Full title:

Decreased confidence in loss-avoidance contexts is a primary meta-cognitive bias of human reinforcement learning

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Abstract

In simple probabilistic instrumental-learning tasks, humans learn to seek reward and to avoid punishment equally well. Despite this remarkable symmetry in choice accuracy between gain and loss contexts, two recent effects of valence have been independently documented in reinforcement learning. First, decisions in a loss-context are slower, which is consistent with the Pavlovian-instrumental transfer hypothesis. Second, the loss context decreases individuals' confidence in their choices. Whether these two effects are two facets of a single process or two independent effects of valence is still unknown. Here, across five experiments, we assessed the relative merit of the two hypotheses. Our results show that, in loss-contexts, the decrease in confidence in one's choices can be robustly observed in the absence of the response time bias. This suggests that the effects of valence on motor and metacognitive responses, although concomitant in most cases, are dissociable. Jointly, these results highlight new important constraints that should be incorporated in mechanistic models of decision-making that integrate choice, reaction times and confidence.

Introduction

In simple probabilistic instrumental-learning tasks, humans can learn to seek reward and to avoid punishment equally-well (Fontanesi, Lebreton, & Palminteri, 2018; Guitart-Masip et al., 2012; Palminteri, Khamassi, Joffily, & Coricelli, 2015; Pessiglione, Seymour, Flandin, Dolan, & Frith, 2006). This is not only robustly demonstrated in experimental data, but also nicely explained by context-dependent reinforcement-learning models (Fontanesi et al., 2018; Palminteri et al., 2015). Yet, on top of this remarkable symmetry in choice accuracy between gain and loss contexts, two recent effects of valence have been uncovered in reinforcement learning.

First, learning from punishment decreases individuals' confidence in their choices (Lebreton, Bacily, Palminteri, & Engelmann, 2018). Confidence judgment is a metacognitive operation defined as the subjective estimation of the probability of being correct (Fleming & Daw, 2017; Pouget, Drugowitsch, & Kepecs, 2016; Yeung & Summerfield, 2012). Second, learning from punishment increases individuals' response times (RT), slowing down the motor execution of the choice (Fontanesi et al., 2018). This robust phenomenon is consistent with Pavlovian-Instrumental Transfer (PIT) hypothesis, which posit that desirable contexts favor motor execution and approach behavior while undesirable contexts hinder them (Boureau & Dayan, 2011; Guitart-Masip et al., 2012).

Yet, whether these two concurrent effects of valence on response times and confidence are two facets of a single process or arise from two independent processes is still unknown. Previous research has yielded conflicting results that generated two opposing hypotheses: the single process hypothesis and the two-independent processes hypothesis. On the one hand, the two independent processes hypothesis is supported by numerous studies documenting behavioral and neural dissociations between perceptual, cognitive or motor operations, and confidence or metacognitive judgments (Fleming, Huijgen, & Dolan, 2012; Miele, Wager, Mitchell, & Metcalfe, 2011; Qiu et al., 2018). Likewise, brain lesions and stimulation protocols have been shown to disrupt confidence ratings and metacognitive abilities without impairing cognitive or motor functions (Fleming et al., 2015; Fleming, Ryu, Golfinos, & Blackmon, 2014; Rounis, Maniscalco, Rothwell, Passingham, & Lau, 2010) - although see also (Bor, Schwartzman, Barrett, & Seth, 2017).

On the other hand, the single process hypothesis is supported by the known links between confidence and RT in human decision making, both in perceptual (Geller & Whitman, 1973; Vickers, Smith, Burt, & Brown, 1985) and value-based tasks (De Martino, Fleming, Garrett, & Dolan, 2013; Folke, Jacobsen, Fleming, & Martino, 2016; Lebreton, Abitbol, Daunizeau, & Pessiglione, 2015). This coupling is notably embedded in many sequential-sampling models accounting for decisions, response times and confidence (De Martino et al., 2013; Moran, Teodorescu, & Usher, 2015; Pleskac & Busemeyer, 2010; Ratcliff & Starns, 2009, 2013; van den Berg et al., 2016; Yu, Pleskac, & Zeigenfuse, 2015). Beyond a simple mechanistic association, it has recently been proposed that we might learn to use our own RT as a proxy for stimulus strength and certainty judgment, and this proposed causal link from RT to confidence has received some support at the experimental level (Desender, Opstal, & Bussche, 2017; Kiani, Corthell, & Shadlen, 2014). This last interpretation could imply that our previously reported effects of valence on confidence are no more than a spurious consequence of the effect of valence on RT (Lebreton et al., 2018): it is indeed possible that participants simply observed that they were slower in the loss context, and used this information to infer lower confidence judgments in these contexts.

Here, we aimed to address this issue. Using two published datasets and original data collected from three new experiments, we tested whether the effects of valence on RT and confidence are two facets of a single process or two independent effects. In the new experiments, we manipulated in several ways the timing of the option-action mapping, such that individuals could make a decision about which stimulus to choose, but had to wait for the stimulus-action-mapping to initiate a motor response. We show that this greatly decreased the RT-confidence correlations, and, in our last experiment, remove the effect of valence on RT altogether. We reasoned that if the valence-induced bias on confidence *disappears* in the absence of the valence-induced slowing of response times, it has to be characterized as a *secondary* metacognitive bias (because it would then be dependent on the RT slowing). On the contrary, if the valence-induced bias on confidence *persists* in the absence of the valence-induced slowing of RT, it has to be characterized as a *primary* metacognitive bias (because it would then be independent on the RT slowing).

In all experiments, we observed a very robust effect of valence on confidence, even in the absence of the valence-induced slowing and in the absence of a significant association between RT and confidence. Our results suggest that valence effects on RT and confidence judgments are dissociable, and therefore, that there is a genuine effect of valence on confidence that causes a *primary* metacognitive bias. This raises important questions regarding the mechanistic models of decision, response times and confidence, and the effects of context valence on decision-making.

Methods

Subjects

All studies were approved by the local Ethics Committee of the Center for Research in Experimental Economics and political Decision-making (CREED), at the University of Amsterdam. All subjects gave informed consent prior to partaking in the study. The subjects were recruited from the laboratory's participant database (www.creedexperiment.nl). A total of 90 subjects took part in this set of 5 separate experiments (see **Table 1**). They were compensated with a combination of a show-up fee (5€), and additional gains and/or losses depending on their performance during the learning task: experiment 1 had an exchange rate of 1 (in-game euros = payout); experiments 2-5 had an exchange rate of 0.3 (in game euros = 0.3 payout euros). In addition, in experiments 2-5, three trials (one per session) were randomly selected for a potential 5 euros bonus each, attributed based on the confidence incentivization scheme (see below).

