reports of confidence and switch in eye gaze. We analyzed the relation between these three measures with preference reversals. Data were collected in the De Martino Lab and analyzed for two distinct purposes for two distinct MSc projects. The results presented here constitute one of the projects. The exclusion criteria for subjects are common for both projects.

3.2 SUBJECTS

UCL's subject pool (SONA) was used to select 29 participants. Nine participants were excluded due to erratic choice patterns which led to unreliable estimations of logistic fits. A beta value of one standard deviation below the average of the group was used as criteria to exclude six subjects and a correlation below 0.5 between choice and eye gaze excluded the other three subjects. The final analysis included twenty subjects; ten females and ten males, between 19 and 73 years old (MN = 30.25 ± 13.09), with body mass index (BMI) between 16.30 and 28.15 (MN = 21.86 ± 3.57). Participants did not present any medical conditions including diabetes, hypoglycemia or hyperglycemia, nor were they dieting or presented food allergies/intolerances that would pose a risk for fasting. In addition, they did not have any current or past psychiatric conditions. As a requisite for participating in the study, subjects were required to have lived at least one year in the United Kingdom to ensure a minimum of familiarity with the products (i.e. snacks) presented during the task. All participants presented normal or corrected to normal vision. They all fully consented to participating in the study (approved by the UCL Research Ethics Committee). Subjects were paid an hourly rate of £10 for compensation and to encourage them to bid on consumption of the items presented.

3.3 INSTRUMENTS

- A head-mounted SR Research Eyelink II eye-tracker
- A 60 Hz LCD computer monitor
- A Microsoft gamepad used for making choices during the task
- A glucometer, a stadiometer and a weighting scale
- A steady stock of 16 items (snacks) per participant bought at most local convenience stores which subjects chose between and bid to consume using the Becker-DeGroot-Marschak (BDM) procedure (Becker, DeGroot, & Marschak, 1964). Refer to appendix for the full list of items and their corresponding image used in the task.

3.4 PROCEDURE

As is expected in behavioral economic paradigms, no deception was used on the participants for obtaining data. To encourage active and truthful participation, subjects had to actually buy one of the products seen in the binary decision task. This was accomplished efficiently through the Becker-DeGroot-Marschak (BDM) procedure where the subjective value given to each item served as a bidding price and was compared to a randomly generated value (Becker, DeGroot & Marschak, 1963). This procedure is widely used in behavioral economics to elicit the true subjective value of different items. DV (difference in value) scores were computed based on stated bids for the items and used as predictors of choice in a logistic regression. We recorded error rates and reaction times which we predicted would be dependent on accuracy and confidence respectively. The experimental design follows the same procedure and analysis as De Martino et al. (2013) with the inclusion of eye-tracking data. Participants made binary decisions between items (snacks and beverages) and reported their subjective confidence of those decisions. Subjective values (between £0 and £3 for example) were assigned to the products during the bidding task. Switches in eye gaze were recorded for every trial.

Participants were asked to fast for four hours previous to the start of the experiment. The sessions lasted 2 hours approximately.

Glucose levels for all subjects were measured. Binary choices between snack items (n = 16) were presented on a LCD computer monitor (60 Hz refresh rate) using high resolution images presented on a black background with an overall size of 50.2 pixels per degree x 8 degrees of visual angle. Participants completed the task with a viewing distance of 750 mm from the screen. Each choice was self-paced (no maximum time length for trials). Pairs of products were presented twice with inverted left-right presentation to avoid any positioning bias that might have occurred for a total of 240 combinations (16x15 for the sixteen products which included duplication of pairs with inverted spatial configuration). Choices were randomized and divided into four blocks (n = 60 binary choices per block) with a forced break of 1 minute (minimum) between blocks and the opportunity of removing the head-mounted eye-tracker during the break. Mean familiarity rating of the items (7.18 ± 2.8) was measured on an integer scale from 1 (low familiarity) to 10 (high familiarity). Participants were informed that the choices made during the task directly affected the probability of obtaining a certain item at the end of the task. A Microsoft gamepad was used for the binary choices where left and right triggers were used for the left and right item presented respectively. Posterior to each binary choice, a white asterisk appeared below the chosen item for 750 ms and then removed. The pair of items was left on the screen for an additional two seconds without the asterisk for analysis of the post-decision eye gaze data. After each choice between items they were required to give a self-report rating of confidence of their choice on a continuous sliding scale going from 1 (low confidence) to 6 (high confidence) without any time constraints. The gamepad's left and right arrows moved the cursor on the rating scale and rating was confirmed by pressing the A button on the pad.

At the end of all the trials, the second stage of the experiment consisted on them bidding on each item in random order from £0 to £3 on a continuous sliding scale to buy the item on that day, with unlimited time to place their bid. They also gave a self-report rating of confidence of their bid on the same scale mentioned previously. A standard PC keyboard was used for both the bidding scale and the confidence rating scale for this stage of the experiment (left and right arrow keys for moving the cursor along the scale and space bar for confirmation). An item was then chosen from one of their previous choices at random. A random 'market price' was extracted from a uniform distribution going from £0 to £3. If the amount they bid on that item (their willingness-to-pay) was greater than the random market price generated, no transaction occurred. If their bid for that item was lower than the random number generated, they received that item and their bid offer was deducted from their compensational stipend. In addition, participants needed to stay in the lab for an extra hour during which they could only consume the product they obtained during the auction (if any). Gaze patterns were only recorded during the first stage of the experiment (binary choice task) and not during the bidding task (based on Becker, DeGroot, & Marschak, 1964). Refer to figure 4 for a visual depiction of both stages of the experiment and figure 5 for a timeline of the study. Both stages of the experiment were rigorously detailed through oral and written instructions (see Appendix).

