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Effects of implicit fear of failure on cognitive processing: A diffusion model analysis

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Abstract Whereas previous studies suggest that individuals with high implicit fear of failure (FF) perform worse on various indicators of general performance, the underlying mechanisms of this effect have not yet been understood. In our experimental study, 280 participants worked on a binary color discrimination task. Half of the participants were frustrated by means of negative performance feedback, while the control group received mainly positive feedback. We employed a diffusion model analysis (Ratcliff in Psychol Rev 85(2):59–108, 1978) to disentangle the different components involved in the execution of the task. Results revealed that participants in the frustration condition adopted more conservative decision settings (threshold separation parameter of the diffusion model). Besides, high implicit FF was related to slow information accumulation (drift), and this relation was stronger in the frustration condition. Participants with higher FF further showed reduced learning rates during the task. Task related intrusive thoughts are discussed as mechanism for reduced performance of high FF individuals. We conclude that diffusion model analyses can contribute to a better understanding of the mechanisms underlying the effects of psychological motives.

Keywords Diffusion model, Achievement motive, Fear of failure

Introduction

Motive Disposition Theory (MDT; e.g., McClelland 1985) proposes three fundamental motives which are assumed to energize and drive behavior: the affiliation motive, the power motive, and the achievement motive. MDT further distinguishes between implicit and explicit motives (e.g., McClelland et al. 1989) and between hope and fear components of these motives (e.g., Sokolowski et al. 2000). In the center of this research are the behavioral correlates of the fear of failure (FF) component of the implicit achievement motive. Previous studies have shown that individuals higher in implicit FF have worse school grades (e.g., Schmalt 1999, 2005) and are less likely to have found a job shortly after their final exams at university (Abele et al. 1999), suggesting a negative association of FF with general performance.

Notably, previous research is characterized by two major shortcomings: first, correlational studies dominate the literature. Controlled experimental settings in which the satisfaction of the achievement motive has been manipulated are rare (see Brunstein and Hoyer 2002, for an exception). To the best of our knowledge, experimental studies that examine the impact of implicit FF on performance dependent on negative performance feedback have not yet been conducted. Second, previous studies did not target the mechanisms underlying differential performance outcomes. For example, the inferior school grades obtained by individuals high in FF might be attributable to reduced speed of cognitive processing (e.g., due to rumination or worry about past or anticipated negative feedback). The inferior grades might, however, also be a consequence of sub-optimal speed–accuracy settings: Individuals high in FF have been described as more diligent (Schmalt et al. 2000) and might thus show more detailed processing of information about one task (e.g., in an exam) with the aim of avoiding mistakes, which in turn results in less time available for the other tasks. Furthermore, the worse performance of individuals high in FF could also be a result of a combination of these two factors.

Accordingly, our study adds to the current literature in two ways: (1) We investigate the predictive validity of the FF component of the achievement motive on task execution in an experimental setting. (2) We disentangle different components involved in task execution (such as speed of information accumulation and speed–accuracy settings) via mathematical modeling. In brief, our study aimed at analyzing how individuals low or high in FF differ in terms of cognitive processes when FF is experimentally aroused.

The remainder of this paper is structured as follows: First, we discuss issues of assessing interindividual differences in motives, focusing on differences between implicit and explicit motives, as well as their approach and avoidance components. Next, we sketch the literature on correlations between the achievement motive and performance measures. We then briefly introduce the diffusion model, the method that we used in our study to disentangle different cognitive components. Finally, we present results from our experimental study comprising data from 280 participants.

Assessing interindividual differences in the achievement motive

The achievement motive has been defined as the "recurrent concern about the goal state of doing something better." (McClelland 1985, p. 595). In the MDT literature, two major approaches to assessing motives prevail: (Semi-) projective measures and questionnaires. It seems, however, that the two assessment methods capture different constructs (McClelland et al. 1989; Spangler 1992) that are referred to as implicit motives and explicit motives, respectively. Most relevant to the present study, previous research shows that it is only the implicit achievement motive that is related to performance outcomes and spontaneous efforts invested in a task (e.g., Brunstein and Hoyer 2002; Brunstein and Maier 2005). The explicit achievement motive, on the other hand, is predictive of behavioral choices (i.e., the choice which behavior to pursue in the first place). Given our focus on performance and efforts in a specific task, we will constrain further elaborations to the implicit achievement motive (for additional information on the differences between implicit and explicit motives, see McClelland et al. 1989).

The assessment of implicit motives is typically based on scoring open responses given by the study participants. For example, in one widely used instrument, the Picture Story Exercise (PSE; e.g., McClelland et al. 1989; Schultheiss and Pang 2007), participants see ambiguous pictures and are asked to write imaginative stories. These stories are later rated according to a scoring system and yield an estimate for participants' implicit motives. Critically, however, typical scoring systems do not provide separate estimates for approach component (e.g., hope of success; HS) and avoidance component (e.g., FF) of the implicit motive (for an exception, see Heckhausen 1963). For example, in the popular scoring system by Winter (1994), only one single category tackles the fear component of the achievement motive while four categories assess different aspects of the hope component. Thus, there is a clear imbalance resulting in the total achievement score being dominated by the hope component. This imbalance is unfortunate, given both theoretical arguments that these two should be separated as well as empirical research showing that the hope and fear components are differentially predictive of cognitions and behavior (e.g., Schultheiss and Brunstein 2005). For example, Pang et al. (2009) showed that implicit HS is related to better memory about a peer described as successful whereas implicit FF correlates with memory about an unsuccessful peer.

One motive measure that allows a separate computation of hope and fear components of implicit motives is the Multi-Motive Grid (MMG; Schmalt et al. 2010; Sokolowski et al. 2000). The MMG is a semi-projective measure that combines features of projective motive measures with elements of questionnaires. In contrast to projective measures like the PSE (e.g., McClelland et al. 1989; Schultheiss and Pang 2007), participants do not need to write stories for each picture. Instead, they state their agreement with a set of dichotomous statements that present motive-relevant feelings and thoughts, taking the role of one of the individuals illustrated in the picture. The MMG measures hope and fear components of the achievement, affiliation, and power motive.

There is an ongoing debate about the validity of the MMG as (pure) measure of implicit motives due to its semiprojective approach. Several researchers regard the MMG as a valid tool for the assessment of implicit motives (e.g., Langens and Schmalt 2008; see also Baumann et al. 2010), and empirical support for the predictive validity of the MMG has been found (e.g., Gable 2006; Langens and Schmalt 2002; Puca and Schmalt 1999). However, others argue that the MMG does not guarantee the pure assessment of implicit motives, but that it comprises results from both implicit and explicit processes because of the restricted response format. Therefore, the MMG has been termed “semi-implicit” in one study (Schüler et al. 2015, p. 852). Schüler et al. (2015) examined correlations between three (semi-)projective measures—the MMG, the PSE and the Operant Motive Test (OMT; Kuhl and Scheffer 1999)—and three questionnaire measures (among them the Personality Research Form; Jackson 1984). Critically, they did not observe substantial correlations between the MMG and the other implicit motive measures. Furthermore, for the MMG more significant correlations with the questionnaire measures emerged than for these implicit–explicit relationships had rather small effect sizes with a maximum correlation of r = .23 and—importantly for the present study—for the achievement motive, the correlations had a maximum size of only r = .12. Thus, the results of the study by Schüler et al. (2015) generally support a separation of the achievement motive scale of the MMG from explicit motives[1].

One main advantage of the MMG is that it allows a separation of fear and hope components whereas for example the scoring manual by Winter (1994), that is commonly used for the scoring of PSEs, mainly focuses on the hope component. Therefore, the comparability of the MMG with the PSE (and the OMT that also focuses on the hope rather than the fear component) is limited which makes it comprehensible that in the study by Schüler et al. (2015) only small correlations emerged. The study by Schüler et al. (2015) does not provide information regarding the fear component that is, however, in the focus of our research. In the following section, we shortly sketch the literature on correlations between the implicit achievement motive and performance measures.

Correlations between the implicit achievement motive and performance measures

The first studies addressing the association of implicit achievement motive and performance date back to the 1950s. For example, McClelland et al. (1953, pp. 237–238) found a correlation of r = .51 between college grades and the implicit achievement motive (based on a Picture Story measure). Weiss et al. (1959) reported a correlation of r = .34 between these two measures.

