



Interpreting Ambiguous Stimuli: Separating Perceptual and Judgmental Biases

Andreas Voss, Klaus Rothermund, Jochen Brandtstädter

► To cite this version:

Andreas Voss, Klaus Rothermund, Jochen Brandtstädter. Interpreting Ambiguous Stimuli: Separating Perceptual and Judgmental Biases. *Journal of Experimental Social Psychology*, 2008, 44 (4), pp.1048. 10.1016/j.jesp.2007.10.009 . hal-00597802

HAL Id: hal-00597802

<https://hal.science/hal-00597802>

Submitted on 2 Jun 2011

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Accepted Manuscript

Interpreting Ambiguous Stimuli: Separating Perceptual and Judgmental Biases

Andreas Voss, Klaus Rothermund, Jochen Brandtstädter

PII: S0022-1031(07)00152-7
DOI: [10.1016/j.jesp.2007.10.009](https://doi.org/10.1016/j.jesp.2007.10.009)
Reference: YJESP 2034

To appear in: *Journal of Experimental Social Psychology*

Received Date: 19 April 2007
Revised Date: 29 September 2007
Accepted Date: 14 October 2007



Please cite this article as: Voss, A., Rothermund, K., Brandtstädter, J., Interpreting Ambiguous Stimuli: Separating Perceptual and Judgmental Biases, *Journal of Experimental Social Psychology* (2007), doi: [10.1016/j.jesp.2007.10.009](https://doi.org/10.1016/j.jesp.2007.10.009)

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Running Head: MOTIVATED STIMULUS INTERPRETATION

Interpreting Ambiguous Stimuli:
Separating Perceptual and Judgmental Biases

Andreas Voss¹, Klaus Rothermund², and Jochen Brandtstädter³

¹ Albert-Ludwigs-Universität Freiburg

² Friedrich-Schiller-Universität Jena

³ Universität Trier

Word Count: 4,899 (text + notes)

Correspondence Address:

Andreas Voss

Institut für Psychologie

Engelbergerstr. 41

79085 Freiburg

Germany

Abstract

Interpreting ambiguous situations is not a purely data-driven process but can be biased towards positive interpretations by top-down influences. The present study tries to identify the underlying processes of these top-down influences. There are two separable types of processes that can be influenced by motivational biases: A *perceptual bias* affects information uptake whereas a *judgmental bias* affects acceptance criteria for positive and negative outcomes. In the present study, motivated influences on perception and judgment were investigated with a simple color discrimination task in which ambiguous stimuli had to be classified according to their dominating color. One of two colors indicated a financial gain or a loss, whereas a third color was neutral. To separate perceptual and judgmental biases, Ratcliff's (1978) diffusion model was employed. Results revealed motivational influences on perception and judgment.

(132 words)

Keywords: perceptual bias; motivated cognition; top down influences; attention; diffusion model; fast-dm

Interpreting Ambiguous Stimuli:

Separating Perceptual and Judgmental Biases

The perception of a situation depends on a complex interplay of bottom-up and top-down processes. In many cases, the evidence is equivocal and top-down processes might automatically “fill the gap”, thereby crucially affecting the appraisal of a situation. Optimistic biases in the interpretation of ambiguous situations have been documented in different studies and have been labeled, for example, as wishful thinking, motivated reasoning, need for specific closure, optimistic bias, or perceptual defense (e.g., Balcetis & Dunning, 2006; Brown, 1986; Ditto & Lopez, 1992; Erdelyi, 1974; Klein & Kunda, 1992; Kunda & Sanitioso, 1989; McGinnies, 1949; Weinstein, 1980). Although the evidence regarding motive-driven influences on judgment and decision making is overwhelming, it is much less clear how such top-down influences operate.

Motivational biases may affect different stages of information processing: On the one hand, motives can bias *perceptual processes* related to detecting and processing positive and negative information. However, top-down influences may also bias *judgmental processes* that are involved in interpreting ambiguous situations. Judgmental biases can operate by an asymmetric setting of thresholds regarding the amount of information that is required to accept a positive or negative conclusion and to terminate information uptake.

From a theoretical point of view it is important to separate top-down influences operating at a perceptual stage from biases that influence judgment and decision making. For example, some theorists have argued that perceptual processes are impenetrable to top-down influences (Pylyshyn, 1999) which would restrict motivational biases to the level of judgment and decision making. Empirically separating perceptual from judgmental biases, however, is a difficult task: Typically, motivated perception manifests itself only in the form of a motivated interpretation of a given situation. Some earlier studies have found support for self-serving tendencies at the decision stage (e.g., Ditto & Lopez, 1992). While providing

positive evidence for self-serving influences on judgment and decision making, these findings do not rule out the possibility that effects of motivated reasoning can also reflect—at least partially—a biased information processing.

In the analysis of top-down influences on perceptual processes, it has always been a key issue to separate perceptual components from response tendencies. For example, a lot of research was concerned with the so-called “perceptual defense hypothesis”, that is, with the assumption of increased perceptual thresholds for threatening information (see Erdelyi, 1974, for a review). However, this line of research was severely criticized—and finally abandoned—because of some theoretical and methodological flaws. Perhaps the most important criticism referred to the failure to show convincingly that results were driven by (automatic) perceptual processes and did not reflect (strategic) response biases (Erdelyi, 1974). This problem is most obvious for studies using embarrassing materials (e.g., the word “penis”) as stimuli (e.g., McGinnies & Adornetto, 1952). Obviously, it makes a big difference for the interpretation of the findings whether participants do not recognize this word or whether they hesitate to utter the word in a scientific lab context.

