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On the Difficulty of Overcoming One's Accuracy Bias for Choosing an Optimal Speed–Accuracy Tradeoff

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Under time pressure, it is usually not possible to respond quickly and accurately at the same time. Therefore, people must trade speed for accuracy, depending on the current payoff conditions. Ideally, they should choose a speed–accuracy tradeoff (SAT) that optimizes their monetary reward. However, this is hardly the case. Rather, persons exhibit an accuracy bias, which is often disadvantageous. To further investigate the role of errors for optimizing reward, we conducted a flanker-task study with different payoff and framing conditions. Whereas the reward for correct responses always increased continuously with speed, the costs of errors varied. In three of four conditions, responding very fast, even with low accuracy, was favorable. Furthermore, in addition to the usual gain framing, half of our participants were instructed according to a loss frame. Whereas framing had little effect on performance, we found a substantial accuracy bias. Only in the most extreme condition some participants overcame their bias and responded very quickly. To examine how SAT strategies differed between participants, we modeled the performance with a sequential-sampling model. The results suggest that various mechanisms were involved in realizing specific SATs. However, they were hardly applied to optimize reward. Rather, participants seem to have optimized their well-being.

Public Significance Statement

For optimizing reward under time pressure (e.g., at the stock market), it is sometimes favorable to trade accuracy for speed. However, this is not what persons usually do. Rather, they exhibit an accuracy bias, that is, they are reluctant to make errors. In the present study we investigated effects of payoff schemes and loss versus gain framing on speed–accuracy tradeoff and observed that even in the most extreme condition, only few persons overcame their accuracy bias. Rather than optimizing monetary reward, it seems that most persons optimized their well-being by avoiding making errors.

Keywords: speed–accuracy tradeoff, flanker task, accuracy bias, drift-diffusion model

In various tasks we are often faced with the problem of deciding which action to perform next. A rational criterion for such decisions would be to select the action that leads to an optimal outcome with respect to our current goal. However, identifying a corresponding action usually requires the collection and processing of information about the current state of the environment and predicting the consequences that possible actions would have, which is effortful and takes time. In some situations, this is not critical, but in others it is. In dynamic environments, for instance, possible actions and/or their outcome might change over time. If the situation is likely to get worse (e.g., in auctions, sports, or stock markets), one must decide quickly which action to perform in order to gain something or, at least, not to lose too much. However, due to the limited time for information processing, decisions under time pressure usually have a reduced accuracy. Therefore, decision makers must decide how much accuracy they are willing to sacrifice for speeding up their responses. Details about such a *speed–accuracy tradeoff* (SAT) are of great interest in various areas of cognitive psychology and neuroscience (e.g., Bogacz et al., 2010; Heitz, 2014).

An important question in this connection concerns reward optimization. Often, the outcomes of decisions under time pressure depend on a specific payoff scheme, that is, on the reward for fast correct decisions and costs for errors. Do people select a SAT that optimizes their reward? Evidence indicates that this is rarely the case. Most people try to perform relatively accurately rather than to optimize their reward (cf., Maddox & Bohil, 1998). This bias suggests that errors play an important role in human behavior and that there is a general tendency to avoid them. A plausible reason for this accuracy bias is that errors elicit negative emotions (Dignath et al., 2020). Thus, it seems that the SAT is not only

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The data and examples of the instructions are provided at OSF: https://osf.io/shq7m/

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determined by the current payoff scheme, but also by the decision maker's willingness to make errors. Because the role of errors for the optimization of reward has rarely been investigated systematically, the aim of the present study was to add further evidence to this issue by conducting an experiment where we systematically varied the costs for errors. Furthermore, we speculated that the acceptance of errors might depend on the framing of the decision task and, therefore, also compared the performance under a gain framing with that under a loss framing (Tversky & Kahneman, 1981).