FIGURE 4. Stages of the Experiment

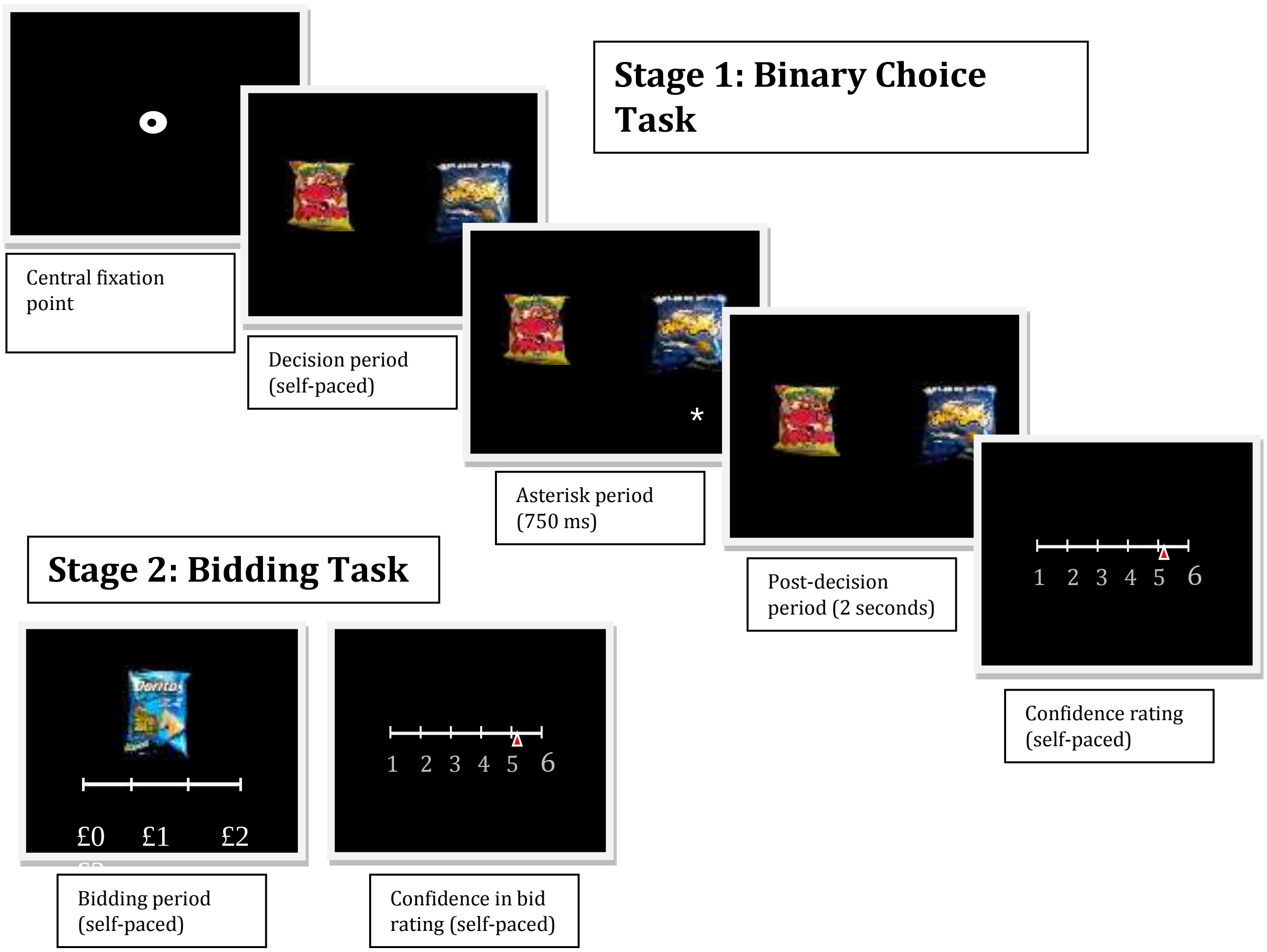
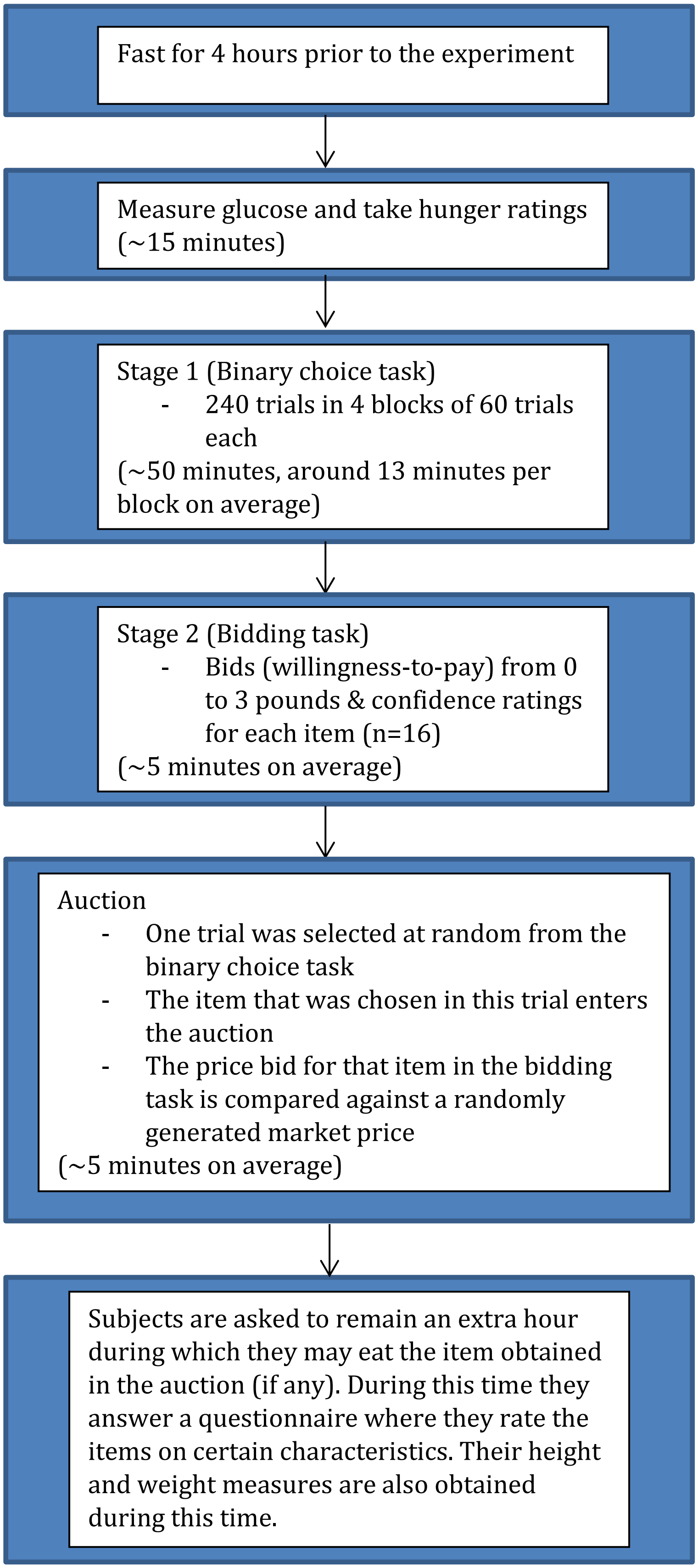


FIGURE 5. Timeline of the study



During the extra hour stay that was required for participants, both height and weight were measured for construction of body mass index for all subjects. Questionnaires asking for subjective ratings of familiarity, frequency of consumption, perceived caloric content, efficiency in reducing hunger, saltiness and sweetness for all products were answered by all participants on an integer scale going from 1 to 10 (low to high respectively).

Both stages of the experiment (the self-paced binary choice task and the bidding task) were programmed using Matlab 8 (MathWorks) with the Psychophysics extension (psychtoolbox.org) and the EyeLink toolbox extension (Brainard, 1997; Comelissen, Peters, & Palmer, 2002).

3.5 ACQUISITION OF EYE-TRACKING DATA

Eye gaze patterns were recorded using a head-mounted SR Research Eyelink II eye-tracker with a four millisecond temporal resolution and sampled at a frequency of 250 hertz. Fixations for gaze were defined above a minimum threshold of 100 milliseconds and saccades were defined above a minimum threshold velocity of 30° per second and a threshold acceleration of 8,000° per second squared. Fixations and saccades were defined by the SR Research Eyelink software under recommendations for cognitive research for the reduction of microsaccade detection (SR Research Ltd, 2002, p. 60). Calibration and validation of calibration was performed before each block of the binary choice task. This ensured that the average error in visual degrees was below 0.5 over the course of the task.

To construct the appropriate regions of interest (ROI) for the eyetracking equipment, the screen was split in half along the horizontal axis in accordance with the presentation of the choices: one item on the far left and one item on the far right along the x-axis and centered on the y-axis. Saccades to either side of the screen were assumed to be directed towards the item on that side. *Switches* were defined conservatively as a fixation on one stimulus followed by an immediate fixation on the alternative stimulus. Fixation on the same ROI or off the screen, followed by a fixation on the alternative item, was not counted as a switch. Only immediately posterior fixations on the alternative item through a single saccadic eye movement were accepted as a switch. Constructing the definition of switches in this way is based on the assumption that this definition captures only the integration of information relevant for the specific process of comparing both items as opposed to capturing information and value integration directed on one item alone.

A central fixation point (a black dot in the center of a white circle) was presented before each choice. This fixation helped normalize initial gaze position before the start of each trial. Since this central fixation point was at the center of the screen and unrelated to the items presented, the first fixation of each trial was discarded for all further analyses.

Two trials from one subject were excluded from further analyses due to missing data caused by a failed connection between the eyetracking equipment and the host computer running the task for those trials.

Each trial was divided into three different periods: the decision period (unlimited time), the asterisk period (750 ms) and the post-decision period (2 seconds). The post-decision period permits analyses of the integration of information, value and confidence posterior to the time of choice. The asterisk phase serves the function of conservatively delineating between the decision period and the post-decision period.