Although the problem is an old one, research on motivational top-down influences on perception and judgment still struggles to solve this issue in a convincing manner. Consider, for example, the study by Balci et al. and Dunning (2006). The authors framed their experiment as a marketing research study, in which either a highly attractive drink or a disgusting drink had to be consumed for later assessment, depending on whether a number or a letter was generated by a random symbol generator. Then, a computer crash was simulated, and participants were asked whether they had seen the result of the random generator before the crash. Directly before the crash, an ambivalent object was presented shortly (e.g., a stimulus that could be seen as the letter “B” or as the number “13”). Stimulus interpretations indicating the appealing drink were *reported* more often than interpretations indicating the embarrassing drink. This result is indicative of motivational top-down influences on

perception, if—and only if—participants really did *see* the “positive” object (i.e., if they were telling truthfully what they had seen).

Even if participants were honest, however, the source of this motivational bias would still be unclear. As demonstrated, for example, by Ditto and Lopez (1992), more information is gathered in case of an undesired event; an effect that has been labeled *motivated skepticism*. In their study, participants were told that a saliva test probed for a (fictitious) medical problem. In case of a negative result, participants tended to stare extensively at the test strap, or they repeated the test several times. This suggests that participants adopted asymmetric decision criteria: If a situation seems to be positive at the first glance, the information uptake is finished quickly (i.e., a liberal response criterion is adopted), whereas the situation is analyzed much more carefully if the stimulus information indicates an undesired event (conservative response criterion). One cannot be sure, however, whether such an effect is based exclusively on different response criteria: Increased latencies in case of negative classifications could also be due to an inhibition of negative information in early perceptual processes. Therefore, the same observed bias in behavioral responses can be based on perceptual biases, asymmetric decision criteria, or both.

The aim of the present study is to separate perceptual and judgmental influences within a single paradigm. Specifically, the dominating color of ambiguous bi-colored stimuli had to be determined in a simple color classification task. In two different blocks of the experiment, one color signaled small financial gains or losses, respectively, while no such consequences were linked to the alternative color. Thus, a motive was induced to perceive stimuli as being dominated by the positive color, or as not being dominated by the negative color. To empirically separate perceptual from judgmental biases, a diffusion model analysis (Ratcliff, 1978) was used. This technique allows an identification of different underlying cognitive processes that contribute to the interpretation of ambivalent stimuli (Voss, Rothermund, & Voss, 2004). Specifically, by simultaneously using speed and error

information, it is possible to separate the rate of information uptake (drift rate, ν) from an asymmetric setting of decision thresholds (relation of starting value to threshold, z/a) in a diffusion model analysis.

Diffusion Model Analysis

Diffusion models provide a unique stochastic approach for separating the underlying processes in speeded binary decision tasks. The method is a variant of continuous sampling models; it is assumed that stimulus information is continuously accumulated until it allows a decision with satisfying certitude (Ratcliff & Rouder, 1998). Technically, information processing is represented by an internal counter that starts with the starting value z (see Figure 1 for a graphical representation of the diffusion process and of the different parameters of the model). The value of the counter changes continuously over time: Information supporting one decision (decision “A”) increases the value of the counter, while information supporting the opposite decision (decision “B”) decreases its value. The decision process is terminated as soon as the counter reaches the critical interval either at the upper threshold (a) or at the lower threshold (0), and the corresponding response is then executed.

The relation of the starting value to the upper threshold (z/a) is an indicator of biases at the judgmental level. Imagine that “A” indicates a positive outcome, whereas “B” indicates a neutral or negative outcome. If z is larger than $a/2$, this means that the starting value is closer to the threshold for the positive decision “A” than it is to the threshold for the negative decision “B”. If z is shifted towards the threshold for the positive outcome, this is indicative of a judgmental positivity bias because less supporting information is needed to reach the positive conclusion “A.” Importantly, biases in the starting value are unrelated to perceptual processes (i.e., biases in information uptake).

The dynamics of the counter over time are described by a diffusion process which involves a systematic component and a random component. The systematic component (the drift rate ν) is constant over time. It is a measure of the ratio of information uptake for

outcome “A” relative to outcome “B” (positive values on v indicate that on average more information is gathered for decision “A” than for decision “B” during a certain time interval, whereas negative values on v indicate that information for “B” is more easily processed). To this linear process, Gaussian noise is added.¹ The random noise results in different process tracks in different decision situations, even if the drift is the same.

The drift rate can be used to tap purely perceptual biases relating to the rate of information uptake for positive vs. negative information. For example, when the evidence for the two alternatives is equally distributed in a situation (i.e., 50% positive and 50% negative information), a positive drift rate would indicate that the positive information is detected and processed more efficiently than the negative one. Similarly, motivational biases in perceptual processing can be investigated if the drift rates are averaged across situations that are equal with regard to the amount of positive and negative evidence (e.g., 60% positive and 60% negative information). If the drift rate is stronger in the former case (60% positive information) than in the latter case (60% negative information), this would yield an overall drift rate that is positive, indicating a positivity bias in perceptual processing. Again, drift rate effects indicate perceptual biases and are unrelated to judgmental processes.