As an experimental paradigm, we used the flanker task (Eriksen & Eriksen, 1974). In this two-alternative forced-choice task, a centrally presented target item must be categorized by pressing a corresponding response button. However, along with the target, irrelevant flanker items are presented, which are either congruent or incongruent, that is, are associated with the correct or the wrong response, respectively. Thus, incongruent flankers produce a response conflict, which usually increases the response time (RT) and error rate, depending on the efficiency of attentional conflict control (Hübner et al., 2010). Accordingly, the flanker task allows one to modulate the error rate and investigate how it is affected by attention and reward. Hübner and Schlösser (2010), for instance, found that monetary incentives improved attention, which increased response speed without reducing accuracy.

To obtain deeper insights into the involved decision processes and strategies in the various conditions examined, we also modeled the data with a sequential sampling model. However, before we report the results of the present study, we first consider the relevant concepts in more detail.

Speed–Accuracy Tradeoff

For various tasks, reaching from perceptual categorization (e.g., Fitts, 1966; Ratcliff & Rouder, 2000; Swensson, 1972b) and memory retrieval (e.g., Banks & Atkinson, 1974; Kounios et al., 1994; Reed, 1973; Wickelgren et al., 1980) to complex mental operations (e.g., Liesefeld et al., 2015), it has been shown that people are able to deliberately trade speed for accuracy. The relation between these two performance measures can be described by a SAT function (SATF). A widely used method to obtain such a function is to systematically vary the time available for performing a task. For instance, participants might be required to respond before a prespecified deadline. If the deadline is varied across conditions, then a corresponding SATF can be visualized by plotting mean accuracy against mean RT for the different deadlines (for an overview see Heitz, 2014). An alternative method for varying SAT is to apply different payoff schemes (see below). Moreover, both methods can be combined. For instance, participants will get some reward for a correct response, but only if it occurs before a deadline.

Formal Models

To get an idea of how persons might control response speed and accuracy, formal models are helpful. Historically, two-state models have been proposed first (cf. Heitz, 2014). According to these models, responses result from two possible response modes: fast guesses and slow stimulus-controlled decisions. Although such models are supported by results of several studies (e.g., Swensson, 1972a; Swensson & Edwards, 1971; Yellott, 1971), it can be assumed that fast guesses reach a relevant proportion only under extreme time pressure, and/or when the reward for fast correct responses outweighs the costs for errors (Heitz, 2014).

Therefore, to obtain a more general account of SAT, sequential sampling models have been developed (e.g., Bogacz et al., 2006; Busemeyer & Townsend, 1993; Fitts, 1966; Ratcliff, 1978, 1985; Ratcliff et al., 2015). These models are based on the assumption that information is extracted from the stimulus and accumulated over time at a certain rate until evidence favoring the one or the other response reaches a corresponding response threshold (also called *boundary* or *criterion*). Thus, under time pressure, the duration of response selection can simply be reduced by lowering the threshold, which is under voluntary control. However, because evidence accumulation is a noisy process, a low threshold also increases the probability that the wrong response is selected, which reduces accuracy. Accordingly, a person can easily trade speed for accuracy by simply adjusting the response threshold.

Dutilh et al. (2011) questioned that SATFs are continuous, that is, that speed can be increased gradually at the cost of accuracy until performance is at chance level (fast guessing), as compatible with sequential-sampling models. Therefore, they proposed that with increasing time pressure, relatively accurate behavior suddenly switches to guessing behavior, and introduced a corresponding phase-transition model, combining sequential sampling and fast guessing. Trimmer et al. (2008) went even a step further and proposed a two-stage model. They assumed that two systems are involved in response selection: A fast system that selects a response on the basis of a single sample of evidence provided by early perceptual information (e.g., low spatial frequencies), and a slower and more accurate sequential-sampling system relying on later information (e.g., high spatial frequencies). These two systems are combined in such a way that, if the fast system does not select a response, sequential sampling starts. The Trimmer et al. (2008) model is similar to the Dual-Stage Two-Phase (DSTP) model of Hübner et al. (2010), which has also been applied for modeling SAT (Dambacher & Hübner, 2015), and which is described in more detail in the Modeling section.