Learning tasks – General

In this study, we iteratively designed five experiments, aiming at investigating the impact of context valence and information on choice accuracy, confidence and response times, in a reinforcement-learning task. All experiments were adapted from the same basic experimental paradigm (see also **Figure 1**): participants repeatedly faced pairs of abstract symbols probabilistically associated with monetary outcomes (gains or losses), and they had to learn to choose the most advantageous symbol of each pair (also referred to as context), by trial and error. Two main factors were orthogonally manipulated (Palminteri et al., 2015): valence (i.e. some contexts only provide gains, and others losses) and information (some contexts provide information about the outcome associated with both chosen and unchosen options –complete information- while others only provided information about the chosen option –partial information). In addition, at each trial, participants reported their confidence in their choice on a graded scale as the subjective probability of having made a correct choice (see **Figure 1**). In all experiments but one (Exp. 2-5) those confidence judgments were elicited in an incentive-compatible way (Ducharme & Donnell, 1973; Lebreton et al., 2018; Schlag, Tremewan, & van der Weele, 2015).

Results from experiment 1 and 2 were previously reported in (Lebreton et al., 2018): briefly, we found that participants exhibit the same level of choice accuracy in gain and loss contexts, but are less confident in loss contexts. In addition, they appeared to be slower to execute their choices in loss contexts. Here, in order to evaluate the interdependence between the effects of valence on RT and confidence, we successively designed three additional tasks (**Figure 1.C-E**). In those tasks, we modified the response setting to blur the effects of valence on RT, with the goal to assess the effects of valence on confidence in the absence of an effect on RT.

Learning tasks - Details

All tasks were implemented using MatlabR2015a® (MathWorks) and the COGENT toolbox (http://www.vislab.ucl.ac.uk/cogent.php). In all experiments, the main learning task was adapted from a probabilistic instrumental learning task used in a previous study (Palminteri et al., 2015). Invited participants were first provided with written instructions, which were reformulated orally if necessary. They were explained that the aim of the task was to maximize their payoff and that gain seeking and loss avoidance were equally important. In each of the three learning session, participants repeatedly faced four pairs of cues - taken from Agathodaimon alphabet. The four cue pairs corresponded to four conditions, and were presented 24 times in a pseudo-randomized and unpredictable manner to the subject (intermixed design). Of the four conditions, two corresponded to reward conditions, and two to loss conditions. Within each pair, and depending on the condition, the two cues of a pair were associated with two possible outcomes (1€/0€ for the gain and -1€/0€ for the loss conditions in Exp. 1; 1€/0.1€ for the gain and -1€/-0.1€ for the loss conditions in Exp. 2-5) with reciprocal (but independent) probabilities (75%/25% and 25%/75%) - see (Lebreton et al., 2018) for a detailed rationale.

Experiments 1 and 2 were very similar (**Figure 1.A-B**): at each trial, participants first viewed a central fixation cross (500-1500ms). Then, the two cues of a pair were presented on each side of this central cross. Note that the side in which a given cue of a pair was presented (left or right of a central fixation cross) was pseudo-randomized, such as a given cue was presented an equal number of times on the left and the right of the screen. Subjects were required to select between the two cues by pressing the left or right arrow on the computer keyboard, within a 3000ms time window. After the choice window, a red pointer appeared below the selected cue for 500ms. Subsequently, participants were asked to indicate how confident they were in their choice. In Experiment 1, confidence ratings were simply given on a rating scale without any additional incentivization. To perform this rating, they could move a cursor –which appeared at a random position- to the left or to the right using the left and right arrows, and validate their final answer with the spacebar. This rating step was self-paced. Finally, an outcome screen displayed the outcome associated with the selected cue, accompanied with the outcome of the unselected cue if the pair was associated with a complete-feedback condition.

In experiment 3, we dissociated the option display and motor response: symbols were first presented on a vertical axis (2s), during this period, participants could choose their preferred symbol, but were uncertain about which button to press to select their preferred symbol. This uncertainty was resolved in the next task phase, in which two horizontal cues indicated which of the left vs right response button could be used to select the top vs bottom symbol (**Figure 1.C**). In addition, we imposed a time limit on the response selection (<1s), to incentivize participants to make their decision during the symbol presentation, and allow only an execution of a choice that was already made during the response mapping screen. In Experiment 4, we added a mask (empty screen 0.5-1s) between the symbol presentation and the response mapping (**Figure 1.D**). This further strengthened the encouragement to make a decision during the symbol presentation to reduce task load, because they would then only have to retain the information about the selected location (top vs bottom) during the mask period. Finally, in Experiment 5, we introduced a jitter (variable time duration; 2-3s) at the symbol presentation screen (**Figure 1.E**) to further discourage temporal expectations and motor preparedness during the decision period. In all experiments, response time is defined as the time between the onset of the screen conveying the response mapping (Symbol for Exp. 1-2; Choice for Exp. 3-5; see **Figure 1**), and the key press by the participant.

Matching probability and incentivization

In Experiment 2-5, participant's reports of confidence were incentivized via a matching probability procedure that is based on the Becker-DeGroot-Marshak (BDM) auction (Becker, DeGroot, & Marschak, 1964) Specifically, participants were asked to report as their confidence judgment their estimated probability (p) of having selected the symbol with the higher average value, (i.e. the symbol offering a 75% chance of gain (G75) in the gain conditions, and the symbol offering a 25% chance of loss (L25) in the loss conditions) on a scale between 50% and 100%. A random mechanism, which draws a number (r) in the interval [0.5 1], is then implemented to select whether the subject will be paid an additional bonus of 5 euros as follows: If $p \geq r$, the selection of the correct symbol will lead to a bonus payment; if $p < r$, a lottery will determine whether an additional bonus is won. This lottery offers a payout of 5 euros with probability r and 0 with probability 1-r. This procedure has been shown to incentivize participants to truthfully report their true confidence regardless of risk preferences (Hollard, Massoni, & Vergnaud, 2015; Karni, 2009).

Participants were trained on this lottery mechanism and informed that up to 15 euros could be won and added to their final payment via the MP mechanism applied on one randomly chosen trial at the end of each learning session (3×5 euros). Therefore, the MP mechanism screens (**Figure 3.A**) were not displayed during the learning sessions.

Transfer task

All subjects also performed a Transfer task (Lebreton et al., 2018; Palminteri et al., 2015). Data from this additional task is not relevant for our main question of interest and is therefore not analyzed in the present manuscript.

Variables

In all experiments, response time is defined as the time between the onset of the screen conveying the response mapping (Symbol for Exp. 1-2; Choice for Exp. 3-5; see **Figure 1**), and the key press by the participant.

Confidence ratings in Exp. 1 were transformed form their original scale (0-10) to a probability scale, (50-100 %), using a simple linear mapping: confidence = (50 + 5 × rating)/100;

Statistics

All statistical analyses were performed using Matlab R2015a. All reported p-values correspond to two-sided tests. T-tests refer to a one sample t-test when comparing experimental data to a reference value (e.g. chance: 0.5), and paired t-tests when comparing experimental data from different conditions.

Generalized linear mixed-effect (glme) models include a full subject-level random-effects structure (intercepts and slopes for all predictor variables). The models were estimated using Matlab's fitglme function, which maximize the maximum pseudo-likelihood of observed data under the model (Matlab's default option). Choice accuracy was modelled using a binomial response function distribution (logistic regression), whereas confidence judgments and response times were modelled using a Normal response function distribution (linear regression).