The diffusion model only centers on the process that leads to the decision. Other processes (like response execution) are absorbed in a response-time constant (t_0) that is added to the exit time of the diffusion process.²

For a given set of parameters the diffusion model allows to predict the response time distributions both for correct responses and for errors. Diffusion model analyses involve a multidimensional search of parameter values, so that the fit between predicted and empiric response-time distributions is optimal. Different fit indices have been proposed for this purpose. We prefer the Kolmogorov-Smirnov statistic (Voss et al., 2004; Voss & Voss, in press b) which has the advantage of being relatively robust against outliers and uses the exact

shape of the distributions. For the diffusion-model analyses described below the free program *fast-dm* (Voss & Voss, in press a) was used.

Overview

In the present study, simple bi-colored stimuli had to be classified according to their dominating color, that is, according to the color of the majority of the pixels of a stimulus (see Figure 2). In two separate blocks of the task, one of two colors signaled a financial gain or loss, respectively, whereas the other one was not associated to any consequences. Most important, the consequences of the color-stimuli (gain vs. loss) were not contingent on the classification decisions that were given by participants. Instead, a strong accuracy motive was induced by introducing a reward for correct color classifications and a penalty for wrong color classifications. If this motivational manipulation leads to a *perceptual* advantage of positive stimulus information (and to a disadvantage of negative information) in comparison with neutral information, such a bias should manifest itself on the drift parameter (v) in the diffusion model analysis: In this case, the drift rate should be biased in favor of the desired information (or against the undesired information). A decisional bias, on the other hand, should manifest itself in the relative position of the starting point (z/a): If z is located closer to the positive threshold or farther away from the negative threshold, so that less information is necessary for classifying a given stimulus as positive and more information is necessary for classifying a stimulus as negative, this would indicate a judgmental positivity bias.

Method

Participants

Twenty-four undergraduate students (18 female; age $M = 24.6$; $SD = 7.0$) participated for a performance related financial reward (see *Procedure* for details).

Design

Essentially, the design consisted of the within subjects factors *Block* (gain vs. loss) and *Stimulus* (56%, 53%, 50%, 47%, or 44% pixels of the valent color). Additionally, the

assignment of colors (blue, green, orange) to valence (gain, loss, neutral), the order of blocks (gain first vs. loss first), and the assignment of colors to response keys (valent color left vs. valent color right) was counterbalanced across participants.

Materials

Squares of 200×150 screen pixels ($105\text{mm} \times 105\text{mm}$) were used as stimuli. Pixels of two colors (valent vs. neutral color) were randomly dispersed in various proportions (see *Design* section).

Monetary Payoffs

Monetary gains and losses were used for two purposes. Firstly, colors were assigned to positive and negative valence, and, secondly, accuracy motivation was induced by a performance related payoff. Opposite payoff rules applied in gain and loss blocks: In gain blocks, participants received 5 EuroCents for each gain stimulus, that is, for each stimulus that was dominated by the positive color (half of the stimuli with equal amounts of positive and neutral color were randomly selected as gain stimuli). At the same time, 5 EuroCent were subtracted from the actual account for each erroneous classification. In loss blocks, 5 EuroCents were removed for each loss stimulus (again, half of the stimuli with balanced colors were considered as loss stimuli), and each correct classification was rewarded with 5 EuroCent.

Procedure

Each of the two blocks consisted of 12 practice trials and 180 experimental trials. Half of these were valent trials (gain or loss), with 56%, 53%, or 50%, respectively, valent pixels in the stimulus (30 times each). Likewise, the 90 neutral trials consisted of 30 trials with 50%, 47%, or 44% valent color in the stimulus. There was no difference in the appearance of valent and neutral “50%-stimuli”, and participants were not aware that such balanced stimuli were used in the experiment. Trials were presented in random sequence.

Trials started with the presentation of a gray square, which was replaced by the stimulus 500 ms later. Now, the dominating color had to be indicated by pressing one of two response keys. For this task, there was a response deadline of 3 seconds, and the remaining time was visualized by a decreasing vertical time bar below the stimulus. Failures to respond in time were treated like errors. Immediately after the response, feedback was given: The name of the dominating color and, depending on the response, the word “correct” or “wrong”, respectively, were presented on the screen. Independent of the subjects response, gains and losses were additionally emphasized by an acoustic signal (see Rothermund, 2003): Each gain stimulus was followed by a sound with increasing pitch (440Hz-840 Hz, 200 ms), whereas losses were followed by a signal with decreasing pitch (440Hz-240 Hz, 200 ms). The current state of the financial account was always presented at the bottom of the screen.

