The dynamics of motivated perception: Effects of control and status on the perception of ambivalent stimuli

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Previous studies on attentional biases often show contradictory results. This suggests that important moderating variables have been neglected so far. We suggest that (1) control over potential consequences and (2) satisfaction with the current status are important factors that need to be considered. We explored the influence of these variables using a colour classification task, where colours are associated with financial gains and losses. Data were analysed with hierarchical logistic regression models and with stochastic diffusion models. The latter approach has the special advantage that it allows separating perceptual and judgemental biases. Results show an overall positive judgemental bias. In the absence of control, this positivity bias increases with the amount of money that has been gained, whereas the opposite pattern is present when dangers can be controlled. In the second experiment, no general feedback was given, which led to an increasing negativity bias. Results are discussed within an action theoretic framework.

Keywords: Attentional bias; Motivated perception; Motivated reasoning; Counter regulation; Control; Diffusion model.

Theories and findings regarding the perception and assessment of ambivalent stimuli can be categorised into two contradictory groups: On the one hand, research on motivated perception (Alter & Balcetis, 2011; Balcetis & Dunning, 2006; Erdelyi, 1974) and motivated reasoning (Ditto & Lopez, 1992; Kunda, 1990; Mata, Ferreira, & Sherman, 2013) suggests an optimistic bias, that is, positive aspects of an situation should drive assessments, and the probability of positive outcomes should be overestimated. One the other hand, many studies report increased automatic attention for negative information (Öhman, Lundqvist, & Esteves, 2001; Pinkham, Griffin, Baron, Sasson, & Gur, 2010; Pratto & John, 1991). These attentional approaches on a negativity bias are flanked by accounts on decision-making that predict general risk avoidance (Tversky & Kahneman, 1981).

Supporters of motivated perception and motivated reasoning accounts claim that a positivity bias helps to maintain the psychological well-being. A negativity bias is often explained by an evolutionary account: it is argued that it is dangerous—and potentially lethal—to miss a danger cue and thus
the automatic direction of attention to dangers brings an evolutionary advantage.

**Moderators of attentional bias**

Findings regarding automatic attention for positive vs. negative stimuli are often inconsistent; one example of contradictory results is the face-in-the-crowd paradigm: different studies show either threat superiority (Öhman, Lundqvist, & Esteves, 2001; Pinkham et al., 2010) or happy superiority effects (e.g., Calvo & Nummenmaa, 2008). Another example is the famous study by Pratto and John (1991), showing greater distraction by negative words in the Stroop task. This result has been questioned by Wentura, Rothermund, and Bak (2000) who showed that relevance of traits—rather than valence—triggers automatic attention. According to Wentura et al., attention is directed to both positive and negative social information if this information is relevant for the observer, which is the case for so-called other-relevant traits like friendliness or aggressiveness, but to a lesser degree for self-relevant traits like happiness or sadness (Peeters, 1983).

These contradictory findings demonstrate that we need to consider more moderator variables to get a better understanding of the on-going processes in the field of motivated perception. Possible moderators comprise situational and dispositional factors.

An important moderating factor that has been investigated thoroughly is the impact of psychological disorders. In a comprehensive meta-analysis, Bar-Haim, Lamy, Pergamin, Bakermans-Kranenburg, and van Ijzendoorn (2007) showed that—across different experimental paradigms—state and trait anxiety predicts a threat bias. The cognitive mechanisms underlying a threat bias in anxious participants were analysed using a diffusion model approach (White, Ratcliff, Vasey, & McKoon, 2010). The authors found that speed of information processing was enhanced for threatening stimuli, even if no distractor were present. An automatic allocation of attention to negative stimuli has also been found for depression (Phillips, Hine, & Thorsteinsson, 2010) and for post-traumatic stress disorder (Cisler et al., 2011).

Some studies investigated the relation of personality and attentional bias. For example, Paelecke, Paelecke-Habermann, and Borkenau (2012) showed that extraversion predicts a positivity bias, whereas neuroticism is associated with a negativity bias, at least when working memory load is high. Not surprisingly, optimism has been shown to correlate with a positivity bias (Segerstrom, 2001).