Lowell (1952) conducted a laboratory study in which participants had to work on a simple, familiar addition task and an unfamiliar scrambled word task. Participants with a high implicit achievement motive (again, measured with a Picture Story Test) showed better performance in terms of a higher number of items solved in a given time in the addition task than the less motivated participants. The authors interpreted this difference in terms of more effort expended by the achievement motivated individuals. In the scrambled word task, which required more learning than the addition task, the highly motivated participants showed more improvement from the beginning to the end of the task in terms of the number of solved items.

In the focus of the previously reported studies was the hope component of the achievement motive, which dominates the applied scoring systems. Some studies, however, also examined performance correlates of the fear component or of a difference measure (HS minus FF). More specifically, Puca and Schmalt (1999)—using the MMG— classified participants who had higher (vs. lower) values of HS than FF as approach-oriented (vs. avoidance-oriented). The study revealed that the avoidance-oriented individuals produced higher error rates than the approach-oriented individuals. Abele et al.

[1] In addition, note that correlations between implicit and explicit motives have also been found in studies using projective measures (e.g., Thrash and Elliot 2002; see also Spangler 1992).

(1999) examined differences between university graduates who had found a job within half a year after finishing university and those who had not yet been employed. The study revealed that individuals without employment had higher implicit FF values (measured with the MMG) than those who had already found a job. The authors did not find any differences for the hope component of the achievement motive between these two groups.

In a study based on the Achievement Motive Grid (Schmalt 1999), the relationships between grade point average and the passive and active forms of FF were examined. Whereas the passive form of FF maps ruminative thoughts about one's competence and withdrawing from achievement settings (example item: "He prefers to do nothing at all."), active FF includes emotional–autonomic features of anxiety (example item: "He doesn't want to do anything wrong"; Schmalt 2005). Schmalt (1999) reported a correlation of $r = -.32$ between the passive form of FF and grade point average. Thus, the higher this FF component, the worse was the grade point average. Active FF, on the other hand, was positively correlated with grade point average ($r = .38$), probably because individuals higher in active FF invested more effort in avoiding failures (see Schmalt 1982). Schmalt (2005) also found a negative relationship between the passive FF factor and grade point average for a short version of the achievement motive grid (see also Schmalt 1976, pp. 134–136).

All of the studies previously reported were correlational, so interpretability of their results in terms of causality is limited. Although the authors of the reported studies assume that differences in FF cause differences in performance, the opposite might be true as well: it could be argued that a repeated experience of bad performance and the associated bad feedback induced fear of failure. While FF as a stable disposition cannot be manipulated in an experiment, it is possible to assess the impact of positive versus negative feedback for participants with high versus low FF. One study with a manipulation of the satisfaction of the achievement motive has been conducted by Brunstein and Hoyer (2002) (see also Brunstein and Maier 2005). The participants in this study received false feedback about their performance in a binary decision task. The authors found an interaction of the manipulation of intraindividual feedback and the implicit achievement motive on mean response time (RT): the higher the implicit achievement motive of the participants, the faster were the responses in the test blocks if they were given negative intraindividual performance feedback (negative trend over the blocks of the experiment). In the positive feedback condition, there was no significant relationship between the achievement motive and mean RT. Besides, there were no significant effects for the accuracy rate. The authors interpreted their findings in terms of increased effort of the participants with a higher implicit achievement motive when given negative performance feedback.

Critically, "performance measures" used in the reported studies are often not clearly interpretable. For example, the higher number of items solved by individuals with a higher achievement motive in the study by Lowell (1952), might indicate that these participants were superior in cognitive speed, or in motoric response speed (i.e., writing down the response). There might also have been differences in speed–accuracy settings between the more and less achievement motivated individuals. Individuals who preferred speed over accuracy might in the end have attained a higher number of solved items due to higher rates of skipping (more difficult) items or due to a fast, less careful processing going along with more errors. Participants who preferred accuracy over speed, on the other hand, might have reached a lower final score as a result of their effort of solving each item accurately. The authors did not report any information on the number of skipped items or the accuracy of the items that were processed.

In the study by Brunstein and Hoyer (2002) it is possible that the achievement motivated individuals, as a consequence of the frustration caused by the negative feedback, wanted to quickly finish the task. This might be the true reason for their faster response times rather than the investment of effort. Note that the absence of a significant effect in accuracy rate does not preclude possible speed–accuracy trade-offs, in particular in easy tasks. Thus, it is possible that the achievement motivated participants favored speed over accuracy. In addition, even if there was no speed–accuracy trade-off, it is still not clear whether the higher "effort" of the achievement motivated participants is attributable to faster accumulation of information or faster motoric responses.

As these examples demonstrate, mean RTs or accuracy rates cannot be interpreted unambiguously in terms of underlying cognitive processes. One approach that helps to disentangle the different components involved in such binary RT tasks is the diffusion model analysis.

Introduction to diffusion modeling

In this section, we will give a brief introduction to diffusion modeling with the aim of conveying some basic knowledge about the model parameters that is required for an understanding of our analyses. We suggest newcomers to diffusion modeling, who are interested in a more profound understanding, to read the introductory articles by Wagenmakers (2009) and Voss et al. (2013) (see also Ratcliff et al. 2016).

The diffusion model (Ratcliff 1978) is a mathematical model that allows to separate cognitive processes in decision tasks. The model has been applied to binary decision tasks, such as recognition memory tasks (e.g., Bowen et al. 2016; McKoon and Ratcliff 2012), lexical decision tasks (e.g., Ratcliff et al. 2004; Wagenmakers et al. 2008), or perceptual tasks (e.g., Ratcliff 2014; van Ravenzwaaij et al. 2012).

To demonstrate the basic ideas of the diffusion model, imagine, for example, a color discrimination task, in which in each trial the participant has to decide on the prevailing color in a square filled of pixels of two colors (e.g., orange and blue; Voss et al. 2004). In Fig. 1, there are two thresholds: the upper threshold is associated with correct responses and the lower threshold with erroneous responses. The figure also depicts the predicted distributions of response times for both correct responses (depicted on the upper part) and for incorrect responses (lower part). The diffusion model aims at separating various cognitive processes that elicit these two response time distributions. To illustrate these processes, consider a single trial where a participant decides whether there are more orange or more blue pixels in a square filled with orange and blue pixels. Let us assume that the correct answer in this trial be blue. Accordingly, in this trial, "blue" is associated with the upper threshold because it is the correct answer and "orange" is associated with the lower threshold.

One main assumption of the diffusion model is that individuals continuously accumulate information from the stimulus (the colored square) until they have collected enough information to reach one of two decisions (primarily orange vs. primarily blue). Random perturbations in this process can overlay the accumulation and cause the participants to end up at different times at the correct boundary or even at the wrong boundary, leading to an incorrect decision. In the exemplary trial in the figure, the participant does arrive at the correct answer ("blue"). The different sizes of distributions at the upper and lower threshold illustrate that in the majority of trials this participant reaches the correct threshold.

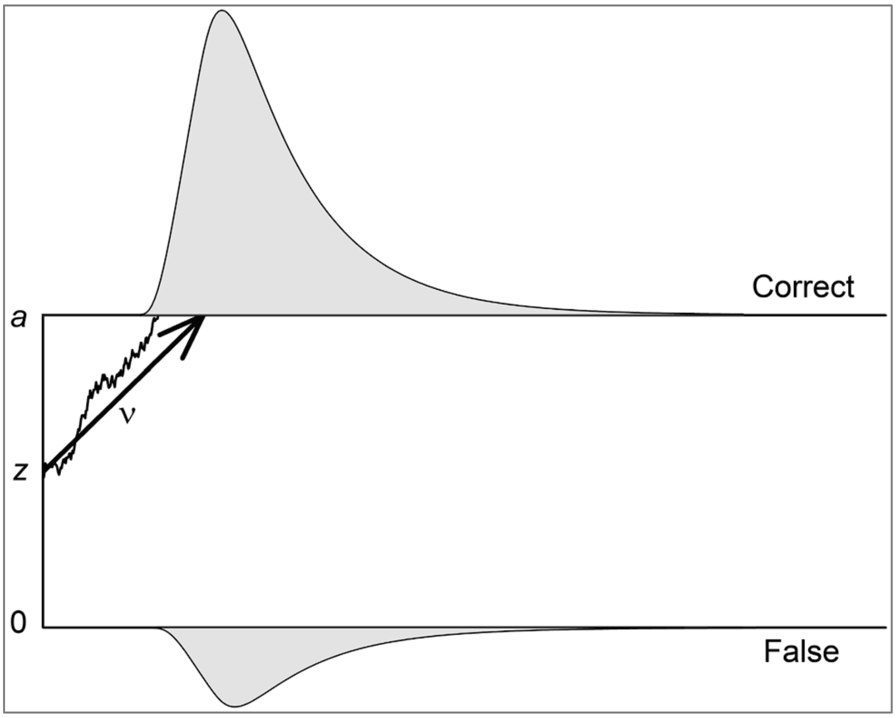


Fig. 1 Illustration of a diffusion process for a color discrimination task. Participants have to assess which of two colors prevails in a square composed of colored pixels. In this example, the thresholds are associated with correct responses (upper threshold) and incorrect responses (lower threshold). The accumulation of information starts at starting point z, here centered between the two thresholds. Information is accumulated with speed v until one of the two thresholds has been reached. Not included in this illustration are non-decisional processes adding to the decisional process and intertrial variabilities of parameters