Results

Response Times and Response Probabilities

For the analysis of response times, responses faster than 100 ms (0.3 %) or slower than 3 seconds (0.1 %) were excluded. Table 1 shows the mean response times as a function of Stimulus Type and Block. A 5 (Stimulus Type) $\times$ 2 (Block Type) repeated measurements ANOVA, revealed a main effect of Stimulus Type, $F(4, 20) = 25.88, p < .001$, partial $\eta^2 = 0.84$, indicating slower responses in trials with ambiguous stimuli. This effect was qualified by a Stimulus Type by Block Type interaction, $F(4, 20) = 8.85, p < .001$, partial $\eta^2 = 0.64$. Responses were generally faster for positive and not-negative stimuli, that is, for stimuli dominated by the valent color in the gain block or by the neutral color in the loss block. The same analysis was conducted with the percentage of color classifications indicating a dominance of the valent color as dependent variable (Table 1). Next to the trivial effect of Stimulus Type, $F(4, 20) = 4923.10, p < .001$, partial $\eta^2 = 1.00$, there was a main effect of Block Type, $F(1, 23) = 37.33, p < .001$, partial $\eta^2 = 0.62$, indicating more “valent” classifications in the gain block. Main effects were again qualified by a Stimulus Type by

Block Type interaction, $F(4, 20) = 9.47$, $p < .001$, partial $\eta^2 = 0.65$, indicating a stronger asymmetry of valent classifications between gain and loss blocks for highly ambiguous stimuli.

Diffusion Model Analysis

The above analyses demonstrate an optimistic bias in participants' responses. To analyze whether this bias is based on perceptual processes, judgmental processes, or both, responses were entered in a diffusion model data analysis which was conducted with *fast-dm* (Voss & Voss, in press a). For each participant and each block, the model's parameters were estimated. The upper threshold always corresponded to the response "valent color" (i.e., gain or loss), and the lower threshold always corresponded to the response "neutral color." For different types of stimuli, different drift rates were allowed. All other parameters were held constant across Stimulus Types. In this model, a bias could be mapped on the relative position of the starting point (z / a), indicating a judgmental bias, or on the drift rate (v), indicating a perceptual bias. Table 2 shows the mean estimates of the parameters and of the fit of the individual models.

Drift rates. The estimated drift rates were entered in a 2 (Block Type) by 5 (Stimulus Type) ANOVA. There were significant main effects of Stimulus Type, $F(4, 20) = 135.92$, $p < .001$, partial $\eta^2 = 0.97$, indicating larger (i.e., more positive) drift rates for the stimuli that were dominated by the valent color, and of Block Type, $F(4, 20) = 11.31$, $p < .01$, partial $\eta^2 = 0.33$, indicating higher (i.e., more positive) drift rates in the gain block compared to the loss block. The latter finding indicates that on average (i.e., across stimulus situations with comparable information asymmetries for positive and negative information), positive information is detected and processed more efficiently than negative information. These effects were not further qualified by an interaction with Stimulus Type, $F(1, 23) = 1.53$, n.s., partial $\eta^2 = 0.23$, indicating that the perceptual positivity bias was independent of stimulus ambiguity.

Relative starting point. Relative starting points were calculated as z divided by a ($z/a = 0.5$ indicates that the starting point is located at the midpoint between thresholds). In the gain block, the relative starting point lay above 0.5, $t(23) = 2.27$, $p < .05$, $d = 0.46$, while in the loss block, the starting point lay below 0.5, $t(23) = -6.57$, $p < .001$, $d = 1.33$. Thus, within both blocks, a judgmental bias was found, indicating that for the positive (not-negative) decision, less information had to be gathered, while more information had to be accumulated before choosing the negative (not-positive) response.

Other parameters. No significant differences between gain and loss blocks obtained for any of the remaining parameters that are contained in the model (a , t_0 , s_z , s_v , s_{t0} ; all $|t| < 1.19$, ns ; see Table 2).

Model Fit. Model fit was assessed in two ways. Firstly, the mean probability values of the KS statistic comparing empirical with predicted distribution functions were computed (see Table 2). Please note that there are five different models for each participant (one for each Stimulus Type), and the p -values presented here are the product of five p -values from the separate KS-tests (Voss & Voss, in press a). According to the combined probability values, significant deviations ($p < .05$) of predicted from observed distribution functions were found for four persons in the gain block, and for two persons in the loss block (no significant deviations were found on the 1% level for the combined p -values, and no deviations were found on the 5% level for the 120 separate tests). Results remain identical, however, if the 6 participants with significant KS values are excluded from the analyses.

Another way to investigate model fit is a graphical visualization of the fit for the combined RT distribution of the complete sample (Klauer, Voss, Schmitz, & Teige-Mocigemba, in press). For this purpose, diffusion models were fitted to the RT-distributions of all subjects for each stimulus and each block, resulting in 10 models,³ based on approximately 720 responses for each of the Stimulus Types 56%, 53%, 57%, and 44% and on approximately 1440 responses for Stimulus Type 50%. Figure 3 displays the model fit. The

graphs represent the merged cumulative distribution functions (CDFs) for correct responses and errors (Voss et al., 2004). As can be seen from Figure 3, the diffusion model is capable to recover the empirical CDFs: There is virtually no difference between the empirical and predicted CDFs.⁴

Discussion

Perceptual and Judgmental Biases in Situation Interpretation

Optimistic biases in the interpretation of situations were investigated with a discrimination task in which specific colors signaled financial gains and losses. Conventional analyses of response latencies and categorization probabilities revealed that the positive and non-negative color responses were more frequent and were executed faster, indicating a positivity bias in the interpretation of these ambiguous situations. Notably, this positivity bias in responding occurred although categorization responses did not have an influence on stimulus-related gains and losses and despite the fact that a strong accuracy motivation was triggered by financially rewarding (punishing) correct (erroneous) responses.