For instance, the linear mixed-effect models for choice accuracy can be written in Wilkinson-Rogers notation as:

Choice_accuracy ~ 1 + Val. + Inf. + Val. * Inf. + Fix. + Stim. + Mask. + Sess. + (1 + Val. + Inf. + Val. * Inf. + Fix. + Stim. + Mask. + Sess. |Subject),

With Val: valence; Inf: information; Fix.: fixation duration (only available in Experiments 4-5); Stim.; stimulus display duration (only available in Experiment 5); Mask: Mask duration (only available in Experiments 4-5); Sess: session number.

Note that Val. and Inf. are coded as 0/1, but that the interaction term Val*Inf was computed with Val. and Inf. coded as -1/1 and then rescaled to 0/1.

Results

First, we evaluated the effects of our manipulation of the display and response settings across the experiments on average levels of choice accuracy and confidence ratings using multiple independent one-way ANOVAs. We found no effect of the experiments on the average levels of choice accuracy and confidence ratings (accuracy: $F(4,85) = 0.98$, $P = 0.423$, $\eta^2= 0.04$; confidence: $F(4,85) = 0.36$, $P = 0.833$, $\eta^2= 0.02$), indicating that learning behavior is comparable across all experiments (**Table 1**). Unsurprisingly, we found a strong effect of the experiments on the average RT (RT: $F(4,85) = 105.83$, $P = 3.53\times10^{-32}$, $\eta^2= 0.83$), validating our decision-response decoupling and time pressure manipulations.

Next, we analyzed the effects of our experimental manipulation (valence and information) on the observed behavioral variables (choice accuracy, confidence, RT), using repeated measure ANOVAs in each individual study (**Figure 2**; **Table 2**). The parallel analyses of choice accuracy and confidence ratings replicated the results reported in (Lebreton et al., 2018): individuals were more accurate in complete information contexts (main effect of information on accuracy, Exp. 2, 3 & 5: $Ps< 0.05$; Exp. 1 & 4: $Ps < 0.1$). In addition, although accuracy was similar in gain and loss contexts (main effect of valence on accuracy, Exp. 1-5: all $Ps > 0.3$), individuals were less confident in loss contexts (Main effect of valence on confidence, Exp. 1-5: all $Ps < 0.01$). These effects were mitigated when more information was available (interaction valence × information on confidence: Exp. 1, 4 & 5: $Ps < 0.05$; Exp. 2: $P < 0.1$).

We also replicated the results reported in (Fontanesi et al., 2018): despite our efforts to cancel valence effects on RTs in experiments 3 and 4, we still observed that participants were slower in loss contexts in experiments 1-4 (Main effect of valence on RT: all $Ps<0.01$). Yet, our results show that in Experiment 5, we were successful in cancelling the effects of valance on RT (main effect of valence on RT: $F(1,17) = 1.97$, $P=0.178$, $\eta^2= 0.001$). Despite this significantly reduced effect of valence on RT, we still observed effects on confidence (main effect of valence on confidence in Exp. 5: $F(1,17) = 16.71$, $P<0.001$, $\eta^2= 0.15$).

We also computed, at the session level (participants underwent 3 separate learning sessions per experiment), the correlations between RT and confidence ratings. When averaged at the individual level and tested at the population level (one sample t-test), this measure of the linear relationship between RT and confidence was very significant in all experiments, except in experiment 5 (**Table 1**).

This indicates that our last design succeeded in fully decorrelating RTs and confidence. This might provide important hints for future studies where such a decorrelation might be required by design (e.g. for functional neuroimaging).

Overall, this first set of results robustly end jointly replicated the effects of valence and information on confidence, choice accuracy and RTs reported separately in (Lebreton et al., 2018) and (Fontanesi et al., 2018) in two new experiments (Exp. 3-4). In addition, in a fifth experiment, (Exp. 5) we successfully canceled the effects of valence on RTs, and thereby any correlation between RT and confidence at the session level, but still observed a robust effect of valence on confidence. This suggests that the effects of valence on motor vs metacognitive responses, although concomitant in general, are partly dissociable.

While this result was accomplished via careful and iterative updating of the experimental design, it is worth noting that this main result mostly relies on a non-significant test in one out of five experiments (absence of effect of valence on RTs in experiment 5). In the following paragraphs, we therefore aim to provide additional confirmatory evidence in favor of our main hypothesis, namely that the valence effect on confidence exists in the absence of a valence effect on RT, using inter-individual differences. We assessed the link between individual slowing down (RT in gain – loss) and individual confidence-bias (confidence in gain-loss) in our full sample and in each individual study using linear regressions (see methods for details). In those regressions, the coefficients for the intercept and slope quantify two different but equally important signals: First, the y-intercept represents a theoretical individual who exhibits no effect of valence on RT (RT in gain – loss = 0, **Figure 3A**): an intercept significantly different from 0 therefore indicates that a significant effect of valence on confidence can be observed in the absence of an effect on RT. Second, the slope quantifies how the effect of valence on confidence linearly depends on the effect on RTs. Both at the population level (i.e. combining data from all five experiments) and in each individual study, the intercepts of those regressions were estimated to be significantly positive (all Ps <0.05; **Figure 3.A-B; Table 3**). This indicates that, despite Exp. 5 being the only experimental setting where the manipulations of display and response modalities successfully cancelled the effects of valence on RT, all five experiments provide evidence for the relative independence of the effects of valence on RT and confidence. Note that at the population level, the slope of the regression was also significantly negative ($\beta = -0.02 \pm 0.01$, $t(88) = -3.32$, $P = 0.001$), indicating that the more participants were slowed down by loss context, the less confident they were in their response. This was not consistently replicated at the experiment level (**Table 3**), probably because our manipulation gradually eliminated/removed all meaningful difference in RT between the experimental conditions.

In order to give a comprehensive overview of the triple dissociation between performance, confidence and RT, and to quantify the effects of the different available predictors on these behavioral measures, we also ran generalized linear mixed-effect regressions. Independent variables included not only valence, information and their interaction, but also the different available timings (e.g. duration of the stimulus or mask display) and a linear trend accounting for the session effects (see methods for details). These sensitive trial-by-trial analyses replicated the main ANOVA results reported above regarding the effects of valence and information on performance, confidence and RT (**Figure 4**; **Tables 4-6**). They notably confirmed that no effect of valence can be detected on RT or performance in experiment 5 ($P = 0.349$ and $P = 0.620$) while a robust effect is observed on confidence ($P = 0.002$).

Finally, we also found that the duration of the symbol presentation (Exp. 5) and of the mask (Exp. 4-5) impact RT (both $Ps < 0.001$) without altering performance or confidence (all $P > 0.3$).

Discussion

The present work investigated the relationship between two main recent findings reported independently: in simple probabilistic reinforcement-learning tasks, learning to avoid punishment increased participants' response time (RT) and decreased their confidence in their choices, without affecting their actual performance (Fontanesi et al., 2018; Lebreton et al., 2018). The valence-induced bias on RT is consistent with – and currently interpreted as – an expression of Pavlovian-Instrumental Transfer (Boureau & Dayan, 2011; Guitart-Masip et al., 2012), whereas the valence-induced decrease in confidence is viewed as a value-confidence interaction potentially generated by mechanisms such as affect-as-information (Lebreton et al., 2018; Schwarz & Clore, 1983).