In contrast to the extensive research on dispositional moderators of attentional bias, environmental or situational variables have been largely neglected. One exception is a study on the role of control (Brandstädter, Voss, & Rothermund, 2004). Brandstädter and colleagues showed that a briefly presented danger signal is more often missed when it signals an uncontrollable loss, whereas sensitivity for danger signals was increased when the loss could be averted by an adequate action. Most importantly, in this study, a yoked control design made sure that the frequency and amount of losses was identical for controllable and uncontrollable dangers. In the present study, we want to investigate the role of control further. Specifically, we test the assumption that the decreased sensitivity for signals announcing uncontrollable dangers fosters a positive evaluation of ambivalent stimuli.

For this purpose, we employ a variant of a colour classification task introduced by Voss, Rothermund, and Brandstädter (2008). In this task, participants have to classify bicolored fields of pixels according to the dominating colour. Thereby, each colour has different financial consequences. Thus, participants develop an interest to see stimuli with the “good” colour prevailing. This paradigm has two important advantages over other more commonly used tasks like the Stroop task (e.g., Pratto & John, 1991), the face-in-the-crowd paradigm (e.g., Öhman et al., 2001) or the dot-probe paradigm (Frewen, Dozois, Joanisse, & Neufeld, 2008). Firstly, the assignment of valence to stimuli is done by an experimental manipulation. This allows for counterbalancing the valences and avoids confounds with other stimulus properties, like, for example, graphical features of schematic faces (Horstmann, Borgstedt, & Heumann, 2006), or
The relevance of traits (Wentura et al., 2000). Secondly, the usage of pixel fields allows fine-graded variations of ambivalence, that is, any ratio of negative to positive information can be chosen.

EXPERIMENT 1

In Experiment 1, participants perceived ambivalent colour stimuli, where the dominating colour determined potential gains or losses. Two groups of participants differed in the amount of control they had over personal financial consequences. Participants with control (C+) had the possibility to choose or to reject each stimulus. Whenever they appraised a stimulus to be negative (i.e., they made a “reject” decision), the danger of losing money was avoided (but there was also no chance of winning). In the group without control (C−), participants also had to classify stimuli as positive or negative. However, in this group, gains and losses were independent of the participants’ classifications. The exact pay-off matrices (see below) used here guaranteed that the financial difference between correct and error responses was equal between both groups, thus making differences in accuracy motivation unlikely. We expect that this absence of control leads to an optimistic bias in the C− group.

Method

Participants

Forty-four undergraduate students (20 females; age range: 18–47 years; \( M = 24.2; \) SD = 5.6) with different majors participated in Experiment 1. Participants were randomly assigned to the conditions with control (C+; \( N = 21 \)) and without control (C− \( N = 23 \)) and without control (C− \( N = 23 \)). Participants were compensated by a performance-related reward (range: 3.70–8.30 Euro; \( M = 6.10; \) SD = 0.86).

Materials

Bicoloured rectangles (200 × 150 pixels, ca. 8.5 × 6.5 cm) that were composed of a random pattern of orange pixels (Red-Green-Blue [RGB] values: 255/128/64) and blue pixels (RGB values: 96/175/255) were used as stimuli.

Design

The design comprised the between-participants factors control (yes: C+ vs. no: C−) and the within-participants factor stimulus type (percentage of pixels in “positive” colour: 46%, 48%, 50%, 52% or 54%). The mapping of colours (orange and blue) to valence (positive and negative) and to response keys (left vs. right) was counterbalanced across participants.

Procedure

The experiment consisted of 10 warm-up trials and 150 experimental trials. Each trial started with the presentation of a fixation cross which was replaced by the colour field after 500 ms. Depending on the colour of the majority of pixels, a left (A) or right (L) response key had to be pressed. The mapping of colours to the keys was visualised by two coloured squares at the lower left and right corner of the screen. When no response was given within 3 seconds, a warning (please respond faster) was presented. A failure to respond within 3 seconds was taken as an incorrect response.

Participants started the experiment with 2 Euro. Depending on the stimulus type, response and group (C+ vs. C−), small amounts of money could be won or lost in each trial (Table 1): In the C+ group, participants could win 10 Cent when a positive stimulus (i.e., a stimulus containing more pixels in the colour that was assigned to the positive valence) was shown, and could lose 10 Cent, when a negative stimulus was shown (half of the stimuli with 50% of pixels in positive colour were assumed to be positive and negative, respectively). Money was only won when a positive stimulus was correctly classified, and money was only lost when a negative stimulus was incorrectly classified.