The main purpose of this study was to separate perceptual and judgmental sources of this positivity bias. This was achieved by a diffusion model analysis of the speeded color classification data, which allows an estimation of parameters that map different aspects of the underlying decision process. A positivity bias in perceptual processes that was reflected in the drift rate (v) indicated more efficient processing of positive and non-negative information. In addition, this procedure also revealed a positivity bias in judgmental processes appearing in the relative position of the starting point (z/a). The starting point was shifted towards the positive threshold in the gain blocks, and away from the negative threshold in the loss blocks, indicating that less positive (than neutral) information was required for classifying a stimulus as positive, while more negative (than neutral) information had to be gathered before a stimulus was evaluated as negative.

In conclusion, our findings support the hypothesis that motivational top-down influences can affect perceptual processes of information uptake as well as processes that are related to judgment and decision making. Apparently, even low-level processing of basic perceptual features can be open to motivational top-down influences. This latter finding highlights the fact that superordinate states (goals, tasks, actions, motives, emotional states, beliefs, expectations etc.) can have a wide-ranging influence on many aspects of information processing. There is already ample evidence that the views we hold of our environment and of ourselves can be biased by personal motives and pre-existing beliefs. The present results go beyond these findings in that they suggest that our information processing system enables a highly flexible configuration of basic processing parameters in the service of varying superordinate orientations (e.g., Bacon & Egeth, 1997; Derryberry & Tucker, 1994; Rothermund, 2003; Rothermund, Voss, & Wentura, in press; Rothermund, Wentura, & Bak, 2001; Tipper, 1992).

Negativity Bias vs. Optimistic Bias

The observed optimistic bias in perception can be considered as a case of “motivated reasoning” (Kunda, 1990), allowing us to assess persons, situations, or outcomes in a desired and self-serving way. At first glance, however, such an optimistic bias in basic perceptual processes seems to contradict findings showing a negativity bias in attention for social information (e.g., Fox et al., 2000; Öhman, Lundqvist, & Esteves, 2001; Pratto & John, 1990).

A closer look at these findings reveals, however, that the apparent contradiction in findings can be resolved. Firstly, most of the studies showing a negativity bias have either compared negative with neutral stimuli, or have not controlled for differences between negative and positive stimuli regarding other variables (e.g., extremity, behavioral relevance, arousal). Follow-up studies therefore have often revealed that attentional effects that have previously been attributed to negative valence are in fact due to other factors that are orthogonal to valence (arousal: Keil & Ihssen, 2004; Schimmack, 2005; behavior relevance:

Wentura, Rothermund, & Bak, 2000). Secondly, biases in the processing of valence are subject to strong interindividual differences. For example, results from a recent meta-analysis indicate that an attentional negativity bias is limited to highly anxious subjects (Bar-Heim, Lamy, Pergamin, Bakermans-Kranenburg, & van Ijzendoorn, 2007) and represents a risk factor for the development and maintenance of pathological symptoms (Mathews & MacLeod, 2005). Studies based on the dot-probe paradigm even revealed a significant threat avoidance effect for healthy control participants, at least when stimulus presentation was subliminal (Stone & Valentine, 2005).

Another important factor that may be responsible for our finding of a perceptual positivity bias is the fact that no behavioral relevance was associated with the valent stimulus information, that is, no possibility to exert control over the appearance or consequences of the positive and negative stimuli was provided. Prior experiments indicated, however, that an optimistic bias is typically present in situations that are uncontrollable or have uncontrollable consequences, whereas the possibility to ward off a threat or to achieve positive outcomes by adequate action is accompanied by a negativity bias in attention, perception, and judgment (Brandtstädter, Voss, & Rothermund, 2004; Rothermund, Bak, & Brandtstädter, 2005; Rothermund, Brandtstädter, Meiniger, & Anton, 2002; Voss, Rothermund, & Brandtstädter, 2006).

Implications for Research on Person Perception and Social Judgment

In this study, different colors were arbitrarily assigned to a positive, negative, or neutral valence. Using dichromatic colored squares without intrinsic social relevance allowed us to control for the exact amount of positive or negative information that was contained in each stimulus, which yielded a perfect situation for the study of motivational influences on perception and judgment. Separating perceptual and judgmental biases with a diffusion model analysis, however, is not restricted to experimental situations with artificial materials but can also be used to study motivational top-down effects in the processing of “real” social

stimuli (e.g., social categories, personality traits, or faces). For example, the present approach can be applied to the face-in-the-crowd paradigm (e.g., Öhman et al., 2001) in order to identify and separate perceptual and judgmental biases in the detection of angry vs. friendly faces. In this paradigm, participants have to detect either a positive or negative face in a crowd of neutral distractor faces in a visual search task. By using the full information that is contained in the response time distributions for both erroneous and correct decisions in this paradigm, the diffusion model allows an estimation of separate parameters for perceptual sensitivity (i.e., the drift rate, ν) and judgmental biases (i.e., the relative starting value, z/a).⁵ A comparison of the drift rates for trials with friendly vs. aggressive faces would reveal differences in perceptual sensitivity, whereas differences in the relative starting value would indicate asymmetric decision criteria (e.g., more/less information is necessary to accept the presence of a friendly vs. aggressive face). Such an analysis could help to disentangle some of the inconsistencies in the findings that have recently been reported with this paradigm (e.g., Horstmann & Bauland, 2006; Juth, Lundqvist, Karlsson, & Öhman, 2005; Öhman et al., 2001).