3.6 DATA ANALYSIS

All variables were transformed into z-scores for intersubject comparison unless stated otherwise.

As mentioned earlier, signed DV (difference in value) scores were computed based on stated bids for the items and used as predictors of choice in a logistic regression. Absolute difference in value |DV| was used as a predictor of preference reversals in a different set of logistic regressions.

Trials were separated into low and high confidence trials, using a median split of confidence ratings, for separate analysis of the logistic regressions. This resulted in two logistic regressions per subject, each regression with its own slope with DV as sole predictor in the models. Difference scores between high and low confidence slopes were computed. Each low confidence slope was subtracted from the high confidence slope for each subject's psychometric curve (High confidence slope – Low confidence slope) providing a measure referred to as the difference in slopes for confidence (DSC). Subjects with low difference in slope values represent the group with low metacognitive ability and vice versa. This measure represents subjects' metacognitive capacity.

The same procedure was realized using switch in eye gaze; trials were separated into low and high switch trials, using a median split of switch in eye gaze. The same difference score for these slopes (High switch slope – Low switch slope) were calculated for difference in slopes when trials were separated by switch in eye gaze (DSS).

To reduce the intrinsic effect of reaction time on switch in eye gaze, switch was divided by reaction time (Switch/RT). This is due to the fact that with slower reaction times, the greater the probability of having more switches. Since the task is self-paced, switch should account for individual differences in cognitive processing. Furthermore, slower reaction times are correlated with choice difficulty which is also necessary to control for when analyzing switch as a measure of uncertainty.

We defined preference reversals as the pairs of trials where choice was reversed on the second presentation for the same items. Six logistic regression models were constructed for analysis of preference reversals. Their comparison is based on the Bayesian Information Criterion (BIC):

$$\text{BIC} = -2 \text{ log likelihood of the model} + (k * \ln(n))$$

where k represents the number of parameters in the model and n represents the number of observations.

4. RESULTS

This results section is divided into three parts: 1) *Confidence ratings and changes in choice accuracy* where we present the replication of the De Martino et al. (2013) findings in regards to confidence ratings, 2) *Switch in eye gaze and changes in choice accuracy* where we present switch in eye gaze between items as another measure of uncertainty akin to confidence ratings, 3) *Confidence ratings, switch in eye gaze and preference reversals* where we present the comparison of the predictive power of both confidence ratings and switch in eye gaze in a proposed set of preference reversal models.

4.1 CONFIDENCE RATINGS AND CHANGES IN CHOICE ACCURACY

As mentioned in the methods section (see Data Analysis) unsigned difference in value (DV) was computed as the difference between stated bids in the bidding task (Value of item on the right – value of item on the left) across all trials. In accordance with other studies (De Martino et al., 2013; Boorman, Behrens, Woolrich & Rushworth, 2009; Sugrue, Corrado & Newsome, 2005), DV was a consistent predictor of participants' choices presenting an average 82.64% (8.67% s.d.) classification accuracy when fitted to a logistic regression model. Absolute difference in value (|DV|) explained an average 19.4% (13.98% s.d.) of the variation in subjects' confidence ratings. The same partial independence between |DV| and confidence ratings observed in the De Martino et al. (2013) study was also observed in our data ($r = 0.398$, $p < 0.001$). This finding is essential in replicating the fact that confidence account for changes in choice accuracy.

According to the procedure used in De Martino et al. (2013), splitting the logistic regression fits into high and low confidence trials showed that higher confidence is related to higher choice accuracy. This was also true for this dataset for 18 out of 20 subjects, though higher confidence was not related to higher choice accuracy for the remaining two subjects. The change in choice accuracy due to splitting trials in high and low confidence trials is reflected in the slope of the logistic fit. Figure 7 shows the difference between high (mean = 5.17 ± 2.81 s.d.) and low confidence slopes (mean = 2.89 ± 1.61 s.d.) which was significant ($t_{19} = 4.455$, $p < 0.001$). There was considerable variation between subjects' metacognitive ability (see Appendix for the individual logistic regression curves). Confidence level also had an effect on reaction times (RT), with main effects of both confidence ($p < 0.001$) and |DV| ($p < 0.001$) and an interaction effect ($p = 0.002$). The interaction effect had not been reported as significant in De Martino et al. (2013).

4.2 SWITCH IN EYE GAZE AND CHANGES IN CHOICE ACCURACY

Switch in eye gaze between items (for exact definition see Acquisition of Eye-tracking Data in the Methods Section) was recorded on a trial by trial basis with the help of a head-mounted eyetracker. Choice difficulty, represented by |DV|, accounted for an average 4.32% (4.45% s.d.) of the variation in switch in eye gaze with a negative correlation between |DV| and switch ($r = -0.186$, $p < 0.001$). In regards to confidence ratings, a negative correlation between switch and confidence rating data was observed ($r = -0.324$, $p < 0.001$) (i.e. the more confident a subject has in a choice, the less amount of switches in eye gaze between items realized by the subject), while a linear regression model for confidence while controlling for |DV| also showed that switch is a significant predictor of confidence ($\beta = -0.191$, $p < 0.001$).

A correlation between switch and reaction times was calculated and proved a positive relationship ($r = 0.592$, $p < 0.001$). In opposition to confidence ratings, switch in eye gaze between items is intrinsically related to RT. Similar to the relationship between |DV| and confidence with RT mentioned above, switch and |DV| have main effects and an interaction effect when regressed on RT (for all three predictors, $p < 0.001$). To reduce the effect of reaction time on switch in eye gaze, switch was divided by reaction time (Switch/RT) (see Data Analysis in Methods). The correlation between switch (now divided by RT) and confidence ratings was weakened but significant ($r = 0.159$, $p < 0.001$). This correlation is now positive due to the non-linear relationship between switch in eye gaze and RT.

To ensure switch in eye gaze was not being driven by choice difficulty (|DV|), a linear regression model of confidence ($F_{(2,4795)} = 501.729$, $p < 0.001$) showed that switch was a significant predictor (standardized beta 0.121, $p < 0.001$) over and above |DV| (standardized beta 0.386, $p < 0.001$).

When we performed logistic regressions predicting choice through DV, now using switch instead of confidence ratings, we separated trials in either high or low switch (median split). We were able to show a significant change in slope ($t_{19} = 2.42$, $p = 0.026$) between high switch group (mean = 3.89 ± 2.04 s.d.) and low switch group (mean = 3.25 ± 1.66 s.d.) (Figure 7). The effect switch had on revealing choice accuracy, shown by the slopes of the high switch group and the low switch group, was smaller than the revealing effect of confidence ratings. Difference scores between high and low slopes were calculated for both logistic regression models separated by confidence, and models separated by switch in eye gaze (see Data Analysis in the Methods section for more details). The difference in slopes for confidence (DSC) were significantly greater than the difference in slopes for switch (DSS) although they were correlated ($r = 0.55$, $p < 0.012$, DSC mean = 2.28 ± 2.29 s.d., DSS mean = 0.64 ± 1.18 s.d., $t_{19} = 3.83$, $p < 0.001$).

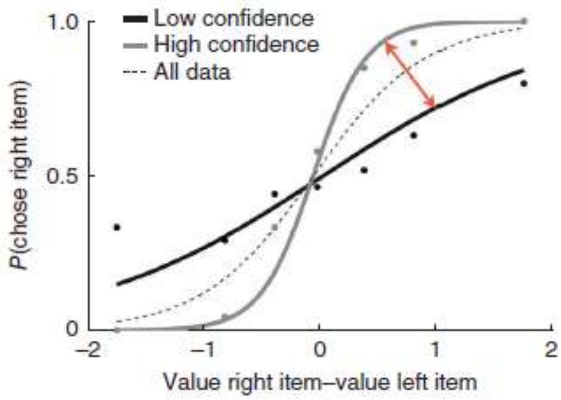


FIGURE 6. Median split of confidence applied to logistic regressions with DV as predictor (taken from De Martino et al., 2013). Dotted line shows a logistic fit using DV as a predictor (Value of right item minus value of left item) of choosing an item presented on the right side of the screen. After splitting for high and low confidence (gray and black lines respectively), the red arrows represent a measure of metacognitive ability (DSC). This figure also represents the intuition behind difference in slopes between high and low switch trials (DSS).