We will now describe three main diffusion model parameters that are also the dependent variables in our subsequent analyses. The accumulation of information has a mean speed v across all trials of the experiment. Usually, the sign of this so-called drift rate will be positive indicating that in the majority of trials the process will end at the correct response threshold (a negative sign indicates that the process ends mostly at the lower threshold). Higher drift rates lead to faster responses and fewer errors.

The threshold that is reached and the time required for this process do not only depend on the drift rate, but also on the distance between the two thresholds. If individuals are more careful, the threshold separation (parameter a) is larger, and decisions take longer, but there will be fewer errors. Thus, threshold separation is a measure of speed–accuracy settings. Higher values indicate a preference for accuracy over speed and lower values a preference for speed at the cost of a higher error rate.

Finally, the diffusion model estimates the duration of nondecisional processes (parameter t_0). These non-decisional processes include the encoding of information prior to the accumulation of information and the motoric response execution (mostly, the pressing of one of two keys) succeeding the decision. So far, we presented three parameters of the basic diffusion model, which are in the focus of most diffusion model studies. Another main diffusion model parameter that has been investigated in several studies, but that is not of relevance for the present study, is the so-called starting point *z*. It defines the position from which the information accumulation begins. In Fig. 1, z is centered between thetwo thresholds, indicating that there is no bias for either of the two thresholds.[2]

In contrast to the classical method of analyzing mean RTs (of correct responses) and accuracy rates, the application of the diffusion model allows an analysis of several distinct components measuring specific characteristics of the task and/or participant. The disentangling of these different parameters is possible because the model uses information not only about mean RTs of correct responses and error rates, but also considers the complete shape of the response time distributions of both correct and error responses. The diffusion model analysis, thus, allows answering more specific research questions. For example, when differences in response times are observed, with this method it becomes possible to test whether these differences are based on speed of information accumulation (drift rate), on changes in speed–accuracy settings (threshold separation), or on the speed of encoding and response execution (non-decision time).

The validity of the diffusion model parameters has been demonstrated in several experimental validation studies and correlational studies (Arnold et al. 2015; Ratcliff et al. 2010; Schmiedek et al. 2007; Schubert et al. 2015; Voss et al. 2004), and recent research also showed satisfactory reliability for the diffusion model's parameters (Lerche and Voss 2017b; Yap et al. 2012).

The present study

With the present study, we aimed at expanding prior findings on the relation of the implicit achievement motive with performance. Our focus was thereby on the fear component of the achievement motive that has been addressed less often in prior research than the hope component (Pang 2010). Specifically, we investigated whether implicit FF that has been aroused by false performance feedback affected (1) speed of information accumulation (drift rate), (2) speed–accuracy settings (threshold separation) or (3) speed of encoding and response execution (non-decision time), or a combination thereof.

Critically, prior correlational research about FF and measures of performance does not allow clear-cut predictions as to which specific process might differ as a function of FF. The reported poorer school grades of individuals higher in passive FF (e.g., Schmalt 1999) point at a reduction of the drift parameter of the diffusion model. Individuals high in FF might have reduced speed of information accumulation (i.e., lower drift rates) compared to their less fearful counterparts. A reduced speed of information accumulation could be explained by the fearful individuals being more prone to repetitive negative thinking (Ehring and Watkins 2008) when given negative feedback about their performance. Accordingly, in our study, we expected individuals high in FF to display lower drift rates when they are repeatedly given negative performance feedback (Hypothesis 1a). Furthermore, we hypothesized that individuals high in FF—also due to repetitive negative thinking—have lower

[2] In addition to these four main diffusion model parameters (v, a, t_0, z), the model is often expanded by assuming intertrial variabilities of drift rate, starting point and non-decision time (e.g., Ratcliff and Rouder 1998; Ratcliff and Tuerlinckx 2002). These variability parameters, however, cannot be estimated as accurately as the main diffusion model parameters, and they are typically of less psychological interest (especially, the intertrial variabilities of starting point and drift rate; Lerche and Voss 2016; Lerche et al. 2017).

learning rates (reduced increases in drift rate from the first to the second half of trials) when they are given negative performance feedback, in comparison with participants in the control condition or with participants lower in FF (Hypothesis 1b).

However, it is also plausible that not (only) the drift rate, but (also) the threshold separation parameter of the diffusion model varies between individuals differing in FF. Remember that this parameter captures how cautious individuals are in their decisions, that is how much information they collect prior to taking a decision. Schmalt et al. (2000, p. 32) reported that FF enhances thoroughness, accurateness and the continuous striving not to make mistakes. Accordingly, in our study we expected individuals higher in FF to have larger threshold separations, especially if given negative performance feedback, because these individuals will try to avoid further negative feedback (Hypothesis 2).

Finally, regarding the non-decisional component of the diffusion model, we do not have any specific hypothesis. If at all, rumination about the negative feedback might not only slow down the speed of information accumulation, but also the speed of encoding of information and of the motoric response. We will investigate effects on the non-decisional component in a more exploratory fashion without clear a priori hypotheses.

In sum, we were interested in the differences in information processing between individuals low and high in implicit FF as a function of the arousal of the respective motive component. To disentangle the different processes involved in task execution, we conducted a diffusion model analysis. Up to date, to our knowledge, nobody has applied a diffusion model to the field of achievement motivation.

Method

Participants

The data presented in this manuscript were collected in the course of three different studies that had very similar procedures. One aim of these studies was the analysis of the affective consequences of negative performance feedback. Results concerning these dependent variables are reported in Neubauer et al. (2017). The present paper focuses on the analysis of behavioral consequences (i.e., performance measures) of negative performance feedback. The samples of the three studies consisted of N_1 = 66, N_2 = 85, and N_3 = 129 participants, respectively. All participants were recruited in Heidelberg, Germany. As the factor sample did not moderate our results, in the following, we report descriptive and inferential statistics based on the entire sample of N = 280 (77% females; age range 16–67 years, M = 23.41, SD = 7.40). Ninety-one percent of the participants were students and 45% of them studied psychology.

Design, measures, and procedure

The main procedure of the laboratory session was identical in the three studies.[3] All instructions, questionnaires and tasks were computerized. After the collection of demographic data, participants

[3] Study 3 differed from studies 1 and 2 in that a daily-diary part preceded the laboratory session.

filled in a short version of the Multi-Motive Grid (MMG; Schmalt et al. 2010; Sokolowski et al. 2000). This was followed by the execution of a binary decision task with false performance feedback. After that, participants filled in additional questionnaires not relevant for the present study.

The MMG is composed of 14 pictures, and each motive component is measured by 12 statements (several binary items are presented for each picture). Thus, the value range of each component spans from 0 (no agreement with any of the statements) to 12 (agreement with all of the statements). Of central interest to our study is the fear component of the achievement motive. FF is measured by the items “Thinking about lacking abilities at this task” and “Wanting to postpone a difficult task for a while”. The observed values for FF obtained in our sample ranged from 0 to 12, thus covering the entire value range, with a mean of 4.58 (SD = 2.19) and an internal consistency of Cronbach’s α = .54.4.[4]

For the experimental task, participants were randomly assigned to either the performance frustration or control group. False feedback was given in reference to the performance in a color discrimination task. The cover story of the task read as follows: “A large scale assessment at several German Universities (HU Berlin, Heidelberg, Leipzig, Trier) aims at developing norm data for the following color perception task. Initial studies suggest that color perception might be an important predictor of intelligence. You will now work on this color perception task. You will see a black square, followed by a square filled with pixels of two different colors, orange and blue. Your task will be to decide, whether there are more blue or more orange pixels in this square. […] You will receive points for each rating. Try to be both as accurate and as fast as possible in your decision. The difference in color proportions is only small and many participants find this task rather challenging. If you cannot decide for sure, follow your first impression. Your score will be computed based on so-called stochastic diffusion models using an algorithm that incorporates accuracy and speed of your decision, as well as difficulty of the trial. You will receive feedback about your performance after every fourth trial. For this feedback, you will see a scale in the middle of the screen with your current score and the average score of all other participants who have worked on this task (so far: 254 participants). You will start at 0 points and you can gain a maximum of 100 points. On average, the other participants have scored (frustration group: 90.3; control group: 72.5) points.”