Diffusion model analyses can be used to investigate biases in perception and judgment in diverse areas of social information processing. In principle, a diffusion model analysis can be applied to all paradigms in social cognition and social perception research that are based on repeated fast binary decisions (e.g., visual search, recognition tasks, evaluation, and social categorizations). We thus recommend the diffusion model as a powerful tool that allows an identification of the basic underlying processes of positivity and negativity biases in perception and judgment.

References

- Balcetis, E., & Dunning, D. (2006). See what you want to see: Motivational influences on visual perception. *Journal of Personality and Social Psychology*, 91, 612-625.
- Bacon, W. F. & Egeth, H. E. (1997). Goal-directed guidance of attention: Evidence from conjunctive visual search. *Journal of Experimental Psychology: Human Perception and Performance*, 23, 948-961.
- Bar-Haim, Y., Lamy, D., Pergamin, L., Bakermans-Kranenburg, M. J., & van Ijzendoorn, M. H. (2007). Threat-related attentional bias in anxious and nonanxious individuals: A meta-analytic study. *Psychological Bulletin*, 133, 1-24.
- Brandtstädter, J., Voss, A., & Rothermund, K. (2004). Perception of danger signals: The role of control. *Experimental Psychology*, 51, 1-9.
- Brown, J. D. (1986). Evaluations of self and others: Self-enhancement biases in social judgments. *Social Cognition*, 4, 353-376.
- Derryberry, D., & Tucker, D. M. (1994). Motivating the focus of attention. In P. M. Niedenthal & S. Kitayama (Eds.), *The heart's eye* (pp. 167-196). San Diego, CA: Academic Press.
- Ditto, P. H., & Lopez, D. F. (1992). Motivated skepticism: Use of differential decision criteria for preferred and nonpreferred conclusions. *Journal of Personality and Social Psychology*, 63, 568-584.
- Erdelyi, M. H. (1974). A new look at the new look: Perceptual defense and vigilance. *Psychological Review*, 81, 1-25.
- Fox, E., Lester, V., Russo, R., Bowles, R. J., Pichler, A., & Dutton, K. (2000). Facial expressions of emotion: Are angry faces detected more efficiently? *Cognition and Emotion*, 14, 61-92.
- Horstmann, G., & Bauland, A. (2006). Search asymmetries with real faces: Testing the anger-superiority effect. *Emotion*, 6, 193-207.

- Juth, P., Lundqvist, D., Karlsson, A., & Öhman, A. (2005). Looking for foes and friends: Perceptual and emotional factors when finding a face in the crowd. *Emotion*, 5, 379-395.
- Keil, A., & Ihssen, N. (2004). Identification facilitation for emotionally arousing verbs during the attentional blink. *Emotion*, 4, 23-35.
- Klauer, K.C., Voss, A., Schmitz, F. , & Teige-Mocigemba, S. (in press). Processing Components of the Implicit Association Test: A Diffusion-Model Analysis. *Journal of Personality and Social Psychology*.
- Klein, W. M., & Kunda, Z. (1992). Motivated person perception: Constructing justifications for desired beliefs. *Journal of Experimental Social Psychology*, 28, 145-168.
- Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, 108, 480-498.
- Kunda, Z., & Sanitioso, R. (1989). Motivated changes in the self-concept. *Journal of Experimental Social Psychology*, 25, 272-285.
- Mathews, A., & MacLeod, C. (2005). Cognitive vulnerability to emotional disorders. *Annual Review of Clinical Psychology*, 1, 167-195.
- McGinnies, E. (1949). Emotionality and perceptual defense. *Psychological Review*, 56, 244-251.
- McGinnies, E. & Adornetto, J. (1952). Perceptual defense in normal and in schizophrenic observers. *Journal of Abnormal and Social Psychology*, 47, 833-837.
- Öhman, A., Lundqvist, D., & Esteves, F. (2001). The face in the crowd revisited: A threat advantage with schematic stimuli. *Journal of Personality and Social Psychology*, 80, 381-396.
- Pratto, F., & John, O. P. (1991). Automatic vigilance: The attention-grabbing power of negative social information. *Journal of Personality and Social Psychology*, 61, 380-391.

- Pylyshyn, Z. (1999). Is vision continuous with cognition? The case of impenetrability of visual perception. *Behavioral and Brain Sciences*, 22, 341-423.
- Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, 85, 59-108.
- Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, 9, 347-356.
- Ratcliff, R., & Tuerlinckx, F. (2002). Estimating parameters of the diffusion model: Approaching to dealing with contaminant reaction and parameter variability. *Psychonomic Bulletin and Review*, 9, 438-481.
- Rothermund, K. (2003). Motivation and attention: Incongruent effects of feedback on the processing of valence. *Emotion*, 3, 223-238.
- Rothermund, K., Bak, P. M., & Brandtstädter, J. (2005). Biases in self-evaluation: Effects of attribute controllability. *European Journal of Social Psychology*, 35, 281-290.
- Rothermund, K., Brandtstädter, J., Meiniger, C., & Anton, F. (2002). Nociceptive sensitivity and control: Hypo- and hyperalgesia under two different modes of coping. *Experimental Psychology*, 49, 57-66.
- Rothermund, K., Voss, A., & Wentura, D. (in press). Attentional counter-regulation in affective processing: A basic mechanism that warrants flexibility in emotion and motivation. *Emotion*.
- Rothermund, K., Wentura, D., & Bak, P. (2001). Automatic attention to stimuli signalling chances and dangers: Moderating effects of positive and negative goal and action contexts. *Cognition and Emotion*, 15, 231-248.
- Schimmack, U. (2005). Attentional interference effects of emotional pictures: Threat, negativity, or arousal? *Emotion*, 5, 55-66.
- Stone, A., & Valentine, T. (2005). Orientation of attention to nonconsciously recognised familiar faces. *Cognition and Emotion*, 19, 537-558.