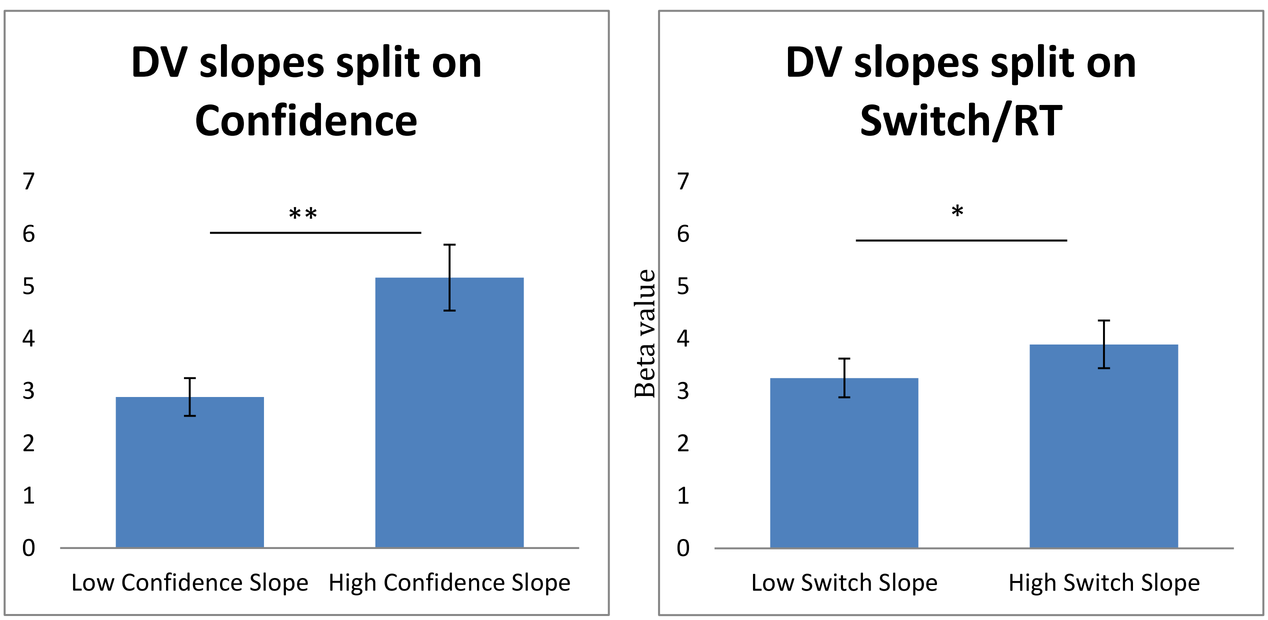


FIGURE 7. a) Difference in slopes (High confidence slope & Low confidence slope). Mean slopes for the logistic fits when split on confidence (median split). Slopes are in arbitrary units but show a significant difference across all subjects (** = p < 0.001). **b)** Difference in slopes (High switch slope & Low switch slope). Mean slopes for the logistic fits when split on switch divided by reaction time (median split). Slopes are in arbitrary units but show a significant difference across all subjects (* = p < 0.05).

4.3 CONFIDENCE RATINGS, SWITCH IN EYE GAZE AND PREFERENCE REVERSALS

All item pairs were presented twice (once in each spatial configuration, see Methods section). With identical choice pairs we could define *preference reversals* as choosing one item on the first presentation (for a given pair of items) but then inverting their choice (i.e. choosing the alternative item) on the second presentation for the same pair of items.

Averaging across subjects, 7.29% (4.001% s.d.) of trials showed this phenomenon. Preference reversal trials did show a significantly lower level of confidence than repetition trials (in arbitrary units: reversal confidence = 3.16 ± 1.377 (s.d.); repetition confidence = 4.29 ± 1.34 (s.d.); t_{2398} = 10.753, $p < 0.001$). This result is a direct replication of the same relation isolated by De Martino et al. (2013). We checked for stability of confidence ratings between presentations. Unlike De Martino et al. (2013), we did find that confidence ratings for the first presentation of item pairs (mean = 4.209 ± 0.542 s.d.) were significantly lower than the second presentation of item pairs (mean = 4.339 ± 0.545 (s.d.); t_{19} = -3.289, p = 0.004).

We then ran a similar analysis using this time the number of switches. We found that switch was, contrary to confidence, a poor predictor of preference reversal (reversal switch = 1.248 ± 0.703 (s.d.); repetition switch = 1.281 ± 0.737 (s.d.); t_{2398} = 0.57, p = 0.569). Switch was also significantly lower for the first presentation of item pairs (mean = 1.28 ± 0.279 s.d.) than for the second presentation of item pairs (mean = 1.46 ± 0.365 (s.d.); t_{19} = -6.014, $p < 0.001$).

In a logistic regression model, confidence was a negative predictor (β = -0.563, $p < 0.001$) of reversing on the subsequent trial and so was |DV| (β = -1.178, $p < 0.001$; model's -2log likelihood = 1104.309, Nagelkerke's R2 = 0.144). The finding that confidence was a negative predictor of preference reversals replicates the De Martino et al. (2013) finding.

To further elucidate the relationship between |DV|, switch, and confidence, six different logistic regression models were analyzed for predicting preference reversals (PR) on subsequent trials:

1) PR = |DV| + Switch/RT

2) PR = |DV| + Switch/RT + (|DV|*Switch/RT)

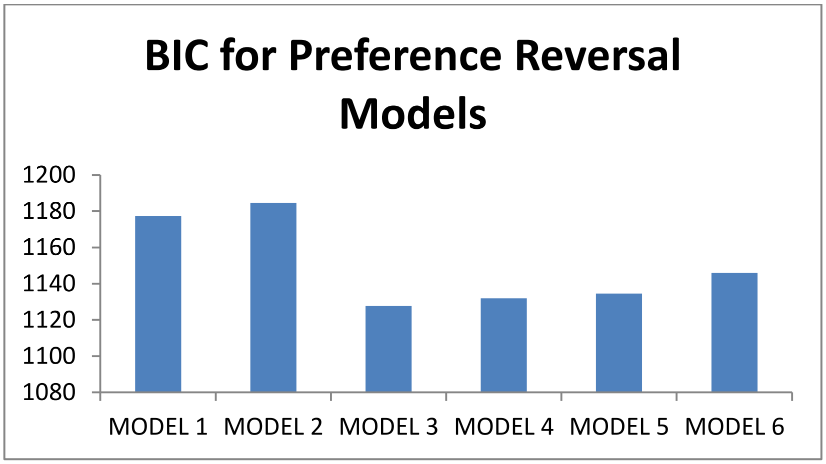
3) PR = |DV| + Confidence

4) PR = |DV| + Confidence + (|DV|*Confidence)

5) PR = |DV| + Switch/RT + Confidence

6) PR = |DV| + Switch/RT + (|DV|*Switch/RT) + Confidence + (|DV|*Confidence)

The Bayesian Information Criterion (BIC) for each model is presented in Figure 8. This statistic is applied to the -2log likelihood of each model and penalizes for every extra parameter in the model (see Data Analysis). When comparing BIC statistics between models, model 3 proved to be the best with unsigned DV ($\beta = -1.178$, $p < 0.001$) and confidence ($\beta = -0.563$, $p < 0.001$) as predictors. When controlling for |DV| in the models, we can see that neither switch nor any of its interaction terms can significantly predict preference reversals, whereas confidence can.