The color discrimination task was adopted from Voss et al. (2004). In each trial, a square filled with pixels of the colors orange (R = 255, G = 100, B = 0) and blue (R = 0, G = 100, B = 255) was shown. The participants had to indicate which of the two colors prevailed. There were two difficulty levels (easy: 53% dominant color, 47% other color; difficult: 51.5% dominant color, 48.5% other color). The task comprised 100 trials with the four different conditions of dominant color (blue vs. orange) × difficulty (easy vs. difficult) appearing equally often. The order of trials was randomized for each participant. After every four trials, participants received feedback, allegedly on their performance in the last four trials.

[4] Due to the intended heterogeneity of the ambiguous pictures used in implicit motive measures, it is common to find lower internal consistencies in comparison with explicit motive measures. It has been demonstrated that the lower reliability does not compromise the construct validity of the measures and it has been argued that the assumptions of classical test theory are not appropriate for projective motive measures (e.g., Atkinson 1981; Reuman 1982). The stability of overall sum-scores, which is satisfactory, is seen as more important than internal consistency (e.g., Schultheiss et al. 2008). Furthermore, recent studies that applied dynamic Thurstonian item response theory have shown good reliability of both the PSE (Lang 2014) and the Operant Motive Test (Runge et al. 2016).

More specifically, the feedback was presented in form of two markers on a scale ranging from 0 to 100. The markers indicated the progress reached by the participant ("You") and by the ostensible prior participants ("Others"). After the first four trials, the markers moved from the start position (0) upward. Following the next four trials, the markers always started at the positions of the previous feedback. In the frustration condition, in 80% of the feedback trials, the "You"-bar moved less than the bar of the prior participants indicating that the other participants had reached more points. In the other 20%, the own bar made a greater movement upward than the bar of the others. In the control condition, the percentages were reversed with 80% of positive and 20% of negative feedbacks. From the beginning of the task on, the participants could see the final score reached by the "Others" (90.3 points in the frustration condition and 72.5 points in the control condition).

Following the last feedback, participants additionally read one of the following messages, depending on the condition: "Final score others: 90.3. Your final score: 72.5. This corresponds to a percentile rank of 13 which means that 87% of the other participants have scored higher than you." (frustration condition) or "Final score others: 72.5. Your final score: 90.3. This corresponds to a percentile rank of 87 which means that you have scored higher than 87% of the other participants." (control condition).

According to the motive literature, motives need to be incentivized in order to affect behavior (e.g., McClelland et al. 1989). In our study, FF was first aroused by the task instructions emphasizing both the difficulty of the task and the ostensible close relation of task performance with intelligence. These instructions were the same for all participants. Additionally, the negative performance feedback in the frustration condition was supposed to further arouse FF. Hence, rather than arousing FF in only one condition, we aimed at arousing it in both conditions, but to varying degrees. The experiment was concluded by a complete debriefing about all aspects of the study.

Parameter estimation

The data of color discrimination tasks have been successfully fitted by diffusion models in a number of studies (e.g., Germar et al. 2014; Voss et al. 2004, 2008; Voss and Schwieren 2015). In our study, the parameters of the diffusion model were estimated using the software fast-dm-30 (Voss and Voss 2007, 2008; Voss et al. 2015).[5] First, we estimated parameters for the total number of n = 100 trials. As we were also interested in learning effects, we additionally divided the total number of trials in two sets of n = 50 trials each (in the following, also termed blocks). We then computed behavioral measures and estimated diffusion model parameters separately for each block.[6]

Due to the restricted trial numbers, we kept the model as simple as possible. More specifically, the thresholds of the model were associated with correct responses (upper threshold) and incorrect responses (lower threshold) and the relative starting point was fixed at .5 (i.e., assuming a centered starting point). Besides, we fixed the three intertrial variabilities to zero. In particular, the intertrial variability of drift rate and threshold separation cannot be estimated well, especially with small to medium-sized trial numbers (Lerche and Voss 2016; see also van Ravenzwaaij et al. 2017). Accordingly, we estimated the following three parameters: threshold separation, drift rate and non-

[5] Fast-dm-30 can be downloaded from http://www.psych ologi e.uniheidelberg .de/ae/meth/fast-dm/index - en.html. Note that in addition to the command line program, recently, also a graphical user interface developed by Stefan Radev is available.

[6] We are aware that n = 50 is a small trial number for diffusion model analyses. However, recent simulations have shown that the diffusion model can, under certain conditions, supply reliable results even for such small trials numbers (Lerche et al. 2017).

decision time; the Kolmogorov–Smirnov optimization criterion was used for all analyses (see Lerche et al. 2017, for a discussion of different optimization criteria).

Table 1 Hierarchical regression oft he behavioral variables and diffusion model parameters on group and FF

Step	Variable	Mean RT	Accuracy	*a*	*v*	t_0
1	Intercept	2.95*** (0.01)	0.76*** (0.01)	1.56*** (0.05)	0.73*** (0.04)	0.45*** (0.01)
	Group[a]	-0.04* (0.02)	-0.00 (0.01)	-0.13* (0.07)	0.07 (0.05)	-0.01 (0.01)
	FF	0.01* (0.00)	-0.01* (0.00)	0.02 (0.01)	-0.04** (0.01)	0.00 (0.00)
	R^2 (adjusted)	.02	.01	.01	.03	.00
2	Intercept	2.95*** (0.01)	0.76*** (0.01)	1.56*** (0.05)	0.73*** (0.04)	0.45*** (0.01)
	Group[a]	-0.04* (0.02)	-0.00 (0.01)	-0.13* (0.07)	0.07 (0.05)	-0.01 (0.01)
	FF	0.01* (0.01)	-0.01* (0.00)	0.04 (0.02)	-0.06*** (0.02)	0.01 (0.00)
	Group x FF	-0.01 (0.01)	0.00 (0.01)	-0.03 (0.03)	0.05* (0.02)	-0.00 (0.01)
	R^2 (adjusted)	.02	.01	.01	.04	-.00

The diffusion model parameter *a* measures speed–accuracy settings, the drift rate *v* the speed of information accumulation, and t_0 the time required for non-decisional processes (e.g., encoding and motoric response execution)

The table contains unstandardized regression coefficients with standard errors in parentheses. Fear of failure was centered on the sample mean before the analyses

**p* < .05; ***p* < .01; ****p* < .001

[a]0 = frustration; 1 = control

Results

Extreme values in the individual logarithmized RT distribution—defined as being more than three interquartile ranges outside the first and third quartile (Tukey 1977)—were removed prior to all analyses. The criterion led to an exclusion of 1.7% of all trials. Based on the Tukey criterion, we also identified individuals with very low accuracy rates in one or both blocks of the color discrimination task. An exclusion of these participants (N = 13) did not alter the pattern of results. Therefore, we report the analyses based on all participants. The fit values of the Kolmogorov–Smirnov criterion in our study were satisfactory (n = 100 trials: all *p*s ≥ .227, M = .857, SD = .160; n = 50 trials: all *p*s ≥ .380, M = .918, SD = .112). The Figs. 4, 5 and 6 in the “Appendix” comparing observed and predicted RT statistics further demonstrate that the diffusion model provided a good account of the data.

In hierarchical regression analyses, in a first step, we regressed the different dependent variables on condition (0 = frustration, 1 = control) and FF (centered on the sample mean). In a second step, we further included the interaction term condition × FF (see also Table 1). As dependent variables, we first examined mean logarithmized RT of correct responses (“mean RT”) and accuracy rate. For mean RT, there was a main effect of condition with faster mean RTs in the control group compared to the frustration group, $b = -0.04$, $p = .047$. The main effect of FF was also significant, $b = 0.01$, $p = .037$. The higher FF, the slower were the mean RTs. The interaction term entered in step 2 was not significant ($b = -0.01$, $p = .213$). Regarding accuracy, individuals with higher FF showed smaller accuracy rates ($b = -0.01$, $p = .028$). Hence, higher FF was associated with lower task performance.