- Tipper, S. P. (1992). Selection for action: The role of inhibitory mechanisms. *Current Directions in Psychological Science*, 1, 105-109.
- Voss, A., Rothermund, K., & Brandtstädter, J. (2006). Motivated binding: Top-down influences in the encoding of compound objects. In: H.D. Zimmer, A. Mecklinger, & U. Lindenberger (Eds.): *Handbook of binding and memory: Perspectives from cognitive neuroscience* (pp. 363-373). Oxford: University Press.
- Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: An empirical validation. *Memory & Cognition*, 32, 1206-1220.
- Voss, A. & Voss, J. (in press a) *Fast-dm: A free program for efficient diffusion model analysis. Behavior Research Methods*.
- Voss, A. & Voss, J. (in press b) *A fast numerical algorithm for the estimation of diffusion-model parameters*. Manuscript submitted for publication.
- Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of Personality and Social Psychology*, 39, 806-820.
- Wentura, D., Rothermund, K., & Bak, P. (2000). Automatic vigilance: The attention-grabbing power of approach- and avoidance-related social information. *Journal of Personality and Social Psychology*, 78, 1024-1037.

Authors' Notes

Andreas Voss, Albert-Ludwigs-Universität Freiburg, Institut für Psychologie, Engelbergerstr. 41, D-79085 Freiburg im Breisgau, Germany; Klaus Rothermund, Friedrich-Schiller-Universität Jena, Institut für Psychologie, Am Steiger 3, Haus 1, D-07743 Jena, Germany; Jochen Brandtstädter, Universität Trier, Institut für Psychologie, D-54286 Trier.

The research reported in this article has been funded by a DFG research project to Jochen Brandtstädter (Br 834/3-4). Correspondence concerning this article should be addressed to Andreas Voss, Albert-Ludwigs-Universität Freiburg, Institut für Psychologie, Engelbergerstr. 41, D-79085 Freiburg im Breisgau, Germany. Correspondence concerning this article should be addressed to Andreas Voss, Albert-Ludwigs-Universität Freiburg, Institut für Psychologie, Engelbergerstr. 41, D-79085 Freiburg im Breisgau, Germany. E-mail: voss@psychologie.uni-freiburg.de.

Footnotes

¹ The amount of noise in the process is defined by the diffusion constant, which acts as a scaling parameter in diffusion model analyses (Voss, Rothermund, & Voss, 2004). For all analyses, we used a diffusion constant of 1.

² Ratcliff's complete diffusion model (Ratcliff & Tuerlinckx, 2002) allows for inter-trial variability of some parameters. For example, it is possible to describe that the actual drift rate may vary from trial to trial (e.g., depending on specific stimulus details or on the alertness of the participant). Therefore, the actual drift rate is assumed to be normally distributed around v with the standard deviation η . Starting point and response-time constant are assumed to be uniformly distributed in the interval from $z - 0.5 s_z$ to $z + 0.5 s_z$ and $t_0 - 0.5 s_{t0}$ to $t_0 + 0.5 s_{t0}$.

³ For the global analysis all parameters were allowed to vary between conditions. This approach is suboptimal for individual analyses, since there were too few trials to reliably estimate $2 (\text{Block Type}) \times 5 (\text{Stimulus Types}) \times 7 (\text{model parameters}) = 70$ parameters.

⁴ Results point in the same direction for the global analyses as for the individual analyses: Numerically, there is a bias present in the starting point as well as in the drift rate. However, a test of significance is not possible.

⁵ Only those trials that contain a valent face ("target-present" trials) are used for this analysis. Parameters are estimated separately for trials containing positive and negative target faces.

Table 1. Mean Responses Times and Response Probabilities.

Stimulus Type ^a	Response Times				Response Frequencies ^b			
	Gain	Loss			Gain	Loss		
	Block	Block	$t(23)^c$	dz	Block	Block	$t(23)^c$	dz
56%	597	691	-4.06**	-0.83	.99	.97	1.39	0.28
53%	713	846	-4.61**	-0.93	.93	.85	3.75**	0.76
50%	857	896	-1.32	-0.27	.59	.41	5.36**	1.09
47%	812	706	2.74*	0.56	.15	.04	5.49**	1.12
44%	672	605	2.85**	0.58	.02	.01	1.13	0.23

^aPortion of pixels of the color indicating gain or loss. ^bPercentage of valent classifications

(i.e., gain or loss). ^cGain block vs. Loss block.