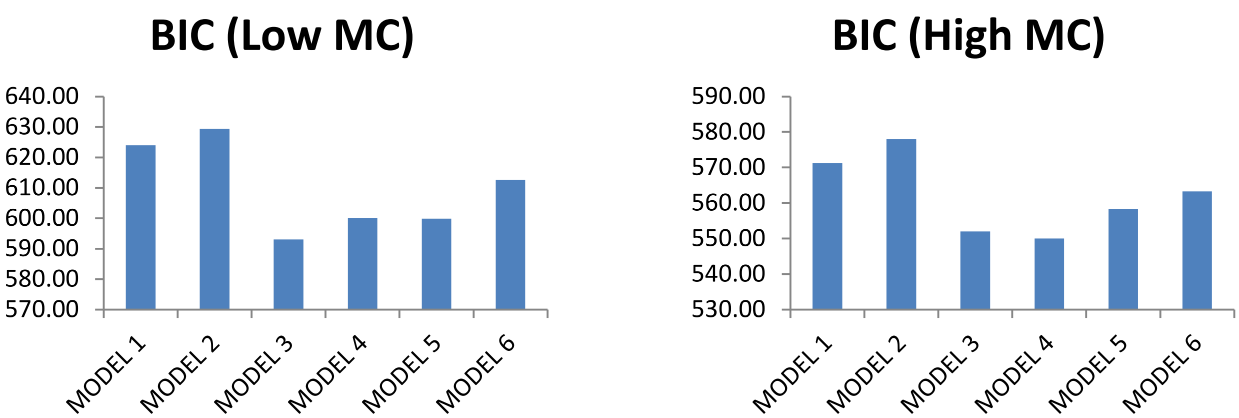


	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
|DV|	-1.581**	-1.551**	-1.178**	-1.345**	-1.175**	-1.318**
SWITCH/RT	-0.186	-0.269	-	-	-0.101	-0.193
|DV|*SWITCH/RT	-	0.156	-	-	-	0.185
CONFIDENCE	-	-	-0.563**	-0.412**	-0.554**	-0.396**
DV*CONFIDENCE	-	-	-	-0.351	-	-0.366
BIC	1177.38	1184.68	1127.66	1131.82	1134.60	1146.01
PSEUDO-R	0.095	0.095	0.144	0.147	0.144	0.148

FIGURE 8. Bayesian Information Criterion (BIC, see Data Analysis for details) for the six preference reversal models for all subjects. TABLE 1. Preference Reversal Models for all subjects. The models use only first presentation trials to predict subsequent preference reversal or repetition. Each row has the beta value for the predictor (** = $p < 0.001$) except for the last two rows which present the BIC and Nagelkerke's pseudo-R square.

In the De Martino et al. (2013) study, the differences in slopes when split on confidence (DSC) provided a relative measure of introspection regarding choice accuracy (i.e. an individual's metacognitive ability, see Data Analysis). A larger value for DSC represents an individual with greater metacognitive capacity. We hypothesized that it could be possible that subjects with more metacognitive capacity (MC) might be able to access information captured by switch in eye gaze between items. Subjects were divided into two groups: high metacognitive capacity (High MC) and low metacognitive capacity (Low MC). This was done through a median split on the original differences in slopes when split through confidence ratings (DSC). Figure 9 shows a comparison of the models shown previously between both groups. For these models, we can see that neither group has switch or any of its interaction terms as a significant predictor for preference reversals.

Interestingly enough, the best model for the High MC group (model 4) has the interaction term between |DV| and confidence (β = -0.967, $p < 0.05$) as a significant predictor of preference reversal while eliminating the main effect of confidence, which indicates that the effect of confidence on preference reversal is mediated by |DV|. The beta values for this model are the highest across all models for both groups.



	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
|DV|	-1.388**	-1.329**	-0.936**	-0.948*	-0.931**	-0.911*
SWITCH/RT	-0.161	-0.363	-	-	-0.072	-0.263
|DV|*SWITCH/RT	-	0.341	-	-	-	0.319
CONFIDENCE	-	-	-0.588**	-0.573**	-0.581**	-0.55**
DV*CONFIDENCE	-	-	-	-0.032	-	-0.069
BIC	623.91	629.37	592.99	600.06	599.85	612.64
PSEUDO-R	0.082	0.085	0.141	0.141	0.142	0.144

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
|DV|	-1.828**	-1.877**	-1.483**	-2.081**	-1.486**	-2.127**
SWITCH/RT	-0.218	-0.119	-	-	-0.138	-0.044
|DV|*SWITCH/RT	-	-0.21	-	-	-	-0.22
CONFIDENCE	-	-	-0.539**	-0.147	-0.525**	-0.138
DV*CONFIDENCE	-	-	-	-0.967*	-	-0.961*
BIC	571.21	578.01	551.98	550.01	558.34	563.23
PSEUDO-R	0.111	0.111	0.149	0.167	0.15	0.169

FIGURE 9. Bayesian Information Criterion (BIC, see Data Analysis for details) for the six preference reversal models for both the High Metacognition (High MC) group and the Low Metacognition (Low MC) group. TABLE 2. Preference Reversal Models for the High Metacognition (High MC) group and the Low Metacognition (Low MC) group. The models use only first presentation trials to predict subsequent preference reversal or repetition. Each row has the beta value for the predictor (* = $p < 0.05$, ** = $p < 0.001$) except for the last two rows which present the BIC and Nagelkerke's pseudo-R square.

We checked for further distinctions between the Low MC and High MC groups. The High MC group showed significantly slower reaction times (mean = 2.35 ± 1.76 s.d.) in their decisions when compared to the Low MC group (mean = 2.19 ± 1.73 s.d., $t_{2398} = -2.268$, $p = 0.023$). We suspected this might be driven by differences in confidence ratings between both groups (i.e. lower confidence is associated with slower RT). Yet this was not the case shown by a t-test comparing confidence rating means ($t_{2352.687} = -0.847$, $p = 0.397$) between Low MC (mean = 4.19 ± 1.466 s.d.) and High MC groups (mean = 4.23 ± 1.274 s.d.) (Figure 10). Switch on the other hand did show a difference between both groups (High MC mean = 1.187 ± 0.709 (s.d.), Low MC mean = 1.371 ± 0.748 (s.d.), $t_{2398} = 6.188$, $p < 0.001$). No differences in the amount of preference reversals between groups was observed ($t_{18} = 0.363$, $p = 0.721$, High MC mean = 8.3 ± 5.33 s.d., Low MC mean = 9.1 ± 4.48 s.d.).