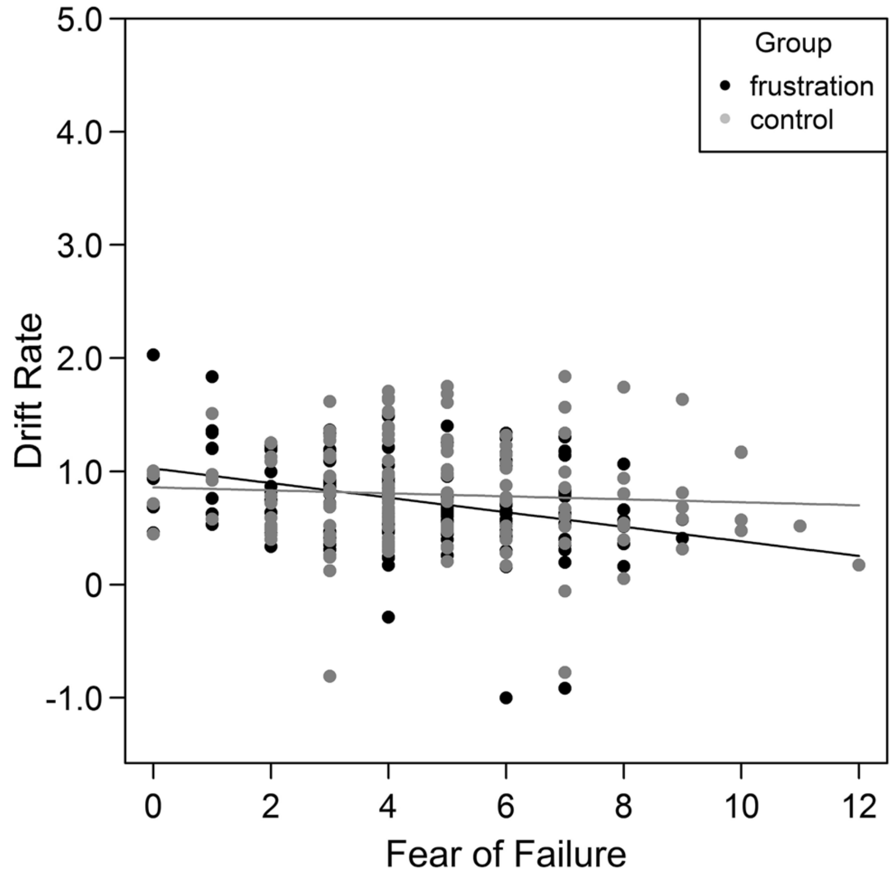


Fig.2 Drift rate depending on group and fear of failure

Next, individual estimates of the diffusion model parameters were entered into the analyses as dependent variables. Drift rate was significantly predicted by FF, $b = -0.04$, $p = .003$. Higher FF was associated with slower accumulation of information. Besides, there was a significant condition × FF interaction, $b = 0.05$, $p = .033$, which is visualized in Fig. 2. Supporting Hypothesis 1a, in the frustration group, participants with higher FF accumulated information more slowly than participants with lower values of FF ($r = -.32$, $p < .001$); in the control group, on the other hand, there was only a very small and non-significant relationship between FF and drift rate ($r = -.07$, $p = .439$).

Table 2 Comparison of variables from the first with the second block

Variable	Part 1		Part 2		*t* (279)	*p*	95% CI		Cohen's d_2
	M	*SD*	*M*	*SD*			*LL*	*UL*	
Mean RT[a]	1109.43	694.07	912.40	457.71	13.13	< .001	138.12	255.93	0.39
Accuracy	.73	.12	.78	.13	-7.15	< .001	-0.06	-0.04	-0.43
a	1.59	0.62	1.40	0.61	6.82	< .001	0.13	0.24	0.41
v	0.64	0.46	1.00	0.70	-9.36	< .001	-0.43	-0.28	-0.56
t_0	0.48	0.16	0.45	0.13	3.27	< .01	0.01	0.05	0.20

The diffusion model parameter a measures speed–accuracy settings, the drift rate v the speed of information accumulation, and t0 the time required for non-decisional processes (e.g., encoding and motoric response execution)

CI confidence interval for the difference score, *LL* lower limit, *UL* upper limit

[a]For the *t* test, the mean logarithmized RTs of correct responses were used, but *M, SD*, 95% *CI* and Cohen's d_z are based on the untransformed values

Table 3 Hierarchical regression of changes in the bahavioral variables and diffusion model parameters from the first to the second set of trials on Group and FF

Step	Variable	Mean RT	Accuracy	*a*	*v*	t_0
1	Intercept	-0.07*** (0.01)	0.04*** (0.01)	-0.20*** (0.04)	0.30*** (0.05)	-0.03*** (0.01)
	Group[a]	-0.01 (0.01)	0.01 (0.01)	0.02 (0.06)	0.12 (0.08)	0.00 (0.02)
	FF	-0.00 (0.00)	-0.01* (0.00)	-0.01 (0.01)	-0.04* (0.02)	-0.00 (0.00)
	R^2 (adjusted)	-.00	.01	-.01	.02	-.01
2	Intercept	-0.07*** (0.01)	0.04*** (0.01)	-0.20*** (0.04)	0.30*** (0.05)	-0.03* (0.01)
	Group[a]	-0.01 (0.01)	0.01 (0.01)	0.02 (0.06)	0.12 (0.08)	0.00 (0.02)
	FF	-0.00 (0.00)	-0.01 (0.00)	-0.01 (0.02)	-0.06* (0.03)	-0.00 (0.01)
	Group x FF	-0.00 (0.00)	-0.00 (0.01)	0.00 (0.03)	0.03 (0.04)	0.00 (0.01)
	R^2 (adjusted)	-.01	.01	-.01	.02	-.01

The diffusion model parameter *a* measures speed–accuracy settings, the drift rate *v* the speed of information accumulation, and t_0 the time required for non-decisional processes (e.g., encoding and motoric response execution)

The table contains unstandardized regression coefficients with standard errors in parentheses. Fear of failure was centered on the sample mean before the analyses

**p* < .05; ****p* < .001

[a]0 = frustration; 1 = control

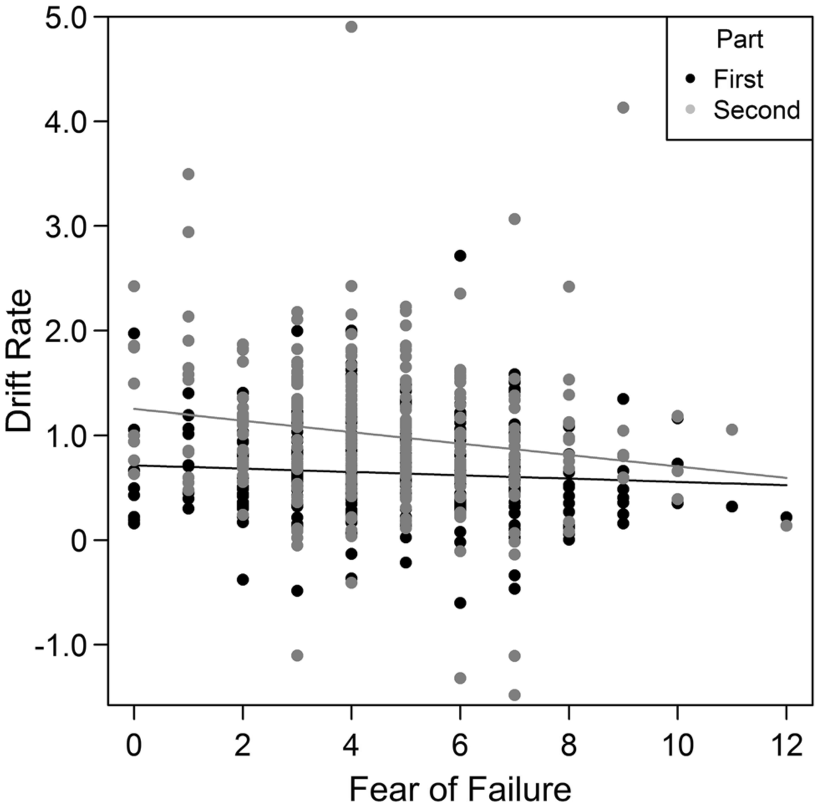


Fig.3 Drift rate depending on part and fear failure

Threshold separation was increased in the frustration group in comparison with the control group, $b = -0.13$, $p = .048$. No other significant effect was found for this parameter. Hence, we did not find support for Hypothesis 2. For non-decision time, no significant effect emerged (*ps* ≥ .153).