One of the motivations behind this new line of studies was to rule out a potential alternative explanation of the observed decrease in confidence: that participants can derive confidence estimates from changes in RT. Indeed, because it has been suggested that humans can infer confidence levels from observing their own response times (Desender et al., 2017; Kiani et al., 2014), the valence-induced bias on confidence - currently replicated in 7 independent experiments (Lebreton et al., 2018; Lebreton et al., 2018)- could be spuriously driven by a Pavlovian-Instrumental Transfer mechanism operating at the level of motor initiation (Boureau & Dayan, 2011; Guitart-Masip et al., 2012). As such, valence-induced confidence biases would then merely reflect a secondary effect of valence mediated by reaction time slowing and not a primary bias on metacognition. Crucially, this possibility is not ruled out by previous studies, where effects of affective states on confidence judgments in perceptual or cognitive tasks typically lacked control over RT (Giardini, Coricelli, Joffily, & Sirigu, 2008; Koellinger & Treffers, 2015; Massoni, 2014) –but see (Lebreton et al., 2018). On a more general scope, this new line of studies also aimed at providing new data to inform models of RT, confidence and decision.

Over five experiments, the first noticeable result is that we systematically replicated previous instrumental learning results using the same paradigm with very consistent effect sizes (Palminteri et al., 2015; Palminteri, Kilford, Coricelli, & Blakemore, 2016): participants learn equally well to seek reward and avoid punishment, and learning performance benefits from complete information (i.e. feedback about the counterfactual outcome). The reliability of the results extended beyond choice behaviour as confidence and RT are respectively lower and slower in punishment contexts, as previously reported (Fontanesi et al., 2018; Lebreton et al., 2018). The second important result is that we observed a significant valence effect on confidence with dramatically reduced (Exp. 3 and 4) or absent (Exp. 5) valence effects on RT. This is a clear indication that the lower confidence observed in the loss-avoidance context is dissociable from the Pavlovian-instrumental transfer bias typically observed in similar contexts and thus represent a primary meta-cognitive bias. This was confirmed by additional evidence from inter-individual difference analyses, which suggest that in all five experiments, a theoretical subject exhibiting no valence-induced bias in RT would still exhibit a valence-induced bias in confidence.

Overall, these last results replicate the confidence bias induced by the context value recently reported in perceptual tasks (Lebreton et al., 2018). In this study, while the incentive determining the context value was displayed after participants made their choice - thereby preventing any context-value effect on RT-, context value still robustly biased confidence. Considering these converging pieces of evidence, we claim that it is even more unlikely that valence-induced bias on confidence reported in human reinforcement-learning (Lebreton et al., 2018) is a simple consequence of a Pavlovian-Instrumental Transfer mechanism operating at the level of motor initiation (Boureau & Dayan, 2011; Guitart-Masip et al., 2012). Note that findings from a recent study (Dotan, Meyniel, & Dehaene, 2018) also challenge the notion that humans infer confidence levels from observing their own response times (Desender et al., 2017; Kiani et al., 2014), and suggests that decision reaction times are a consequence rather than a cause of the feeling of confidence. It is worth noting that in most studies, decision-time (i.e. when participants reach a decision) and response times (when participants indicate their choice) are not experimentally dissociated and often indexed by the same measure (RTs). Here we experimentally delayed the mapping between decisions (in the symbol space) and motor implementation, which resulted in an effective control over response times. Future studies could investigate whether participants can keep track of an internal measure of decision time, which could influence confidence.

Although confidence estimations are reported to be near-optimal in other learning and decision-making contexts devoid of affective components such as incentives, rewards or punishments – see e.g. (Meyniel, Schlunegger, & Dehaene, 2015; Sanders, Hangya, & Kepecs, 2016) – we suspect that the valence-induced confidence biases would generalize above and beyond our investigations in perceptual decision-making and reinforcement learning (Lebreton et al., 2018; Lebreton et al., 2018). If this general influence of affective components on metacognitive judgments of confidence is confirmed, the manipulations of context value (valence) could prove useful to dissociate and investigate important components of decision-making and metacognitive judgments, such as objective uncertainty and subjective confidence (Bang & Fleming, 2018). As a step in this direction, our results actually represent a triple dissociation between choice accuracy, confidence and RT: three measures that, under the general umbrella of 'performance', are often used inter-changeably. Above and beyond the effects of valence and information – which have been independently reported to dissociate confidence and choice accuracy (Lebreton et al., 2018) and choice accuracy and reaction times (Fontanesi et al., 2018) –, the present GLME regressions (**Figure 4**) revealed that increasing the duration of stimulus and mask presentations decreases RT, but has no impact on confidence or choice accuracy. This indicates that the combination of experimental manipulations used in Exp. 5 to blur the effects of valence on RT did not obliterate all informative variance in this behavioral output. In other words, RTs still capture important features of the decision process.

On a more general scope, experimental manipulations allowing triple dissociations between performance, confidence and RTs might be informative to refine decision models concurrently accounting for those three outputs, most of which derive from the sequential sampling framework and are variants of decision diffusion models (De Martino et al., 2013; Fontanesi et al., 2018, 2018; Kepecs, Uchida, Zariwala, & Mainen, 2008; Pleskac & Busemeyer, 2010; Vickers, 1970; Yu et al., 2015; Zylberberg, Fetsch, & Shadlen, 2016). Ultimately, they could also prove helpful to disentangle which variable can account for – or might confound – various physiological response (Urai, Braun, & Donner, 2017).

In summary, the present study replicates the existence of a context-value bias on confidence judgments in human reinforcement-learning (Lebreton et al., 2018), and rules out interpretations based on response times. This bias appears to generalize over a variety of tasks (Jönsson, Olsson, & Olsson, 2005; Koellinger & Treffers, 2015; Lebreton et al., 2018; Massoni, 2014), and could be driven by an affect-as-information process generating a value-confidence interaction (Lebreton et al., 2015; Schwarz & Clore, 1983). Similarly to what happened in the field of economics, we expect that models which best describe confidence formation in humans will not only benefit from strong normative roots (Drugowitsch, 2016; Hangya, Sanders, & Kepecs, 2016; Pouget et al., 2016) but also from systematic investigations of biases observed in confidence judgments (Kahneman & Tversky, 2000).