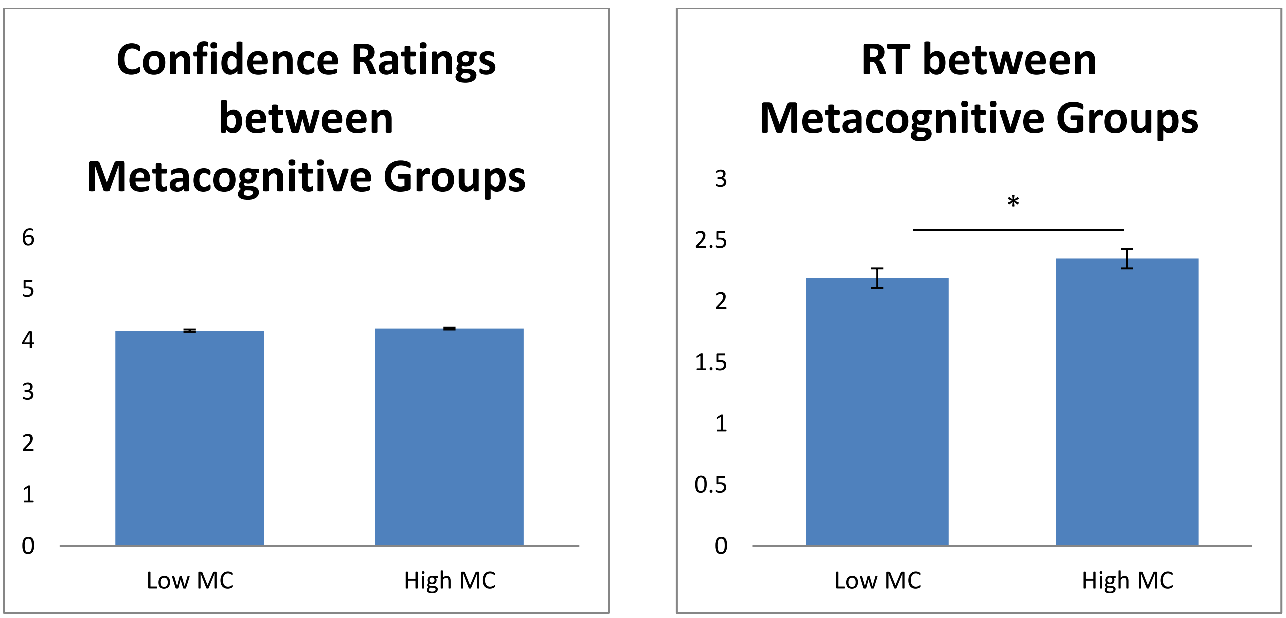


Figure 10. a) Confidence ratings are compared between High and Low Metacognitive groups. b) Reaction times are compared between High and Low Metacognitive groups. (* = p < 0.05).

5. DISCUSSION

Our study largely expanded upon previous research of confidence in value-based choice by De Martino et al. (2013). Since we used a very similar behavioral paradigm our first goal was to replicate the De Martino et al. (2013) findings in relation to confidence as a metacognitive mechanism. This was a necessary step in order to compare metacognitive reports of confidence ratings with low-level switch in eye gaze as measures of uncertainty. Difference in value (DV) was found to be a reliable predictor of subjects' choices with the slopes of the logistic regressions indexing choice accuracy, or equivalently noise present in the decision process (Sugrue, Corrado & Newsome, 2005). We successfully divided trials into high and low confidence groups, and established confidence as a measure representing individual differences in accessing this noise.

The second hypothesis tested whether it was possible to isolate a second-order behavioral mechanism analogous to confidence ratings. Switch in eye gaze between the two items presented was hypothesized to function as such a measure. Our analysis demonstrated that a greater number of switches were related to lower confidence ratings and vice versa. However, this correlation was confounded by reaction time (RT), since increased switching evidently requires more time to perform, this relationship was expected. Controlling for RT in the switch measure thus provided information regarding the amount of switches realized per unit of time. Our analysis allowed for the construction of a model where the relationship between switch and confidence is shown to exist over and above absolute difference in value |DV| (i.e. choice difficulty). This proved that the number of switches across trials was a reliable predictor of confidence even when we controlled for RT or |DV|.

Furthermore our study produced new insights about how the error terms in random utility models are constructed (see Introduction). The stochastic (Blavatskyy, 2007) and random utility theories of choice (McFadden, 1980) are much better explanations for the type of computations observed here than the alternative deterministic theories (Kahneman & Tversky, 1979; Von Neumann & Morgenstern, 1953). These results support the notion that error in value is not just a consequence of measurement error (as assumed by decision-making theories based on random utility, Gul & Pesendorfer, 2006), but uncertainty is intrinsic to value computations implemented by the brain. We make the case, not only that our interactions with uncertainty are a necessary consequence of interactions of our nervous system with the world (Faisal, Selen & Wolpert, 2008), but that this interaction has developed highly sophisticated cognitive mechanisms, with great adaptive value, such as metacognition.

We were therefore able to use switch to split the data by performing a median split dividing choices into high level of switch and low level of switch, similar to the trial separation done by confidence. More specifically, the low switch trials were less accurate in using value to predict choice. Switch in eye gaze was thereby shown to be a basic reporter of noise and therefore a low level behavioral measure of uncertainty. This new measure might be related to the Δe parameter in the race model (see second section of the Introduction) where switch is assumed to be related to changing evidence accumulators (De Martino et al., 2013; Vickers, 1957) while the confidence "read-out" of this uncertainty (Δe) is sensitive to individual metacognitive ability (σ_{conf}). According to this model, switch is a measure of uncertainty that does not require metacognitive access.

Demonstrating that switch functions as a valid measure of choice uncertainty (independent of metacognitive report) allowed us to compare the metacognitive aspects of confidence with switch and their relation with suboptimality in choice. We mostly focused on preference reversal models that is defined here as the pairs of trials where choice was reversed on the second presentation for the same pair. Specifically, we aimed to address the relation between metacognition and changes of preference. A specific type of metacognition, based on confidence judgments, has been proposed to work as an effective error-monitoring mechanism (Fleming et al., 2012; Koriat, 2013; Yeung & Summerfield, 2012). Based on this idea, we tested the relation between this cognitive ability and preference reversals. This distinction is crucial for future metacognition studies comparing humans and animals (Kepecs & Mainen, 2012; Smith et al., 1995; Tolman, 1927) because the encoding of uncertainty is now dissociable from awareness of this uncertainty (i.e. metacognition) as proven with this work.

The main focus of this study was to test differences in accessing noise in value computations in relation to two independent measures of uncertainty; switch and confidence. We found that, contrary to confidence, switch did not account for preference reversals. These results support the hypotheses that metacognitive access (i.e. confidence) is required to allow for corrective mechanisms (i.e. change in preference). We found no empirical evidence for switch effectively predicting preference reversals in any of the models tested in our study. Nonetheless, it is not clear what drives the uncertainty that is indexed by switch. A number of factors could contribute to this such as choice complexity (e.g. number of attributes computed per item) (Kim, Seligman & Kable, 2012; Lim, O'Doherty & Rangel, 2011), familiarity (De Martino et al., 2013) or saliency (Orquin & Loose, 2013), which are not taken into account in this study. Future studies are required to clarify the process that leads to change in uncertainty during value comparison.

To test more stringently the hypothesis that only confidence and not switch is related to preference reversal, subjects were divided into two groups: high metacognitive capacity (High MC) and low metacognitive capacity (Low MC). This was done through a median split on the differences in slopes for confidence (DSC). Splitting subjects into these two groups enabled the comparison between the metacognitive abilities of the High MC group in predicting preference reversals when compared to the Low MC group. The logistic regression analysis based on the metacognitive split showed that the Low Metacognition group was not driving the non-significance of switch as a predictor of preference reversal since it was not significant for any of the High MC models (or of the Low MC models).

An interesting interaction term between |DV| and confidence was found in the best model of the High MC group, indicating that the effect of confidence on preference reversals is likely mediated by |DV| in this group. The interaction term suggests that the variance for confidence may vary according to |DV| levels. Furthermore, the Low MC group does not show this sensitivity, suggesting that the High MC group also has different access to the heteroscedasticity present in the noise of value computations. The High MC group indeed showed a privileged capacity to access noise in value computations but this privilege comes with a cost. In this regard, the High MC group presented slower reaction times when compared to the Low MC group, indicating that better metacognitive ability requires more processing time. Theories that propose metacognition as an epiphenomenal process that gathers information in parallel to other mechanisms can be directly challenged with this finding since slower reaction times suggest the processing is serial not parallel (Timmermans, Schilbach, Pasquali & Cleeremans, 2012).

The sensitivity to this interaction term highlights a key assumption about noise in value computations; the probability distributions that underlie value computations, particularly DV joint probability distributions, have different variance depending on the difficulty of the choice. Furthermore, the main effect of confidence was removed by this interaction term when predicting preference reversals for the High MC group. De Martino et al. (2013) have previously interpreted similar findings as a measure of a good “read-out” of noise present in value computations done in vmPFC, which is why the High MC group is defined in this way.