In the C− group, participants got always 10 Cent after a positive stimulus and lost always 10 Cent after a negative stimulus. Additionally, there was a bonus or penalty (5 Cent) for correct or false responses. Thus, in both groups, the difference of outcomes between a correct and incorrect response was always 10 Cent (Table 1), which ensures a comparable accuracy motivation,
and makes it equally important to process the stimuli carefully. However, in the C+ group, participants can choose strategies of gain maximisation (by preferring the “positive” response) or of loss aversion (by preferring the “negative” response).

After a response key was pressed (or after the warning message in case no response was given within 3 seconds), the amount of money won or lost in the current trial was presented for 500 ms in the centre of the screen. The total amount of money won so far (bank account) was always presented on the lower edge of the screen. The next trial started after an inter-trial-interval of 1000 ms.

Data analysis

Data analysis follows two different objectives that both require sophisticated statistical methods. Firstly, we want to analyse the dependency of motivated perception on the actual status of the participants. For this purpose, the current “bank account” is used a predictor of the actual response in each trial. This is done by using a multi-level approach: Responses (pos. vs. neg.) were entered into a generalised (logistic) linear mixed-effects model (using the glmer procedure from the lme4 package in the R software). This analysis is the hierarchical equivalent to a logistic regression.

Performance in single trials defined level 1 ($N = 6585$) and participants defined level 2 ($k = 44$) of the analysis. We assumed random effects for the intercept and stimulus type (both improved model fit notably) and fixed effects for sex$^1$ (male vs. female), stimulus type ($−2$ to $+2$), control (C+ vs. C−), current account balance (money gained in Euro) and the account balance × control interaction (all predictors were cantered on 0).

A second objective of the current study is to disentangle processes of information uptake from decisional biases. Like in previous work (Voss et al., 2008), for this purpose, the diffusion model (Ratcliff, 1978) is employed: In a diffusion model analysis (see Voss, Nagler, & Lerche, 2013, for a recent introduction), several parameters are estimated from the response time (RT)-distributions of correct responses and error responses; thus, the diffusion model analysis allows disentangling several components of information processing. For our purpose, the so-called drift rate ($v$), measuring speed and direction of information uptake and the starting point of the diffusion process ($z$), measuring judgemental bias, are of interest. Since we also wanted to include the current bank account as a predictor, we split data at the overall median (3.90 Euro) into trials with low vs. high current account.$^2$

Separate drift rates were estimated for all stimulus types and for high vs. low account trials, and

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$^1$ Sex was entered as predictor here because there is evidence that men and women differ in risk perception and risk taking (Byrnes, Miller, & Schafer, 1999)

$^2$ We also conducted an analysis ignoring the current bank account. However, this analysis showed an unsatisfactory model fit.

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Table 1. Wins and losses depending on stimulus type, response and group (C+ vs. C−)

<table>
<thead>
<tr>
<th>Response</th>
<th>Control (C+)</th>
<th>Control (C+)</th>
<th>No control (C−)</th>
<th>No control (C−)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Valence</td>
<td>Valence</td>
<td>Positive</td>
<td>Positive</td>
</tr>
<tr>
<td>Correct (and fast)</td>
<td>+10</td>
<td>0</td>
<td>+10 (+5)</td>
<td>+10 (+5)</td>
</tr>
<tr>
<td>Incorrect (or slow)</td>
<td>0</td>
<td>−10</td>
<td>−10 (−5)</td>
<td>−10 (−5)</td>
</tr>
</tbody>
</table>

Note: Amounts are given in Euro Cent. In the C− group, stimulus-related outcomes (±10 Cent) were independent of responses; however there was a bonus or penalty (±5 Cent) for correct or false responses.
separate starting points were estimated for high vs. low account trials. Because of the small trial number per condition, it is not possible to estimate inter-trial variability of drift and starting point; these parameters were fixed to zero. In total, 15 parameters were estimated from 150 trials for each participant (threshold separation; 2 starting points; 10 drift rates; non-decisional time; inter-trial variability in non-decisional time). Parameters were estimated with fast-dm-30 (Voss & Voss, 2007, 2008; see also http://www.psychologie.uni-heidelberg.de/ae/meth/fast-dm) using the maximum-likelihood criterion.