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Figures

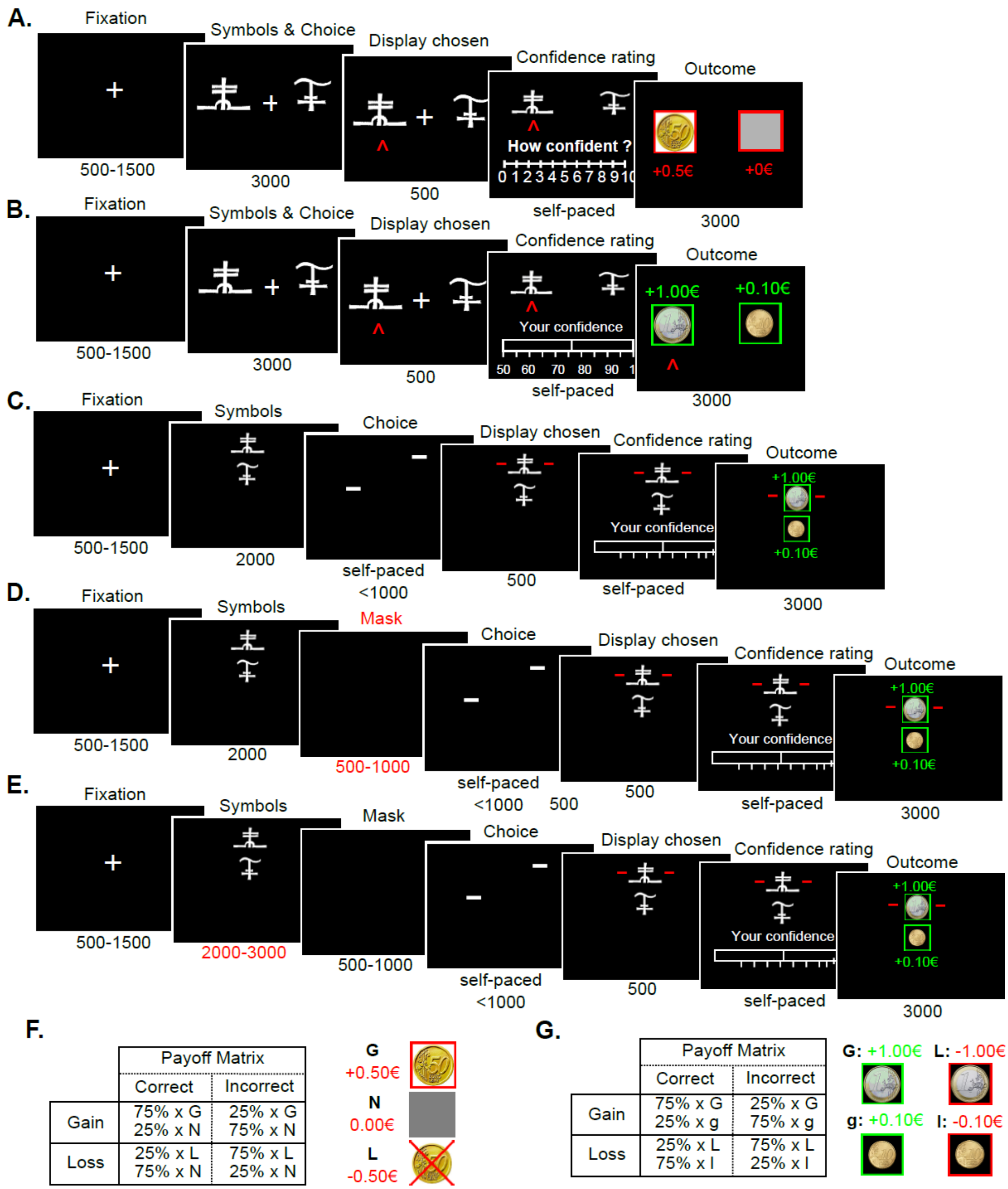

Figure 1. Experimental paradigms

(A-E) Behavioral tasks for Experiments 1-5**.** Successive screens displayed in one trial are shown from left to right with durations in ms. All tasks are based on the same principle: after a fixation cross, participants are presented with a couple of abstract symbols displayed on a computer screen and have to choose between them. They are thereafter asked to report their confidence in their choice on a numerical scale. Outcome associated with the chosen symbol is revealed, sometimes paired with the outcome associated with the unchosen symbol -depending on the condition. Tasks specificities are as follow: **(A)** Experiment 1: symbols are displayed on the left and right sides of the screen. Confidence is reported on a 0-10 Likert scale non-incentivized. **(B)** Experiment 2: similar to experiment, except that confidence is reported on a 50-100% rating scale and incentivized. **(C)** Experiment 3: similar to Experiment 2, except that options are displayed on a vertical axis. Besides, the response mapping (how the left vs right arrow map to the upper vs lower symbol) is only presented after the symbol display, and the response has to be given within one second of the response mapping screen onset. **(D)** Experiment 4: similar to experiment 3, except that a short empty screen is used as a mask, between the symbol display and the response mapping. **(E)** Experiment 5: similar to experiment 4, except that a jitter is introduced in the symbol presentation. **(F)** Experiment 1 payoff matrix. **(G)** Experiments 2-5 payoff matrix..