To examine learning effects during the completion of the task, we first analyzed differences in variables between the first and second block of trials using dependent t tests (Table 2). Then, we examined whether differences between the first and second block of trials (difference = $\text{variable}_{\text{block2}} - \text{variable}_{\text{block1}}$) were predicted by condition or FF (step 1) or the interaction condition × FF (step 2; Table 3).

As expected, mean RTs decreased and accuracy rates increased from the first to the second block (*ps* < .001, $|d_z| \geq 0.39$). Regarding the diffusion model parameters, threshold separation ($p < .001$, $d_z = 0.41$) and non-decision time decreased ($p = .001$, $d_z = 0.20$) and drift rate ($p < .001$, $d_z = -0.56$) increased. Furthermore, there was a significant effect of FF for accuracy, $b = -0.01$, $p = .031$, and for drift rate, $b = -0.04$, $p = .022$. The findings for the drift rate are also depicted in Fig. 3, showing that the increase in drift from the first to the second part of trials was larger for individuals low in FF than for those with higher values of FF. The frustration and control group did not differ in drift rate difference and there were no effects for any of the other variables (all *ps* ≥ .126). Thus, other than expected (Hypothesis 1b), the learning effect was generally smaller for individuals high in FF, not only in the frustration condition.[7]

Discussion

Do individuals high in FF differ in information processing from individuals with low FF? Typical findings of previous correlational studies show that individuals with higher implicit FF feature lower grades at school (e.g., Schmalt 1999) and are less likely to have found an employment half a year after their final examination at university (Abele et al. 1999). Importantly, these previous results do not allow for disentangling the different cognitive processes involved in the behavioral differences. Do individuals higher in FF perform worse at school because of difficulties at concentrating on their homework and school exams? Or do they perform worse because they are more cautious trying to avoid mistakes, but thereby losing time to complete all of their tasks?

In our experimental study based on 280 participants, FF was aroused by the announcement of a difficult task that supposedly provides a measure of intelligence. In addition, in one condition of the experiment, participants received negative feedback on their task performance in comparison with a control group with predominantly positive feedback. We applied a diffusion model analysis (Ratcliff 1978) to disentangle the specific processes involved in task execution. The three diffusion model parameters of interest for our study were drift rate (a measure of speed of information

[7] The focus of our study was on the FF component of the achievement motive that we aimed to arouse with the false feedback manipulation. Thus, we did not have any hypotheses regarding the influence of the hope component of the achievement motive (hope for success; HS). Nevertheless we cannot definitely exclude that HS was also aroused by our manipulation. Therefore, in a set of further analyses, we conducted all regression analyses with HS instead of FF. For one dependent variable, namely the difference in accuracy rates between the two trial blocks, we found a significant effect of the condition × HS interaction ($b = -0.02$, $p = .016$). More specifically, in the frustration group, individuals higher in HS improved more in terms of accuracy rate from the first to the second block ($b = 0.010$, $p = .029$) whereas in the control group there was a tendency for the other way round (i.e., less improvement for the individuals higher in HS, $b = -0.006$, $p = .216$).

accumulation), threshold separation (a measure of speed–accuracy settings) and non-decision time (a measure of the time required for non-decisional components such as encoding of information and motoric response execution).

We had two main hypotheses regarding the diffusion model parameters: (1) We expected that individuals with high FF would have (a) lower drift rates and (b) reduced learning rates (in terms of drift rates) from the first to the second block of trials when their motive is aroused by negative performance feedback. (2) We predicted that individuals with high FF would have larger threshold separations, especially if given negative feedback. That is, they would be more cautious, trying to avoid mistakes as not to suffer from further negative feedback.

Main findings and mechanisms

We found support for Hypothesis 1a: for individuals higher in implicit FF lower drift rates were estimated compared to their less fearful counterparts, especially when negative performance feedback was given. In addition, independent of the feedback condition (and thus partly consistent to Hypothesis 1b), high FF was generally related to less improvement in speed of information accumulation from the first to the second block of the task. Regarding our second hypothesis, we did not observe the expected performance feedback × FF interaction for threshold separation. We only found a significant main effect of the feedback condition: Participants who received negative performance feedback were—independent of the strength of FF—more careful, preferring accuracy over speed more than the participants in the control group. No effect of FF (or the condition) on the duration of non-decisional processes (e.g., encoding and motoric response execution) was revealed in the present data. In sum, FF was exclusively related to one of the parameters of the diffusion model, that is, the speed of information accumulation.

We speculate that the central mechanism underlying the effect of FF on drift rate is repetitive negative thinking (e.g., Ehring and Watkins 2008). In our study, we measured FF using the Multi-Motive Grid (MMG; Schmalt et al. 2010; Sokolowski et al. 2000), which in the terminology used by Schmalt (1982) captures the passive form of FF. This component refers to “ruminative and self-deprecative thoughts about one’s competence” (Schmalt 2005, p. 173) in contrast to the active form of FF which relates to “emotional (physiological) facets of a thwarting event” (p. 173). Whereas individuals high in active FF try to avoid failures by investing effort, individuals high in passive FF are supposed to ruminate about their lack of competence. Ruminative cognition such as intrusive thoughts and worrying, in turn, interferes with cognitive processing (Eysenck and Calvo 1992; Metzger et al. 1990), in particular set shifting and inhibition (Yang et al. 2016). Rumination could therefore serve as a mediator of the observed condition by FF interaction effect on drift rate.

Application of the diffusion model

Our study is, as far as we know, the first one to apply a diffusion model to the field of achievement motivation. Interestingly, only for drift rate, but not for the behavioral variables (mean RT and accuracy rate), a condition × FF interaction was revealed. The problem with using behavioral variables is that they are no process-pure measures. The parameters of the diffusion model, on the other hand, represent much more specific components of information processing. We hasten to add that all effects found in our study were rather small in size. This is typical of studies working with implicit motives and it makes clear that it is all the more important to employ reliable and valid measures of psychological processes. The diffusion model analysis provides such measures (e.g., Arnold et al. 2015; Lerche and Voss 2017b; Voss et al. 2004).

In the past, the diffusion model has usually been employed in studies with trial numbers of several hundreds or even thousands of trials per participant (e.g., Leite and Ratcliff 2011; Ratcliff and Rouder 1998). In our study, we conducted diffusion model analyses based on 100 trials (the total trial number of the color discrimination task) and 50 trials (in our analyses of learning effects). Certainly, 50 trials are at the lower bound of reasonable applications of the diffusion model. However, the results from recent simulation studies suggest that the diffusion model can provide unbiased and reliable results even for such small trial numbers (Lerche et al. 2017). Furthermore, the learning effects from the first to the second set of trials that we found are in line with results from previous diffusion model studies relying on higher trial numbers (e.g., Dutilh et al. 2009; Lerche and Voss 2017b). In particular, we found that participants improved their speed of information accumulation and non-decisional processes from the first to the second part of trials. Furthermore, the participants got less careful with the time, setting lower speed–accuracy settings in the second compared to the first part of trials.

Limitations and future directions

One limitation of our study is that it lacked a condition without any feedback and a positive feedback condition. We only used a frustration condition (80% negative feedback) and a control condition (20% negative feedback). This might (at least partly) explain why we did not find support for Hypothesis 1b. Remember that the increase in drift rate from the first to the second block of trials did depend on the strength of FF, but was independent of the condition. Thus, individuals high in FF showed reduced improvement in speed of information accumulation both in the frustration and control condition. It, therefore, seems possible that merely by announcing a difficult test that is associated with intelligence and the performance feedback—these instructions were identical for all participants—we might have aroused FF to a high degree. The positive feedback in the control condition was—in contrast to our expectations—seemingly not able to counteract this arousal. It is possible that individuals low in FF experienced the increasing difference between their own score and the score of the ostensible other participants in the control condition as reassuring of their competence. Individuals high in FF, on the other hand, might have feared that their performance gets worse with time and that the score of the others will eventually catch up with their score. Thus, their fear was not attenuated by the positive feedback and interfered with learning capabilities (increases in drift rate from block 1 to block 2). In future research, one might consider including a condition without any feedback and/or a more positive feedback condition. We suppose that in a no feedback condition individuals high in FF might not ruminate about their performance and in a more positive feedback condition they might be more likely to stop ruminating. Accordingly, they would show similar performance and learning rate compared to participants low in FF.