As far as differences in metacognitive ability go, there is an interesting question that remains unanswered in this study but could easily be explored using a similar design. We proposed that metacognitive (high level) mechanisms, serve an error-monitoring function as well as an error-correcting function (Fleming et al., 2012; Yeung & Summerfield, 2012). The data presented here suggests that metacognition does serve an error-monitoring function; that is, higher level metacognitive mechanisms do provide a basis for error-monitoring in the case of preference reversals. However, a puzzling aspect of this interpretation is confronted with the fact that no differences in the amount of preference reversals were observed between High and Low MC groups. It is possible that this was due to not having enough statistical power to differentiate between the amounts of preference reversals between both groups. A significant difference in any direction would provide a useful hint as to whether error correction blocks preference reversals in the first place, or actually augments the phenomenon. Although the former option seems more plausible since the slower reaction time for the High MC group could be balanced by blocking preference reversals and avoiding unnecessary corrective actions which would require more time.

6. CONCLUSION

The findings presented in this thesis investigate namely: 1) the relation between uncertainty and value computations, 2) the function of metacognition in the phenomenon of preference reversals. The role of uncertainty in value computations both from an economic point of view (Blavatskyy, 2007; McFadden, 1980) and a neuroscientific point of view (De Martino et al., 2013; Glimcher, 2008) laid the foundations of this investigation. All the behavioral findings from the study done by De Martino et al. (2013) were successfully replicated and expanded upon through the use of a novel metacognitive measure of uncertainty; switch in eye gaze.

The framework describing the three dimensions of metacognition (second-order behaviors, meta-representation & access consciousness, Fleming et al., 2012) permitted us to reinterpret the original findings of De Martino et al. (2013) in the light of two measures of uncertainty; switch and confidence ratings. Only confidence ratings can significantly predict the occurrence of preference reversals.

We demonstrated that switch is in fact related to uncertainty; it is correlated with confidence ratings and it can split the logistic fits predicting choice significantly well. Furthermore, we proved that the non-significance of switch as a predictor of preference reversals was not due to individual differences in metacognitive ability. In other words, only uncertainty that reaches awareness (i.e. appraised uncertainty) is relevant for the phenomenon of preference reversals. Likewise, our analysis presented an unexpected result but in line with our general predictions; individuals with better metacognitive capability are more sensitive to the noise present in value computations, both qualitatively and quantitatively, at least when it comes to predicting subsequent changes of mind for the same choice. Although, this sensitivity to noise shown by the group with better metacognition comes with a cost; they showed slower reaction times. This finding is in accordance with serial processing accounts of metacognition.

Albeit, these findings provide new insights in the difficult problem of how uncertainty, confidence and suboptimality interact during economic choices. Many inquiries remain on the agenda such as the causal link leading from error-monitoring to error-correction. Further studies could be designed to directly dissociate appraised uncertainty (i.e. confidence) from unappraised uncertainty (i.e. switch). For example, transcranial magnetic stimulation (TMS) could be applied to the right rlPFC where confidence is assumed to be read-out to test a causal relationship between this brain area and subjective reports of confidence.

7. ACKNOWLEDGMENTS

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9. APPENDIX

9.1 LIST OF ITEMS USED

Stimuli 1	**Doritos**
Stimuli 2	**Wotsits**
Stimuli 3	**Twix**
Stimuli 4	**M&M's**
Stimuli 5	**Lion**
Stimuli 6	**Bounty**
Stimuli 7	**Walkers Cheese and Onion**
Stimuli 8	**KP Original Salted Peanuts**
Stimuli 9	**Crunchie**
Stimuli 10	**Twirl**
Stimuli 11	**Monster Munch**
Stimuli 12	**Skittles**
Stimuli 13	**Haribo Jelly Bunnies**
Stimuli 14	**Kit Kat**
Stimuli 15	**Mars**
Stimuli 16	**Dormen Cashew**

Instructions

Welcome to the experiment.

Part 1: In the first part of this experiment you will be presented with various food items, which you have to choose among. Two items will be presented at the same time. You will make a choice of either item by pressing the right or left button on a Microsoft gamepad. You have as much time as you wish to make your choice. When you have made a choice an asterisk (*) will appear beneath the chosen item. Your choice should be based on which of the presented items you would most like to eat after the experiment.

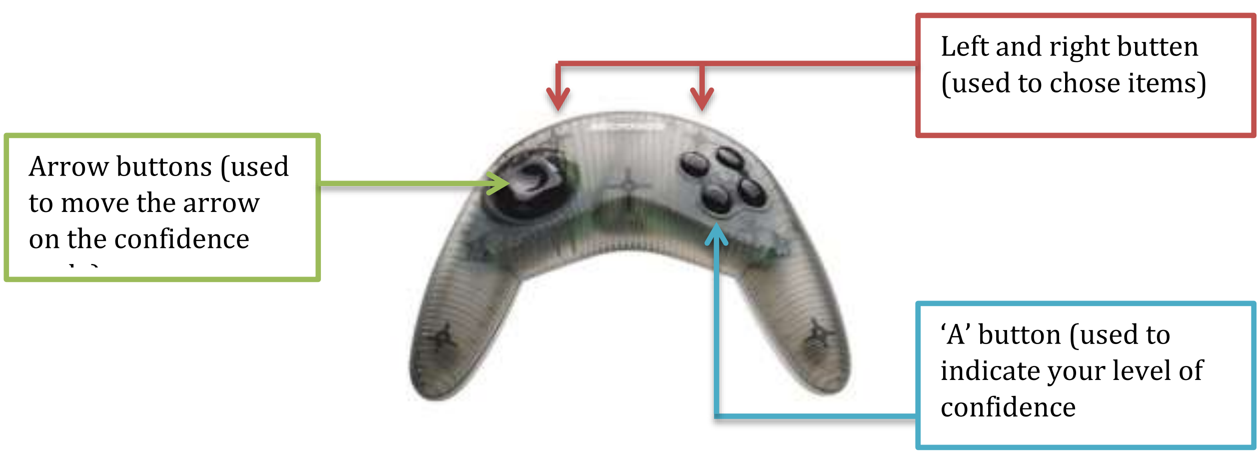
After you have made your choice you will be asked to indicate how confident you are that the item you picked was the right choice. You will indicate your level of confidence on a sliding rating scale (from 1 -6). It is important that you try to use the full range on the scale and think hard about how confident you are after each decision. We are interested in the <u>**relative**</u> confidence with this task, which means that even if your confidence only varies a little during the task please indicate this by using the entire scale.

1 = relatively low confidence

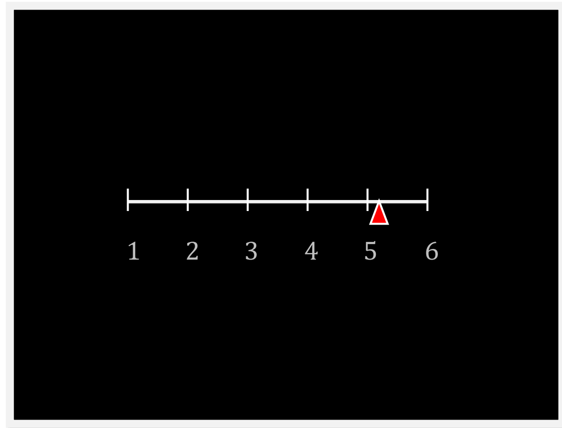
6 = relatively high confidence

To indicate your confidence you use the arrow buttons on the gamepad. When you are happy with the level of confidence you press the 'A' button to move on in the experiment.