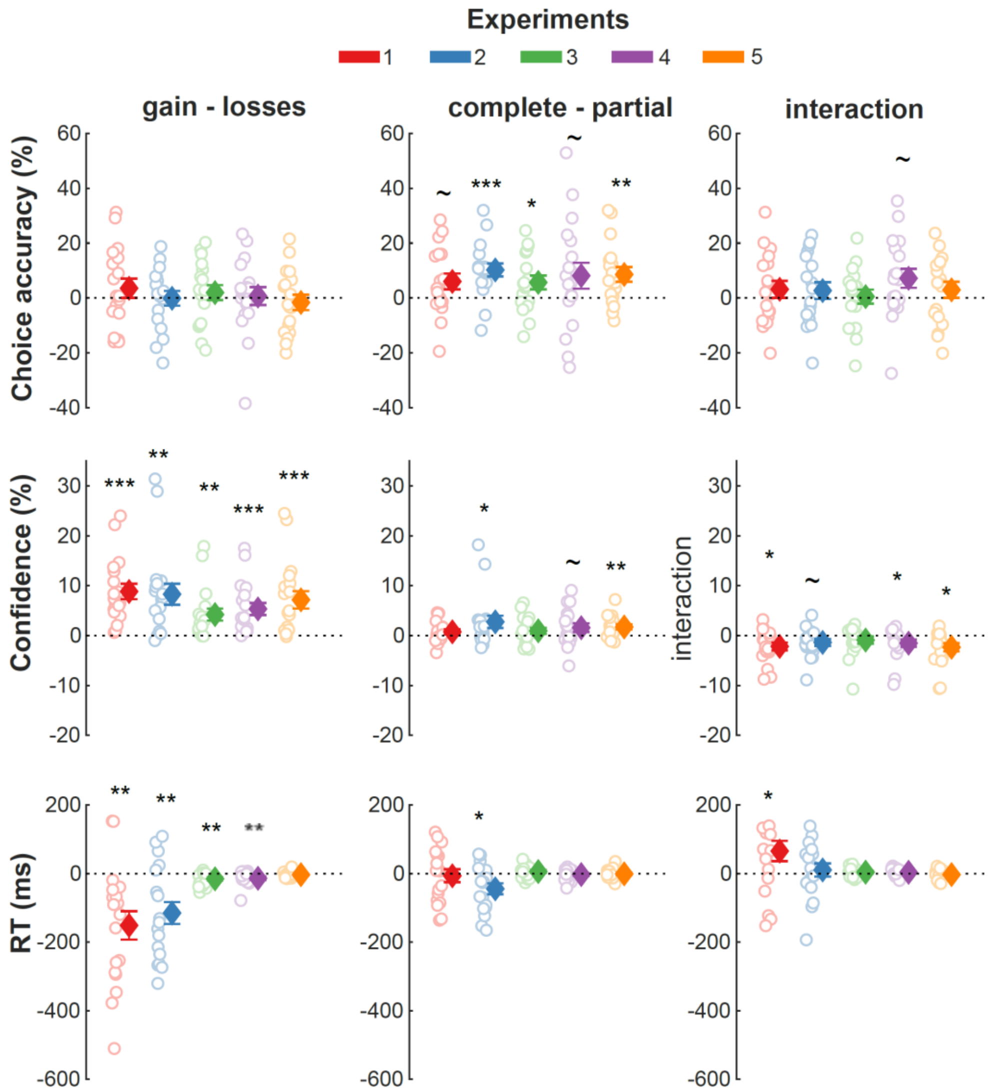

Figure 2. Behavioral results. Effects of the main manipulations (left: valence; middle: information; right: interaction) on the behavior (top: choice accuracy; middle: confidence; bottom: response times). Analyses are independently performed in the five different experiments with repeated-measure ANOVAs. With-filled dots represent individual data points. Diamonds and error-bars represent sample mean ± SEM.

~ P<0.1; * P<0.05; ** P<0.01; *** P<0.001

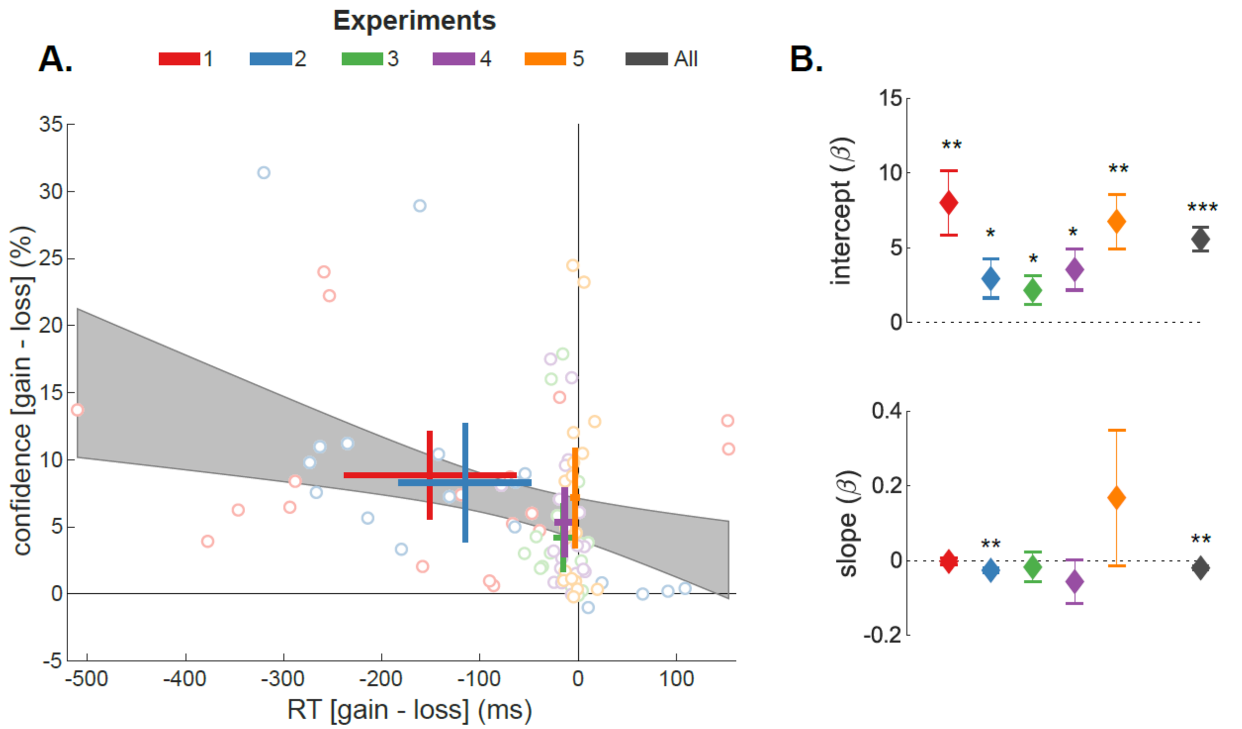

Figure 3. Assessing the link between the effects of valence on confidence and response times. **(A)** Inter-individual correlations between the effects of valence on confidence (Y-axis) and response times (X-axis). Dots represent data points from individual participants. Thick lines represent the mean ± 95%CI of the effects of valence on confidence (vertical lines) and response times (horizontal lines). Experiments are indicated by the dot edge and line color. The black shaded area represents the 95%CI or the inter-individual linear regression. Note that potential outliers did not bias the regression, given that simple and robust regressions gave similar results. **(B)** Inter-individual regressions of the valence-induced RT slowing on valence-induced confidence difference, in the different experiments. Top: estimated intercepts of the regressions. Bottom: estimated slopes of the regressions. Diamonds and error-bars represent the estimated regression coefficients (β) and their standard error.
* P<0.05; ** P<0.01; *** P<0.001