Future studies should also test the generalizability of our findings to different types of tasks. The color discrimination task is a perceptual task that requires no deep information processing. Effects of FF might be larger for tasks that necessitate deeper processing. For example, the figural task developed by Lerche and Voss (2017a) might be used. In this task, the sizes of different rectangles have to be compared. It is a complex task that requires several seconds per trial. As Lerche and Voss (2017a) showed, the diffusion model provides a valid account of the data of this task even if the trials take significantly longer than in the tasks typically used in diffusion model studies. We suppose that performance in such a more difficult decision task that requires enhanced concentration is more likely to be hampered by rumination on negative performance feedback. Accordingly, we expect participants high in FF, in particular if given negative performance feedback, to feature even lower drift rates and reduced learning rates than for easier tasks.

In such a more complex task, it might also be more likely to find differences in speed–accuracy settings between individuals differing in FF. The color discrimination task used in our study was a fast task that might not have allowed for sufficient variance in speed–accuracy settings. This might explain why we did not find support for our second hypothesis: Individuals high in FF did not differ from less fearful individuals in terms of their caution (in neither the frustration, nor the control condition). Only a main effect emerged, with participants adopting more conservative decision settings in the frustration in comparison with the control condition. A study by Ramsay and Pang (2013) showed that specifics both of the picture set used for motive measurement and of the type of task affect the influence of FF on behavioral variables. Most interesting to our research question, in a time-independent task in contrast to a time-dependent task, individuals high in FF (as measured with a PSE based on ambiguous pictures) worked more slowly than the less fearful individuals. They might have adopted more conservative decision settings. A diffusion model analysis could shed further light on this issue. Accordingly, in our study, we might not have found effects of FF on the threshold separation, because the task was too fast, not giving the participants with high FF the opportunity to adopt more conservative decision settings.

Another limitation of our study is that we did not examine the differential effects of inter- and intraindividual feedback. Participants saw how their personal score increased across time (intraindividual feedback), but this feedback was always related to the performance of the "other participants". Hence, the interindividual comparison was targeted in the present research: The participants were told that they were doing better or worse than most previous participants. As the study by Brunstein and Hoyer (2002) showed*, intra*individual feedback might be more relevant for the effort expended on a task by individuals differing in the implicit achievement motive than interindividual feedback (see also Brunstein and Maier 2005; see Pang 2010, for an elaborate theoretical discussion).

For the assessment of the implicit achievement motive Brunstein and Hoyer (2002) used Winter's scoring manual (Winter 1991) that focuses on the hope component. Brunstein and Maier (2005) used the scoring manual by Heckhausen (1963), but were only interested in the hope component. As far as we know, a systematic analysis of the influence of intra- versus interindividual feedback on the arousal of FF is still outstanding. It is questionable whether the differential feedback effects observed by Brunstein and Hoyer (2002) for the hope component are directly transferable to the fear component. Interestingly, in a study by Thrash and Elliot (2002), both individuals high in explicit FF and individuals high in implicit FF set performance goals rather than mastery goals. The goals were assessed with the achievement goals questionnaire by Elliot and Church (1997). Many items measuring performance goals in this questionnaire are clearly framed in terms of an interindividual comparison (e.g., "It is important for me to do well compared to others [on this exam]"). Accordingly, the study by Thrash and Elliot (2002) suggests that there might be differential mechanisms regarding the effect of inter- versus intraindividual feedback on the arousal of the hope and fear component of the implicit and explicit achievement motive. We hope, that these differential mechanisms will be addressed further in future research.

Besides, by linking success versus failure in the task to intelligence our manipulation might have addressed selfefficacy in addition to FF. The fact that we found a significant interaction effect of the manipulation with implicit FF suggests that our manipulation did really affect this motive component. However, it is still possible that the manipulation additionally affected self-efficacy. We hope that future research will help to disentangle effects of feedback on FF from effects on self-efficacy.

For the assessment of implicit FF we used the MMG (Schmalt et al. 2010; Sokolowski et al. 2000). There is a debate on whether the MMG really allows the assessment of implicit motives rather than semi-implicit motives (e.g., Schüler et al. 2015). It remains an open question whether ostensibly "pure" implicit measures such as the PSE would reveal diverging results from the ones presented in the current study. Thus, it would be interesting to use a different measure of implicit motives in future studies. For example, one could use the PSE and a coding manual that clearly distinguishes between the hope and fear component of the achievement motive (see Heckhausen 1963; Pang 2006) to test whether our findings can be replicated with a different implicit motive measure.

Besides, we only measured implicit FF. In a future study, one might also consider measuring explicit FF (e.g., Lang and Fries 2006) in addition to implicit FF. The (possibly more conscious) setting of the threshold separation might be influenced more by explicit rather than implicit FF.

Conclusions

Our study exemplarily showed the possible benefits of applying the diffusion model to investigate questions of motivational psychology. More specifically, in our experimental study, individuals higher in implicit FF whose motive was aroused by negative performance feedback featured reduced speed of information accumulation (drift rate of the diffusion model). Furthermore, high FF individuals showed reduced learning rates. Fear of failure was not associated with differences in decision caution or the duration of nondecisional processes (e.g., speed of motor response execution). By disentangling different components involved in decision tasks, the diffusion model can contribute to a better understanding of the mechanisms underlying cognitive processes in performance differences between individuals high and low in fear of failure.

Compliance with ethical standards

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Appendix

See Figs. 4, 5 and 6.

Fig.4 Graphical inspection of model fit: relationship between empirical and predicted statistics for parameter estimation based on *all trials*