Payoff Schemes and Optimization

As mentioned, SAT can also be influenced by a payoff scheme. If combined with a deadline, there are different events that can be rewarded or punished. More specifically, in addition to rewarding timely correct responses, there are two types of errors that can be punished: response errors and timeout errors. Accordingly, either one of the two error types, or both can be punished (e.g., Dambacher et al., 2011). A further possibility is to reward correct responses and punish errors continuously, depending on their speed (e.g., Swensson & Edwards, 1971). In the present study, we applied such a scheme. For our objective, a continuous payoff scheme had the great advantage that reward could be varied over a wide range of RTs with little risk of observing timeout errors, which were not in our focus.

As mentioned, an important question is to what extent decision makers optimize their reward for a given payoff scheme. For answering this question, though, one needs to know the objective relations between speed, accuracy, and reward, which are mostly difficult to compute. A common approach to solve this problem is to apply a sequential sampling model and derive how reward varies with the response threshold, that is, with the SAT. The SAT that maximizes reward can then be compared to those chosen by participants in an experiment. In a specific application of the sequential sampling idea, Gold and Shadlen (2002) considered an experimental paradigm, where, instead of the number of trials in a block, as usual, the duration of a block is fixed. They hypothesized that participants select a response threshold that optimizes the reward rate, that is, the average number of rewards per unit of time. Optimizing this rate is possible, because it is a concave function of the response threshold (Bogacz et al., 2006). However, when Bogacz et al. (2010) tested the reward-rate hypothesis, they found that their participants were slower and more accurate than predicted by optimization.

Although examining the reward rate revealed some insight into the performance in SAT experiments, the approach is rather special. Evidence indicates that merely adjusting the response threshold, as assumed, is not the only way to meet time pressure. Decision makers might also adjust the time spent for stimulus encoding, which not only affects the nondecisional time (see below), but also the rate of evidence accumulation (Dambacher & Hübner, 2015; Rae et al., 2014). Thus, effects of speed pressure can be more diverse than often assumed.

Accuracy Bias and the Role of Errors

Although practice and specific instructions can improve reward optimization in simple sensorimotor tasks (Evans & Brown, 2017), most studies found that participants are more concerned about being accurate than about optimizing their reward (e.g., Bogacz et al., 2010; Pitz & Reinhold, 1968). Moreover, the deviation of the achieved reward from the optimum increases with task difficulty (Balci et al., 2011; Starns & Ratcliff, 2012), suggesting that the more difficult the task, the more cautiously people respond. In view of the cautious performance observed in a multidimensional perceptual-categorization tasks, Maddox and Bohil (1998) hypothesized that participants optimize a combination of reward and accuracy and proposed their COBRA (competition between reward and accuracy) model.

These results seem to indicate an accuracy bias, that is, the tendency to weight accuracy more than speed. Several reasons have been proposed why participants may care about accuracy (cf. Bogacz et al., 2006). One reason could be compliance. Already Swensson (1972a) argued that fast responses might be experienced as fast guesses and, therefore, considered as cheating, which evokes unpleasant feelings. Recently, Fiedler et al. (2020) proposed a similar account. They argue that the accuracy bias is due to the social surplus meaning of accuracy, which implies carefulness and responsibility. Speed and errors, in contrast, are associated with risk, carelessness, and sloppiness. Thus, the accuracy bias could reflect a quasimoral norm.

The violation of such a norm also has psychophysiological consequences. Studies show that response errors activate the defensive motivational system, which, according to the *affective-signaling hypothesis* elicit negative affect. Response errors produce, for example, larger skin conductance responses and greater heart-rate deceleration than correct responses, suggesting that they are perceived as aversive and distressing events (for overviews of the physiological results and theories see Dignath et al., 2020; Koban & Pourtois, 2014).