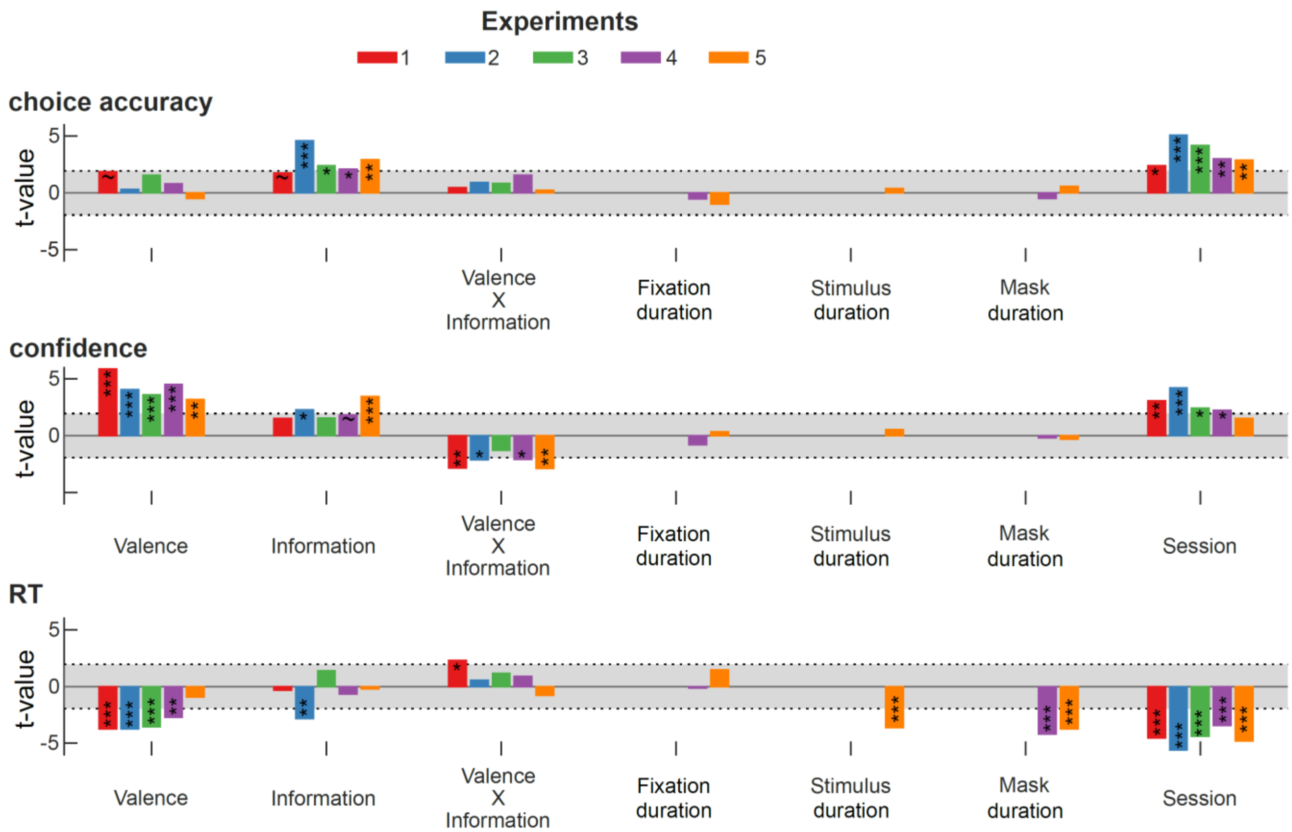

Figure 4. Generalized linear mixed-effects models. Estimated standardized regression coefficients (t-values) from generalized linear mixed-effects (GLME) models, fitted in the different experiments. Top: logistic GLME with choice accuracy as the dependent variable. Middle: linear GLME with confidence as the dependent variable. Bottom: linear GLME with RT as the dependent variable; Shaded area represent area where coefficients are not significantly different from 0 (abs(t-value)< 1.95; p>0.05).

~ P<0.1; * P<0.05; ** P<0.01; *** P<0.001

	Exp. 1	**Exp. 2**	**Exp. 3**	**Exp. 4**	**Exp. 5**
Gender M/F	8/10	8/10	10/8	10/8	6/12
Age mean ± STD	24.6 ± 8.5	24.6 ± 4.3	22.72 ± 3.24	23.84 ± 4.12	20.61 ± 1.77
Performance mean ± SEM	76.50 ± 2.38	77.04 ± 1.69	80.00 ± 2.82	75.33 ± 2.34	73.40 ± 2.83
Confidence mean ± SEM	79.19 ± 1.49	81.11 ± 1.58	78.78 ± 2.61	78.35 ± 2.24	78.09 ± 1.75
Correlation(conf, perf) mean ± SEM t(17) (P-val)	-0.39 (0.12) -3.41 (0.003)**	-0.67 (0.06) -11.13 (<0.001)***	-0.23 (0.10) -2.27 (0.036)*	-0.25 (0.07) -3.55 (0.003)**	-0.05 (0.07) -0.72 (0.482)

Table 1. Demographics and behavior.
The correlation between confidence and performance was performed at the session level using Pearson's R, then averaged at the individual level. Reported statistics correspond to a random-effect analysis (one sample t-test) performed at the population level.
STD: standard deviation. SEM: standard error of the mean. T: Student t-value.

			Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5
Performance	**val.**	F(1,17), [η^2]	1.04, [0.01]	0.00, [0.00]	0.40, [0.00]	0.01, [0.00]	0.33, [0.00]
		(P-val.)	(0.323)	(0.971)	(0.538)	(0.912)	(0.571)
	inf.	F(1,17), [η^2]	4.28, [0.04]	18.64, [0.15]	5.56, [0.04]	3.26, [0.06]	10.17, [0.07]
		(P-val.)	(0.054)~	(0.001)***	(0.031)*	(0.089)~	(0.005)**
	val×inf	F(1,17), [η^2]	1.06, [0.01]	0.77, [0.01]	0.06, [0.00]	4.36, [0.04]	1.04, [0.01]
		(P-val.)	(0.319)	(0.393)	(0.816)	(0.052)~	(0.326)
Confidence	**val.**	F(1,17), [η^2]	33.11, [0.27]	15.43, [0.19]	12.18, [0.03]	19.14, [0.07]	16.71, [0.15]
		(P-val.)	(<0.001)***	(0.001)***	(0.003)***	(<0.001)***	(<0.001)***
	inf.	F(1,17), [η^2]	2.00, [0.00]	4.92, [0.02]	2.28, [0.02]	3.21, [0.01]	11.07, [0.01]
		(P-val.)	(0.175)	(0.040)*	(0.149)	(0.091)~	(0.004)**
	val×inf	F(1,17), [η^2]	7.58, [0.02]	4.25, [0.01]	1.61, [0.01]	4.46, [0.01]	7.87, [0.02]
		(P-val.)	(0.014)*	(0.055)~	(0.222)	(0.050)~	(0.012)*
RT	**val.**	F(1,17), [η^2]	13.25, [0.03]	13.15, [0.08]	12.47, [0.01]	11.23, [0.01]	1.97, [0.00]
		(P-val.)	(0.002)**	(0.002)**	(0.003)**	(0.004)**	(0.178)
	inf.	F(1,17), [η^2]	0.12, [0.00]	7.64, [0.01]	1.82, [0.00]	0.31, [0.00]	0.09, [0.00]
		(P-val.)	(0.733)	(0.013)*	(0.195)	(0.586)	(0.766)
	val×inf	F(1,17), [η^2]	4.94, [0.01]	0.36, [0.00]	1.32, [0.00]	2.32, [0.00]	0.70, [0.00]
		(P-val.)	(0.040)*	(0.558)	(0.266)	(0.146)	(0.414)

Table 2. Repeated measure ANOVAs.
val: valence; inf: information;
SEM: standard error of the mean
~ P<0.1; * P<0.05; ** P<0.01; *** P<0.001

		Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	All
Intercept	β ± SE	8.02 ± 2.15	2.94 ± 1.29	2.16 ± 0.95	3.54 ± 1.37	6.76 ± 1.81	5.58 ± 0.78
	t-val	3.72	2.27	2.27	2.58	3.73	7.19
	(P-val)	(0.002)**	(0.037)*	(0.038)*	(0.020)*	(0.002)**	(<0.001)***
Slope	β ± SE	-0.003 ± 0.009	-0.03 ± 0.01	-0.02 ± 0.04	-0.06 ± 0.06	0.17 ± 0.18	-0.02 ± 0.01
	t-val	-0.27	-3.55	-0.46	-0.97	0.81	-3.32
	(P-val)	(0.793)	(0.003)**	(0.662)	(0.35)	(0.368)	(0.001)**