Results

Before all analyses, trials in which participants failed to respond within 3 seconds were discarded (0.2%). Then, probabilities of positive assessments were analysed with a hierarchical logistic regression. To disentangle perceptual bias and judgmental bias, RT distributions were additionally entered into a diffusion model analysis.

Hierarchical logistic regression

Regression parameters for fixed effects are presented in Table 2. Results show a positive intercept ($p < .001$), indicating an overall positivity bias in responses. Then, we observed a trivial effect of stimulus type, indicating that the probability of positive responses increased with the percentage of positive information in stimuli ($p < .001$) and a tendency of an enhanced positivity bias for women that just missed the conventional criterion of significance ($p = .06$). Overall, control had no impact on assessments; however, results revealed an interaction of control and bank account ($p < .001$; Figure 1, left panel): In the C+ group, attention shifted from a positivity bias to a negativity bias with growing bank account, whereas the positivity bias increased continuously within the C− group.3

Diffusion model analyses

Results from two participants had to be discarded because there were no valid responses for one stimulus type in one condition (they performed poorly and consequently had only a few trials with a high bank account). Data from three more participants were ignored because the diffusion model analyses resulted in unrealistic high estimates for the drift rates for easy stimuli (which is also based on too few data points); however, including these participants in the following analyses does not change the pattern of significances. Results for the remaining 39 participants are presented in Table 3. In the following, only results for drift rates and starting points are discussed because the other parameters are not of importance for the present study.

Table 2. Results for fixed effects from the generalised linear mixed-effects model (Experiment 1)

<table>
<thead>
<tr>
<th>Effect</th>
<th>Experiment 1</th>
<th>Experiment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.35</td>
<td>0.25</td>
</tr>
<tr>
<td>Sex</td>
<td>−0.28</td>
<td>−0.09</td>
</tr>
<tr>
<td>Stimulus type</td>
<td>1.24</td>
<td>1.39</td>
</tr>
<tr>
<td>Control</td>
<td>−0.04</td>
<td>−0.20</td>
</tr>
<tr>
<td>Account balance</td>
<td>−0.06</td>
<td>−0.11</td>
</tr>
<tr>
<td>Control × account balance</td>
<td>−0.20</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Note: Dependent variable: 0 = “negative” colour, 1 = “positive” colour; sex: −0.5 = female, +0.5 = male; stimulus type: −2 = negative colour dominant; +2 = positive colour dominant; control: −0.5 = C+, +0.5 = C−; account balance was centred on zero.

3In this paradigm, most participants won continuously some money so that there is a high correlation of bank account with trial number ($r = 0.85$). Therefore, it is difficult to separate effects of bank account from pure sequence effects. Nonetheless, the model fit in terms of the Akaike Information Criterion (AIC) of the bank-account model was better than the fit of a model with trial number (AIC = 6140 vs. 6147). A statistical comparison is not possible because both models have the same degrees of freedom.
0 to 1, with 0.5 representing an unbiased decisional process. The higher the starting point, the more biased is the decision in favour of a positive response. In this study, all starting points were above 0.5, indicating an overall positive bias (Table 3). However, in the group without control, this difference just missed statistical significance, \( t(18) = 1.83; p = .08 \), indicating a fairly unbiased decision in this condition. In all other conditions, there were clear biases, with \( t(18) = 4.23, p = .001 \), for C- and high account; \( t(19) = 3.48, p < .01 \), for C+ and low account; and \( t(19) = 2.83, p = .01 \), for C+ and high account. Individual estimates for relative starting points were entered in a 2 (control) by 2 (bank account) analysis of variance (ANOVA) with repeated measurement on the latter factor. In this analysis, no main effects were revealed (both \( F(1,37) < 2.06; p > .16 \)). However, there was an interaction of both

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**Figure 1.** Predicted probability of positive assessments of ambivalent stimuli as a function of control and current bank account. The grey dotted line indicates chance level (p = .50).
factors, $F(1,37) = 7.69; p < .01; \eta^2_p = 0.17$, revealing a reduction (increase) of positivity bias with increasing bank account for the C− group (C+ group).