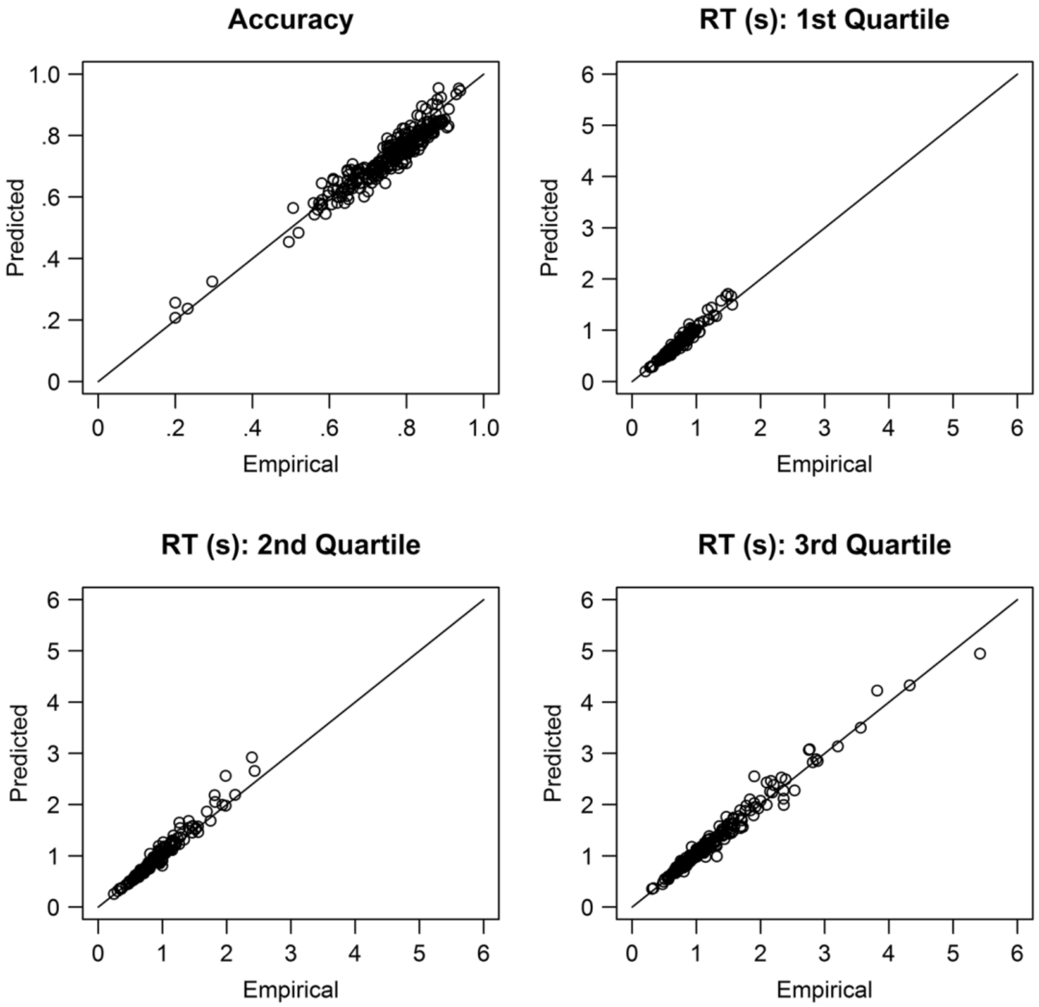
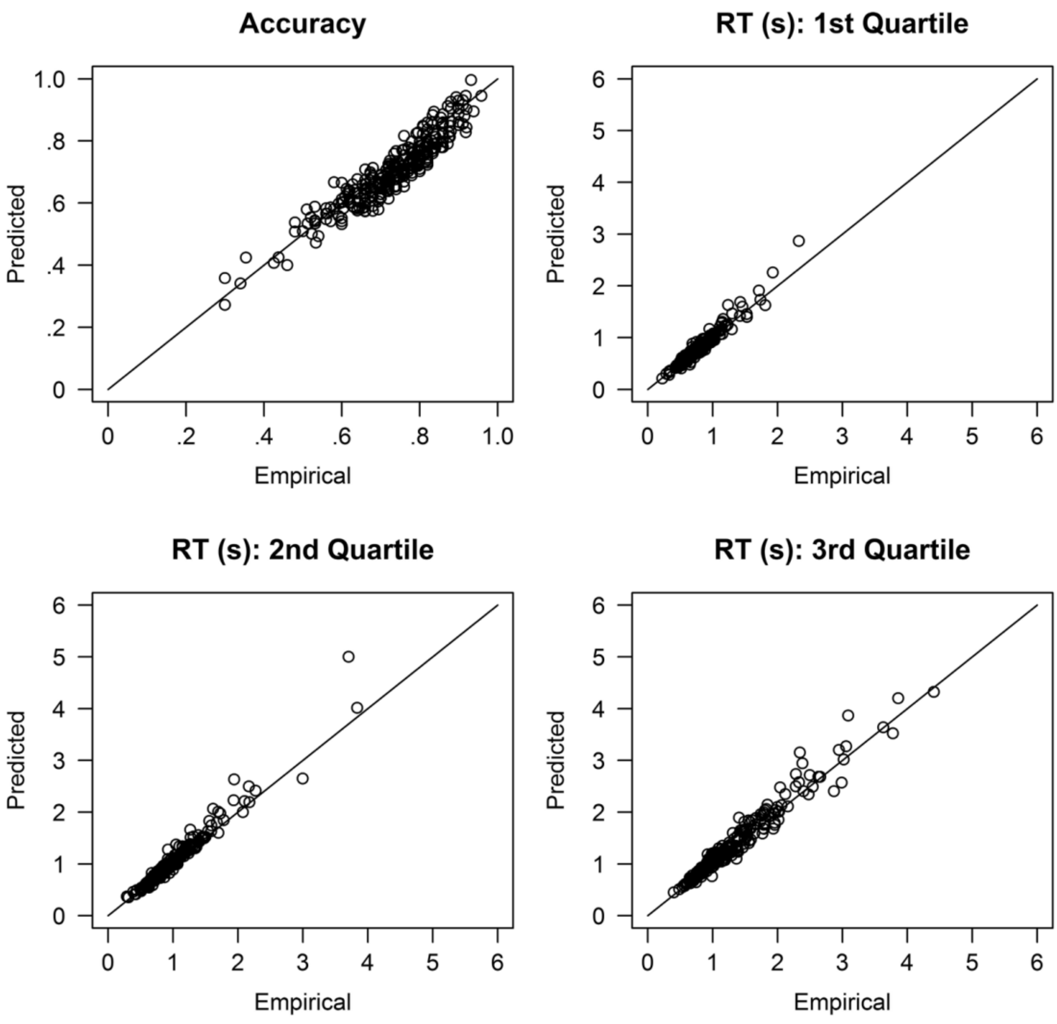


Fig.5 Graphical inspection of model fit: relationship between empirical and predicted statistics for parameter estimation based on the *first block of trials*



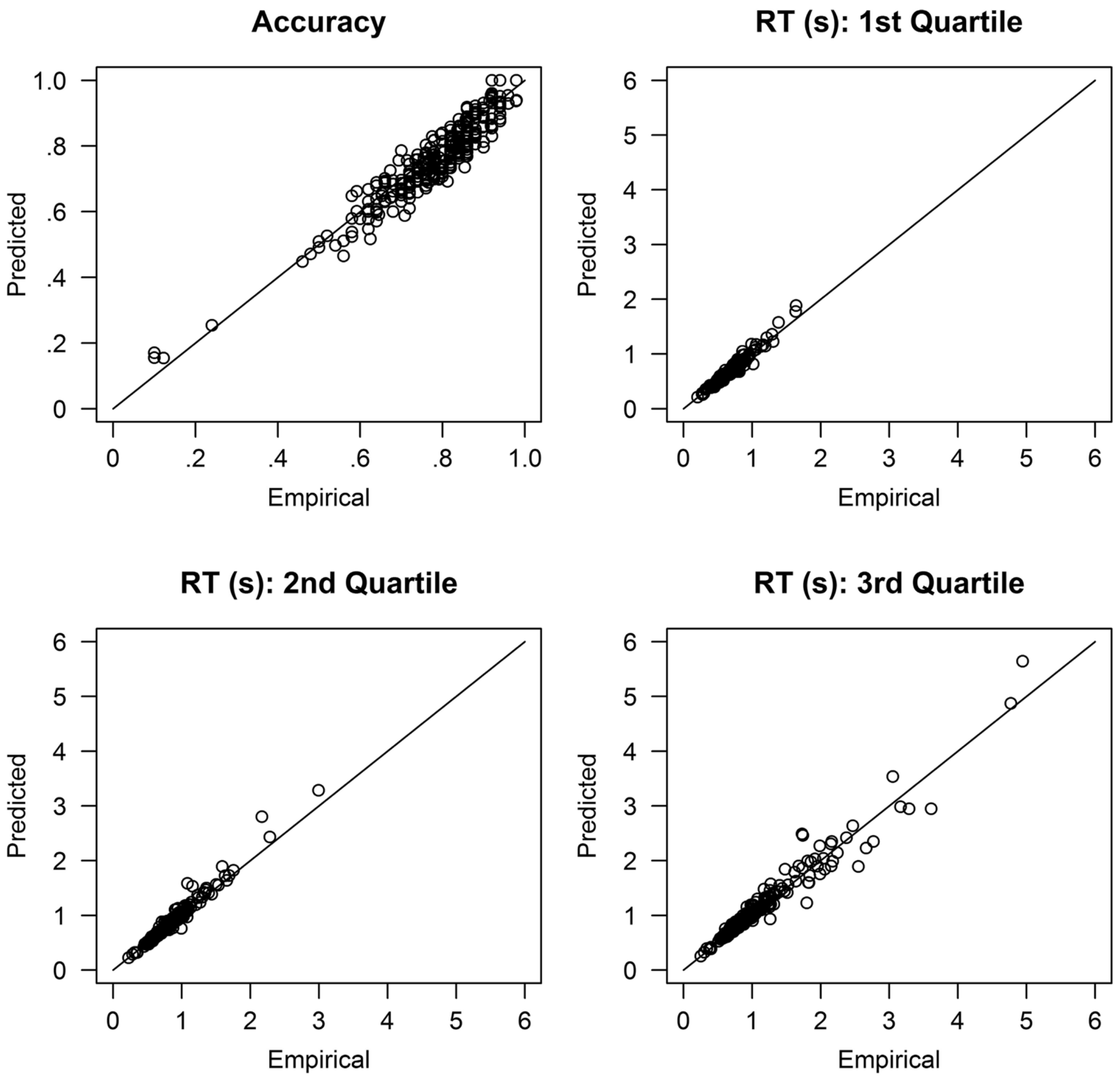


Fig.6 Graphical inspection of model fit: relationship between empirical and predicted statistics for parameter estimation based on the second block of trials

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