The following figure illustrate where the buttons are situated on the gamepad:



The two following screenshots illustrate an example of the task:

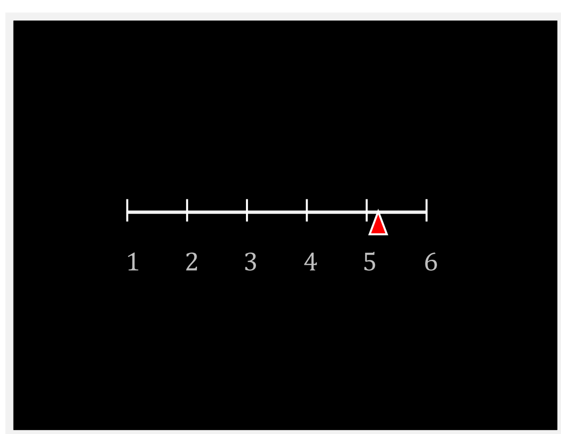


In the example illustrated above the participant is asked to indicate their preference between the Doritos and the Twix. In this example the participant chose the Twix. In the second screen the participant is asked to indicate how confident he or she is with the choice. In this example the participant was reasonably confident of their decision so they've selected a confidence rating just above 5.

Part 2: In the second_part of the experiment you will have the chance to purchase one of the items you chose in an auction. You will be shown each of the items you previously chose between, one by one. You are asked to rate how much you are willing to pay for the individual items on a sliding scale from £0-£3. You indicate your bid by moving the arrow keys on the keyboard. Press the spacebar when you are ready to move on and are satisfied with your bid.

After each submitted bid you will be asked to indicate how confident you are that the bid you submitted for the item was your correct valuation of it. This is just like in the first stage of the experiment; a scale from 1 (indicating relatively low confidence) up to 6 (indicating relatively high confidence). Slide the scale left and right using the left and right arrow keys on the keyboard. Press the spacebar when you are ready to move on.

The following screenshots provides an example of the bidding task:



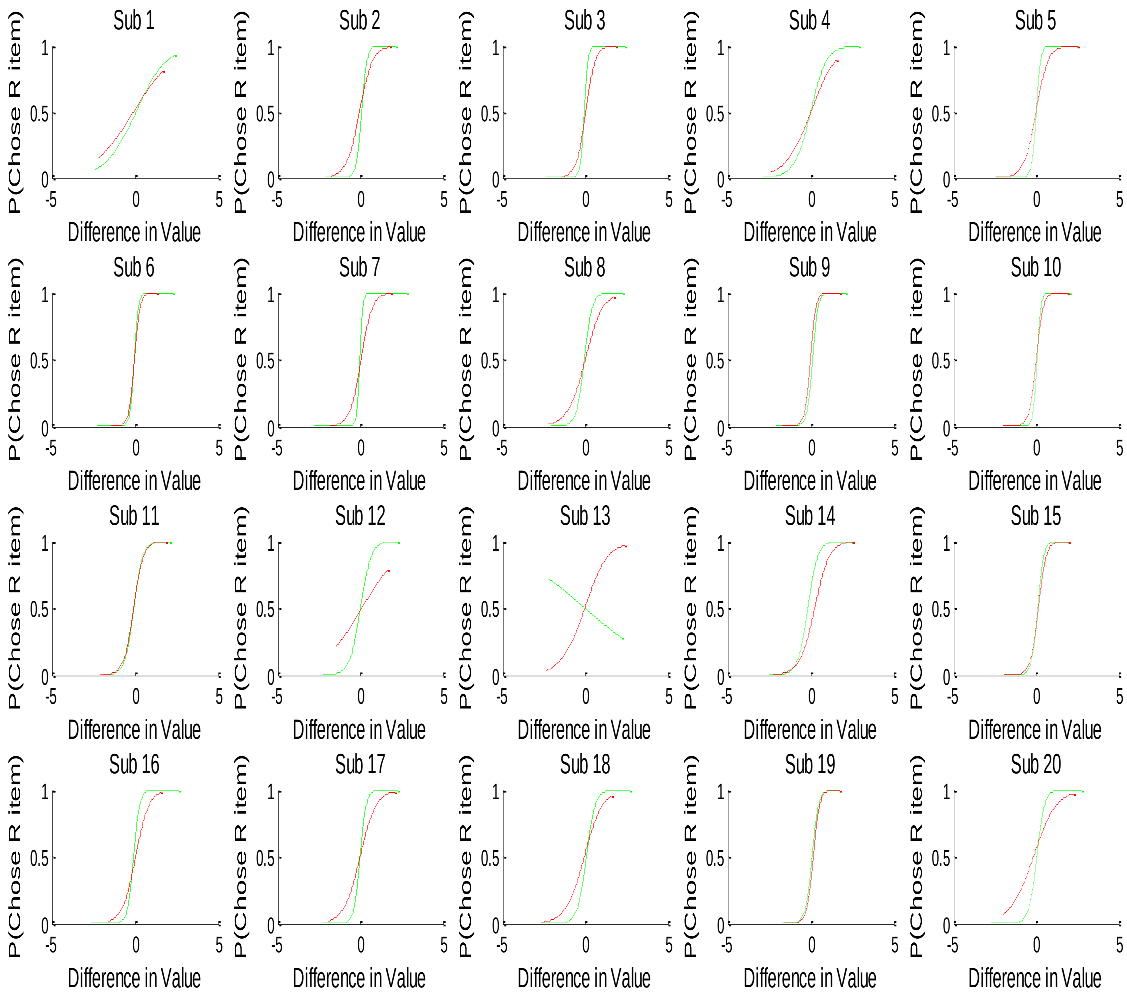
Think carefully about the price you bid. Each bid should be the maximum price you are prepared to pay to consume each of these items. After you have indicated your bids one of the trials of the items you chose in the first part of the experiment will be drawn at random. If the value of you bid for this item is higher than or equal to the generated market value you will purchase the item. In order to establish what the price of the item is and if you buy the item or not we will run an auction.

Example of how the auction works:

We start by looking at your bid for the item (i.e. the maximum price you were happy to pay for it). For example, let's say the item is a pack of M&Ms and your bid for it in the experiment was £1.60. The "market price" of the snack (e.g. the pack of M&Ms) will be randomly generated by computer using a random number generator which can generate a price between £0.10 and £3.00 in 10 pence increments. Let's say for example that the cost of the pack of M&Ms generated randomly is established to be £1.10. Since the maximum price you bid (£1.60) is higher than the cost of the item (£1.10) you will buy the item in this instance. However, it is important to realise that you do not pay £1.60 for the item, but the cost of M&Ms (£1.10). This might seem strange but think of each price that you bid as the maximum price you are happy to pay, not the price of the item randomly generated. If the price generated was instead established to be £2.10, since this price is higher than your bid of £1.60 you won't purchase the pack of M&Ms. It's therefore in your interest to state the truthful price you are willing to pay for each item in part 2 of the experiment since this does not affect the cost of the item to you, but it does affect the probability that you buy the item. Please be aware that you will be required to stay 1 more hour with us after the experiment and the ONLY FOOD you will be allowed to consume during this time will be any item bought during the experiment – we will be very strict about this. So when you are deciding how much bid for an item ask yourself how much YOU want that item and how much you are ready to pay for consuming that snack at this time (disregarding how much you would usually expect to pay for each of these items in a grocery store). This is not such an unusual situation and a real-life example might help to clarify the point. Imagine you go to the cinema and want to buy some popcorn to eat during the film; here it has probably occurred to you at one time or another that the cost of popcorn would be a lot less outside of the cinema (e.g. in a supermarket or at your home) than the prices being demanded by the cinema snack counter. However, if you want to consume popcorn during the film, you have to pay the prices they're proposing and it's up to you to decide if this is a price you are happy paying or not. If you purchase a snack item in the auction the price you pay for the item will be deducted from your final payment for participation. Before each part of the experiment we will run some practice trials to make sure you are comfortable with the task and everything is clear. If you have any further questions before the real experiment begins, please feel free to ask. It is important that you are clear about these instructions before we start.

Part 3: In the third part of the experiment you will be asked to fill out a questionnaire involving details about the different food items, such as familiarity and how efficiently you believe they are in reducing hunger.

9. 3A LOGISTIC FITS SPLIT ON CONFIDENCE



9.3B LOGISTIC FITS SPLIT ON SWITCH/RT