* $p < .05$; ** $p < .01$

Table 2. Results of the Diffusion Model Analysis. Mean values (and standard deviations) for all parameters and for the fit indices.

Parameter	Gain Block	Loss Block	$t(23)^a$	dz
a	1.41 (0.33)	1.46 (0.30)	-1.18	-0.24
z/a	.55 (0.12)	.40 (.08)	6.54**	1.34
$v_{56\%}$	4.86 (1.35)	4.40 (1.54)	1.21	0.25
$v_{53\%}$	2.48 (1.16)	2.19 (1.09)	0.97	0.20
$v_{50\%}$	0.12 (0.34)	-0.06 (0.50)	1.64	0.33
$v_{47\%}$	-1.78 (0.85)	-2.44 (0.87)	2.58*	0.53
$v_{44\%}$	-3.82 (1.17)	-4.70 (1.67)	2.31*	0.47
t_0	0.45 (0.06)	0.46 (0.05)	-1.33	-0.27
s_z	0.15 (0.08)	0.17 (0.10)	-0.89	-0.18
sv	0.31 (0.20)	0.39 (0.31)	-1.01	0.21
s_{t0}	0.16 (0.08)	0.16 (0.09)	-0.04	0.00
Fit, p -value ^b	.29 (.21)	0.27 (0.19)	0.50	0.10

^aGain block vs. Loss block. ^bMatch between predicted and empirical distributions (probability value of the Kolmogorov-Smirnov statistic).

* $p < .05$. ** $p < .01$

Figure Captions

Figure 1. The Diffusion Model. The diffusion process starts in each trial of an experiment from the interval s_z around z and is driven by a constant drift with mean v and standard deviation η . Outside the thresholds, the distribution of predicted exit times are sketched. In gray color, a sample pass for one specific process is depicted.

Figure 2. Sample stimulus of the color categorization task (gray = orange, black = green).

Figure 3. Graphic Display of Model Fit. The Figure shows the combined cumulative distribution functions (CDFs) of response times for errors and correct responses for all five stimulus types and for both experimental blocks. Erroneous responses were multiplied by -1 before merging the distributions of correct times and error times. Therefore, erroneous responses are represented on the left sides of the graphs, and the level at time zero indicates the percentage of errors. The predicted CDFs are represented by gray lines. The black diamonds show the 100ms quantiles of the empirical cumulative RT distributions. Predicted and empirical CDFs are virtually identical, which indicates excellent model fit.

Figure 1

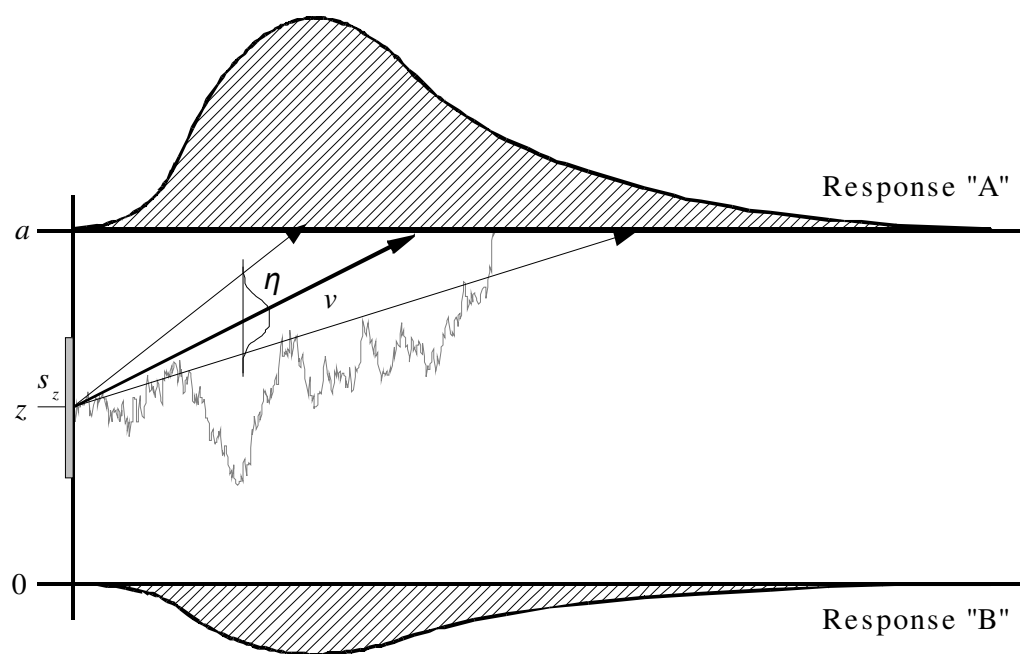


Figure 2

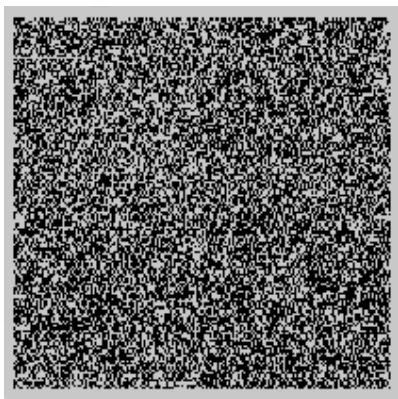


Figure 3