Drift rates are a measure of speed and direction of accumulation of information, with positive (negative) values indicating that more positive (negative) information is accumulated, and values around zero revealing the absence of systematic information uptake. Estimates were entered into a 2 (control) by 2 (bank account) by 5 (stimulus type) ANOVA, with repeated measurement on the latter two factors. Results revealed a trivial main effect of stimulus type, $F(4,148) = 242.01; p < .001; \eta^2_p = 0.87$, indicating that an increasing amount of positive information is accumulated when more pixel in the positive colour are presented. The only other significant effect was a stimulus type by bank account interaction, revealing higher absolute values of drift when bank account is high. Presumably, this reflects a pure practice effect because higher absolute values indicate better performance in the later trials, when more money has been gained.

Model fit was assessed with a simulation study. First, 1000 random parameter sets were drawn from a multi-dimensional normal distributions defined by the covariance matrix of estimated parameters (using the `mvtnorm` library from the R package). From each of these parameter sets, one data-set was simulated using the `construct-samples` routine from `fast-dm-30`, matching trial numbers of the real data-sets. Then, parameters were re-estimated. From the distribution of the resulting fit indices (i.e., the log-likelihood of the solutions), the 5% percentile was taken as a critical value ($\text{LL}_{\text{crit}} = -145$). From participants’ data, only two models (5%) had a worse fit than this critical value, thus matching the expected number of random misfits. The pattern of significances of the analyses reported above does not change, when data from these two models is ignored.

### Discussion

In the present study, we investigated the perception and assessment of ambivalent stimuli as a...
function of control over possible losses. For this purpose, one group (C+) could avoid any loss by classifying a stimulus as being dangerous; in this case, also no money could be lost or won. Another group (C−) of participants assessed the same stimuli; however, stimulus-related gains and losses were independent of participants’ assessments. At the same time, accuracy motivation was held constant between both groups by implementing additional rewards (losses) for correct (erroneous) responses in the C− group.

A hierarchical logistic regression of responses revealed that for participants in the C+ group with an increasing amount of money judgements switched from positivity bias to negativity bias, while an opposite pattern was observed in the C− group. This effect was further investigated with a diffusion model analyses (Ratcliff, 1978) that takes not only responses but also response latencies into account. Results showed that there was an overall positivity bias in starting point, indicating that the criterion for positive responses is more liberal than for negative responses (this is similar to a response bias in signal detection theory). With a growing bank account, this positivity bias increased in the C− group and decreased in the C+ group. Since the diffusion model analysis revealed no effects of bank account on the parameter mapping information uptake (i.e., drift rate), we assume that the effects observed in the regression model are based on judgemental biases rather than on perceptual processes. Note that we found motivated perceptual biases with the same kind of stimuli previously (Voss et al., 2008), which demonstrates the possibility to observe such effects.

As mentioned earlier, bank account was closely confounded with trial number. This makes it difficult to disentangle effects of the two factors. We believe that the actual status is the important variable here because the hierarchical logistic regression showed better fit when account was entered than when trial number was entered. To analyse this issue more closely, we conducted a second study, in which participants did not get feedback on their current bank account. Therefore, they remained unsure whether a satisfactory amount of money was already reached.

**EXPERIMENT 2**

Experiment 2 was almost identical to Experiment 1. The only difference lies in the absence of feedback regarding the total amount of money that has been earned so far. We expect that this manipulation diminishes the effects of the C+ group reported above.

**Method**

**Participants**

Forty-four undergraduate students (22 females; age range: 18–58 years; $M = 23.2$; $SD = 6.14$) participated in Experiment 2. They were compensated by a performance-related financial reward (range: 4.40 €–7.90 Euro; $M = 6.47$; $SD = 0.68$). Participants were randomly assigned to the groups with and without control (C+: $N = 25$; C−: $N = 19$).

**Procedure**

Design, materials and the procedure were nearly exactly identical to Experiment 1. However, in Experiment 2, the total bank account was not presented on the screen. Trial-wise feedback regarding the amounts of money gained or lost in the actual trial was shown after responses as before.

**Results**

In Experiment 2, only eight trials (0.1%) had to be discarded because no response was given within 3 seconds. The same set of analyses as above was conducted.