Table 3. Estimated coefficients from inter-individual robust regressions.
For each individual, we estimated the net effect of valence on RT and confidence, by computing the averaged difference of these behavioral measures in the gain versus loss contexts. For analyses restricted to single experiment, we used robust regressions to decrease the vulnerability of our estimates in the relatively small samples (n=18). For the combined analysis (n=90), simple and robust regressions gave similar results, and we only report here the results of the simple regression.
β: estimated regression coefficient. SE: estimated standard error of the regression coefficient.
~ P<0.1; * P<0.05; ** P<0.01; *** P<0.001

		Exp. 1	**Exp. 2**	**Exp. 3**	**Exp. 4**	**Exp. 5**
Val.	β ± SE t-val (P-val)	0.40 ± 0.21 1.86 (0.063)~	0.08 ± 0.18 0.32 (0.748)	0.16 ± 0.27 0.58 (0.561)	0.15 ± 0.19 0.78 (0.43)	-0.08 ± 0.17 -0.50 (0.620)
Inf.	β ± SE t-val (P-val)	0.31 ± 0.18 1.74 (0.081)~	0.72 ± 0.16 4.59 (<.001)***	0.52 ± 0.22 2.40 (0.016)*	0.63 ± 0.30 2.10 (0.036)*	0.51 ± 0.18 2.92 (0.004)**
Val xInf	β ± SE t-val (P-val)	0.10 ± 0.20 0.47 (0.638)	0.20 ± 0.21 0.92 (0.356)	0.16 ± 0.19 0.83 (0.405)	0.36 ± 0.23 1.56 (0.118)	0.04 ± 0.18 0.23 (0.814)
Fix (s)	β ± SE t-val (P-val)	-	-	-	0.18 ± 0.35 -0.51 (0.611)	-0.28 ± 0.28 -0.99 (0.322)
Stim (s)	β ± SE t-val (P-val)	-	-	-	-	0.03 ± 0.07 0.37 (0.713)
Mask (s)	β ± SE t-val (P-val)	-	-	-	0.14 ± 0.29 -0.47 (0.637)	0.17 ± 0.28 0.57 (0.567)
Sess.	β ± SE t-val (P-val)	0.34 ± 0.14 2.40 (0.016)*	0.78 ± 0.15 5.08 (<0.001)***	0.58 ± 0.14 4.17 (<0.001)***	0.46 ± 0.15 3.00 (0.003)**	0.30 ± 0.10 2.89 (0.004)**

Table 4. Estimated coefficients from generalized linear mixed-effect models on performance
β: estimated regression coefficient for fixed effects. SE: estimated standard error of the regression coefficient.

Val: valence; Inf: information; Fix.: fixation duration; Stim.; stimulus display duration; Sess: session number.

~ $P<0.1$; * $P<0.05$; ** $P<0.01$; *** $P<0.001$

		Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5
Val.	β ± SE	8.85 ± 1.51	8.29 ± 2.05	4.23 ± 1.17	5.34 ± 1.19	7.19 ± 2.27
	t-val	5.86	4.04	3.59	4.50	3.16
	(P-val)	(<0.001)***	(<0.001)***	(<0.001)***	(<0.001)***	(0.002)**
Inf.	β ± SE	0.76 ± 0.51	2.75 ± 1.20	0.95 ± 0.61	1.55 ± 0.85	1.73 ± 0.51
	t-val	1.49	2.28	1.55	1.82	3.43
	(P-val)	(0.135)	(0.022)*	(0.120)	(0.069)~	(<0.001)***
Val xInf	β ± SE	-2.16 ± 0.76	-1.38 ± 0.65	-0.90 ± 0.69	-1.51 ± 0.72	-2.36 ± 0.82
	t-val	-2.85	-2.12	-1.31	-2.10	-2.89
	(P-val)	(0.004)**	(0.034)*	(0.192)	(0.036)*	(0.004)**
Fix (s)	β ± SE				-1.11 ± 1.40	0.49 ± 1.43
	t-val	-	-	-	-0.79	0.34
	(P-val)				(0.428)	(0.734)
Stim (s)	β ± SE					0.21 ± 0.39
	t-val	-	-	-	-	0.53
	(P-val)					(0.596)
Mask (s)	β ± SE				0.27 ± 1.48	-0.40 ± 1.32
	t-val	-	-	-	-0.18	-0.30
	(P-val)				(0.854)	(0.761)
Sess.	β ± SE	2.99 ± 0.98	2.84 ± 0.68	1.75 ± 0.73	1.96 ± 0.89	1.20 ± 0.80
	t-val	3.05	4.19	2.41	2.23	1.50
	(P-val)	(0.002)**	(<0.001)***	(0.016)*	(0.026)*	(0.133)

Table 5. Estimated coefficients from generalized linear mixed-effect models on confidence

β: estimated regression coefficient for fixed effects. SE: estimated standard error of the regression coefficient.

Val: valence; Inf: information; Fix.: fixation duration; Stim.; stimulus display duration; Sess: session number.

~ P<0.1; * P<0.05; ** P<0.01; *** P<0.001

		Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5
Val.	β ± SE	-151.12 ± 40.37	-115.63 ± 30.96	-15.31 ± 4.33	-13.49 ± 4.97	-3.23 ± 3.44
	t-val	-3.74	-3.73	-3.53	-2.71	-0.94
	(P-val)	(<0.001)***	(<0.001)***	(<0.001)***	(0.007)**	(0.349)
Inf.	β ± SE	-6.57 ± 19.58	-44.37 ± 15.75	5.81 ± 4.13	-2.81 ± 4.28	-0.80 ± 3.78
	t-val	-0.34	-2.82	1.41	-0.65	-0.21
	(P-val)	(0.737)	(0.005)**	(0.160)	(0513)	(0.832)
Val xInf	β ± SE	65.58 ± 28.77	10.59 ± 18.88	3.75 ± 3.25	3.67 ± 4.19	-3.04 ± 3.85
	t-val	2.28	0.56	1.15	0.88	-0.79
	(P-val)	(0.023)*	(0575)	(0.249)	(0.381)	(0.430)
Fix (s)	β ± SE				-2.37 ± 16.13	18.56 ± 12.77
	t-val	-	-	-	-0.15	1.45
	(P-val)				(0.883)	(0.146)
Stim (s)	β ± SE					-12.18 ± 3.37
	t-val	-	-	-	-	-3.61
	(P-val)					(<0.001)***
Mask(s)	β ± SE				-68.34 ± 16.35	-54.20 ± 14.55
	t-val	-	-	-	-4.18	-3.73
	(P-val)				(<0.001)***	(<0.001)***
Sess.	β ± SE	-152.43 ± 33.63	-146.28 ± 26.13	-26.93 ± 6.14	-32.55 ± 9.51	-27.22 ± 5.64
	t-val	-4.53	-5.60	-4.38	-3.42	-4.79
	(P-val)	(<0.001)***	(<0.001)***	(<0.001)***	(<0.001)***	(<0.001)***

Table 5. Estimated coefficients from generalized linear mixed-effect models on response times.

β: estimated regression coefficient for fixed effects. SE: estimated standard error of the regression coefficient.

Val: valence; Inf: information; Fix.: fixation duration; Stim.; stimulus display duration; Sess: session number.

~ P<0.1; * P<0.05; ** P<0.01; *** P<0.001