**Hierarchical logistic regression**

Results for fixed effects from the generalised linear mixed-effects model ($N = 6592$; $k = 44$) are presented in Table 2. As before, there was a positive intercept ($p = .001$) and a strong effect of...
stimulus type ($p < .001$). Additionally, there was an effect of bank account ($p < .001$), indicating a decrease in positivity bias with growing gains. No other effects were significant.

Diffusion model analyses

Diffusion model parameters were estimated as in Experiment 1. Mean estimates are presented in Table 4. This time, valid models could be estimated for all participants and, consequently, none had to be excluded.

Analyses of starting points revealed significant positivity biases ($z > 0.5$) for low and high bank accounts in the C+ group, $t(24) = 3.42; p < .01$, and $t(24) = 4.07; p < .001$, respectively, and for the high account trials of the C− group, $t(18) = 2.67; p < .05$, but not for low account trials in the C− group, $t(18) = 1.05; p = .31$. A 2 (control) by 2 (bank account) ANOVA revealed no significant effects, all $F(1,42) < 2.68; p > .10$.

Drift rates were entered in a 5 (stimulus type) by 2 (control) by 2 (bank account) ANOVA. Results show significant main effects of stimulus type, $F(4,168) = 272.63; p < .001; \eta^2_p = 0.87$, and of bank account, $F(1,42) = 5.07; p < .05; \eta^2_p = 0.11$. The latter effect reveals a general shift from positivity bias to negativity bias in later trials (with higher bank accounts). Additionally, there was a stimulus type by bank account interaction, $F(4,168) = 3.69; p < .01; \eta^2_p = 0.09$, showing higher absolute values of drift (i.e., a better performance) in trials with higher accounts. No other effects emerged.

Model fit was again assessed with a simulation study. For 3 of the 44 participants (6.4%), model fit was worse than the cut-off criterion from simulations (i.e., the 5% percentile: LL = −114.6). This value is very close to the number of models expected to fail arbitrarily (5%). The pattern of significances

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Without control (C−) N = 19</th>
<th>With control (C+) N = 25</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Starting point</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low bank account</td>
<td>0.53 (0.13)</td>
<td>0.57 (0.11)</td>
<td>−0.04</td>
</tr>
<tr>
<td>High bank account</td>
<td>0.57 (0.12)</td>
<td>0.59 (0.11)</td>
<td>−0.02</td>
</tr>
<tr>
<td><strong>Drift</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ST1 (46% pos.); low BA</td>
<td>−1.91 (1.75)</td>
<td>−2.44 (1.55)</td>
<td>0.53</td>
</tr>
<tr>
<td>ST2 (48% pos.); low BA</td>
<td>−0.90 (0.75)</td>
<td>−1.21 (0.92)</td>
<td>0.30</td>
</tr>
<tr>
<td>ST3 (50% pos.); low BA</td>
<td>0.50 (0.83)</td>
<td>−0.07 (0.99)</td>
<td>.57*</td>
</tr>
<tr>
<td>ST4 (52% pos.); low BA</td>
<td>1.09 (1.13)</td>
<td>1.19 (1.09)</td>
<td>−0.10</td>
</tr>
<tr>
<td>ST5 (54% pos.); low BA</td>
<td>2.50 (1.41)</td>
<td>2.64 (1.50)</td>
<td>−0.14</td>
</tr>
<tr>
<td>ST1 (46% pos.); high BA</td>
<td>−2.56 (1.73)</td>
<td>−2.95 (1.39)</td>
<td>0.39</td>
</tr>
<tr>
<td>ST2 (48% pos.); high BA</td>
<td>−1.31 (1.33)</td>
<td>−1.61 (1.09)</td>
<td>0.30</td>
</tr>
<tr>
<td>ST3 (50% pos.); high BA</td>
<td>−0.36 (0.86)</td>
<td>−0.48 (1.00)</td>
<td>0.11</td>
</tr>
<tr>
<td>ST4 (52% pos.); high BA</td>
<td>1.03 (0.49)</td>
<td>1.30 (0.92)</td>
<td>−0.27</td>
</tr>
<tr>
<td>ST5 (54% pos.); high BA</td>
<td>2.52 (1.04)</td>
<td>2.97 (1.54)</td>
<td>−0.44</td>
</tr>
<tr>
<td><strong>Threshold separation</strong></td>
<td>1.46 (0.31)</td>
<td>1.25 (0.29)</td>
<td>.21*</td>
</tr>
<tr>
<td><strong>Non-decisional-time</strong></td>
<td>0.51 (0.18)</td>
<td>0.49 (0.05)</td>
<td>0.02</td>
</tr>
<tr>
<td><strong>Variability of none-decisional-time</strong></td>
<td>0.25 (0.19)</td>
<td>0.19 (0.06)</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Note: A diffusion constant of $s = 1$ was used. Upper (lower) threshold of the model represent positive (negative) responses. ST = stimulus type; BA = current bank account. *$p < .05$.  

Table 4. Mean parameter estimates (SDs in parentheses) from the diffusion model analysis (Experiment 2)

Although there was no explicit feedback on the current bank account, we entered this variable into analyses to permit comparisons with results from Experiment 1. Bank account effects suggest that participants kept an internal account, that is, they had a general idea of the sum of trial-wise pay-offs (which were still reported). Interestingly, the model including bank account still had a better fit compared with a model with trial number as predictor.
did not change, when models with poor fit were excluded from analyses.

**Discussion**

Again, we found an overall positivity bias in the hierarchical analysis (positive intercept). Diffusion model analyses show that this effect is primarily based on asymmetric response criteria (starting points above 0.5). Criteria for positive responses were more liberal than for negative responses.

The hierarchical analyses revealed further a continuous shift of judgement bias from positive to negative for both groups. Diffusion model analyses mapped this effect on drift rate, indicating that attentional processes are involved. In Experiment 2, the effect of current status did not differ between participants with and without control, suggesting that the group differences observed in Experiment 1 were based on the feedback of the current status. The comparison of trends between Experiments (Figure 1) implies that—in contrast to our expectations—feedback influenced the C− group rather than the C+ group. When no control is possible and feedback is given, perception seems to be driven by a congruency effect, that is, information matching the current status (or probably rather the satisfaction with this status) get more attention.

**GENERAL DISCUSSION**

**Optimistic bias vs. automatic attention for dangers: The role of control**

The main goal of the present study was investigating the role of control in the perception of ambivalent stimuli. Based on prior results from a study on the identification of briefly presented stimuli (Brandstädter et al., 2004), we expected more positive assessments for participants without control because the attention for negative information should be reduced in this group. However, the pattern of results proved to be more complex: The predicted pattern was present only when participants had a high amount of money won already and information on this was present on the screen.

For participants with control, we observed initially a positivity bias that shifted with growing bank account towards a negativity bias. We assume that this shift in bias is caused by a growing satisfaction with the current status of goal attainment. When no control was possible (i.e., stimulus-related gains and losses were independent of participants’ responses), positive status feedback increased the probability of positive assessments notably. This effect is most evident for stimuli with equal amounts of positive and negative information (i.e., stimulus type 3).

**Motivated perception vs. motivated reasoning**

It remains an important question at which stage of processing the effects reported here are located.

Some researchers might claim that motivational effects as observed here reflect cognitive processes rather than perception (e.g., Pylyshyn, 1999) because (early) visual processes are assumed to be immune against top-down influences (like expectations or hopes). However, there are several arguments supporting a concept of motivated perception. Firstly, there is a recent empirical evidence for a certain degree of top-down influence even on early visual processes. For example, Müller, Heller, and Ziegler (1995) present data suggesting that distractor effects of singleton stimuli in a visual search task depend on the activated task set (cf. also Krummenacher & Müller, 2012).

A second line of argumentation supporting the notion of motivated perception is based on a wider perspective on perception. We do not exclusively limit the term perception to early visual processes but refer to a longer period of information sampling. It is less controversial that attention in a search task can be guided by top-down information (Wolfe, 2007). Similarly, we expect that in our paradigm motives guide attention to areas of the ambivalent stimuli that are dominated by a specific colour, thus influencing the information uptake.

Finally, we aimed at empirically disentangling biases in perception and in judgement by
employing a diffusion model approach. The task employed in this study was chosen because it is well suited for diffusion model analyses (Voss, Rothermund, & Voss, 2004). This technique allows for separating perceptual from judgemental biases (Voss et al., 2008). We assume that perceptual biases operate largely automatically via the allocation of attention, whereas judgemental biases may have a large strategic component.

In the current study, we found generally a positivity bias on starting point, indicating asymmetric response criteria. This finding supports the so-called motivated scepticism approach on motivated reasoning (Ditto & Lopez, 1992). Information sampling is continued longer, if the gathered evidence suggests a negative outcome, and it is aborted sooner when positive implications seem likely. However, this motivated scepticism was overruled by a strong risk aversion in the C+ group, when the accumulated gains had grown to a satisfactory amount of money. Then, even weak hints of negativity drove judgements to negative decisions.

Drift rates reflect the speed of information uptake. Unlike in the study of Voss et al. (2008), we did not find a general positivity bias, nor did we observe an effect of control, suggesting a limited impact of top-down processes on the encoding of stimuli. However, in Experiment 2, a perceptual negativity bias developed with growing bank account. We assume that the effect of the (unknown) real bank account is mediated by the effect of the estimated account, based on trial-wise feedback on gains and losses.

The counter regulation approach

Performance from the C+ group from Experiment 1 may be considered the condition with the highest ecological validity: Typically, one is quite aware of one’s current status (e.g., regarding the achievement of personal goals), and many real dangers can be averted with timely actions. Consequently, the shift from positive to negative bias might reflect a typical pattern in the process of goal achievement. While positive stimuli signalling the chance of progress are important as long as little has been achieved, cognitive processing will be tuned towards the defending one’s achievements by concentration on dangers when one is close to his or her desired goals. This principle has recently been denoted as counter-regulation of attention (Rothermund, Voss, & Wentura, 2008; Wentura, Voss, & Rothermund, 2009). The counter-regulation approach assumes that attention is shifted automatically towards negative (positive) stimuli, when the motivational system is focused on gaining (not losing).

CONCLUSIONS AND OUTLOOK

The current study demonstrates the complexity of processes that are involved in motivational influences on perception and reasoning. To get a better understanding of attentional biases, it is essential to consider moderating factors and mediating cognitive or emotional processes. We addressed both issues: As important—a previously neglected—moderating variables we identified control and current status. Cognitive processes were assessed using a diffusion model account. This account may help as well to improve understanding of the relation of psychological disorders and attentional biases. The experimental paradigm employed here could well be used to address this issue.

We finish this discussion in the following with the presentation of some methodological and conceptual caveats. Firstly, one might argue that the negativity bias observed for stages with high bank accounts in the C+ groups reflects risk aversion rather than true assessments of stimuli. This is of course a valid argument; however, we consider risk aversion to be conceptually equivalent to a motivated bias. Also, weak negative information is considered to be enough to classify a stimulus as dangerous.

Secondly, our implementation of control might be criticised because learning experience differs. Participants in the C− group lose after every negative stimulus (resulting in a stronger association of this kind of stimulus and losing), whereas participants in the C+ group often avoid losing money by correctly identifying the danger (thus possible evoking a feeling of success). Future studies
could and should address this issue experimentally, for example, by implementing a probability of loss after danger in the C− group that is matched with the performance from the C+ group. However, we consider this unproblematic because although participants in the C− group experienced more losses they still developed a positivity bias.

Thirdly, there is a confound of trial sequence and account balance. With the present data, it is not possible to disentangle effects of time, practice and financial gains because these are highly correlated. We inserted bank account (and not trial sequence) in our models because this resulted in better model fit. Nonetheless, one should think about other experimental manipulations of current status that allow disentangling this from other sequence effects.

Finally, we must concede that trial number is lower than typically used in diffusion model analyses, especially when the high number of parameters is considered. We still believe that results are trustworthy for two reasons: Firstly, estimates are within typical ranges, and the manipulation of stimulus type is mapped as expected. Secondly, we recently investigated systematically the quality of parameter estimates as a function of trial number and estimation procedure (Lerche, Voss, & Nagler, submitted): In a series of simulation studies, we got high correlations of true and re-estimated parameter values even with very low trial numbers (even using a minimum of only 24 trials). Nonetheless, for future studies, the use of larger trial numbers is highly recommended.

REFERENCES