These results and considerations suggest that participants in a SAT experiment do not try to optimize their monetary reward, but rather their well-being, which presumably also includes to earn a satisfactory amount of money. Consequently, the accuracy bias might only be overridden in situations where speed and errors are associated with less negative associations and/or where reward is very high, as, for instance, in the study of Swensson and Edwards (1971).

Gain Versus Loss Framing

As we have seen, errors in SAT experiments often result in losses. Therefore, the accuracy bias might also be related to loss and risk aversion observed in economic decisions. Risk aversion denotes the tendency in monetary gambles to prefer options with a high win probability, even if riskier alternatives have a higher expected value (e.g., Dambacher et al., 2016; Tversky & Kahneman, 1992). A similar concept is loss aversion, which describes the phenomenon that people prefer to avoid losses rather than make equivalent gains. The assumed reason for this preference is that losses appear larger than equivalent gains (Tversky & Kahneman, 1991).

For the objective of the present study the related framing effect (Tversky & Kahneman, 1981) is most interesting. It shows that choice performance can systematically be modulated by framing the possible options in terms of gains or losses. Under a gain frame, participants tend to prefer safe options and avoid risky ones, whereas the opposite holds under a loss frame. Unfortunately, up to now, framing effects have mainly been investigated in the context of gambling (e.g., Rubaltelli et al., 2012; Shelley, 1994). Here, we extended the framing manipulation to a SAT experiment and speculated that similar effects might also occur for the acceptance of response errors. If, under a loss frame, loss is the standard outcome whose amount can be reduced by fast responses, then errors might have fewer negative connotations and, therefore, are easier to accept. Thus, if persons under the usual gain framing restrict their speed of responding to prevent errors and corresponding unpleasant feelings, even if this is suboptimal with respect to reward, then performance might be different under a loss framing.

The Present Study

The aim of the present study was to further investigate the accuracy bias and its effect on reward optimization under time pressure. For this objective we varied the payoff scheme and the framing in a flanker task. In four payoff conditions, reward for correct responses increased in the same way continuously with response speed over a relatively large time range. However, errors were punished differently. In two of the four conditions fast errors even produced a reward. Our specific questions were to what extent participants optimize their reward depending on error punishing and framing, and which strategies they apply. Adjustments of the response threshold to optimize reward would be compatible with simple sequential-sampling models. However, there are also other mechanisms. For instance, effort can be increased to mobilize further resources for speeding up stimulus processing and motoric responding. Moreover, especially in the flanker task, conflict resolution can be improved by increasing attentional selectivity (Dambacher & Hübner, 2015; Hübner et al., 2010). Finally, it is also possible to guess on some trials.

We expected that, due to the accuracy bias, most participants will not optimize their reward. Nevertheless, we predicted strategy differences between the payoff and framing conditions. Especially under a loss framing and in the conditions with little or no costs for fast errors participants should speed up responding and be more willing to make errors for increasing their profit.

In addition to analyzing the data statistically, we also modeled the data with a diffusion model for conflict tasks. This allowed us to examine which strategies our participants applied.

Experiment

The design of our flanker-task experiment consisted of four main conditions, each with an individual payoff scheme. In all schemes, reward for correct responses increased continuously for every millisecond decrease in RT within the range from 650 to 150 ms. However, the costs of errors differed between the schemes. To promote an adaptation of performance, feedback was provided after each trial and after each block.

Different participants were assigned to the four main conditions. Additionally, the corresponding groups were split into two subgroups with a different framing for each. For one subgroup the instruction set the focus on possible gains, whereas for the other group the focus was directed to possible losses.

Method

Participants

Of main interest were the two main effects of framing and payoff. Although we had some experience with payoff effects (Dambacher et al., 2011), the continuous payoff scheme applied here was rather special. Moreover, experience with framing effects in this specific context was lacking. Therefore, we planned to find effects of medium size, which corresponds to f = .25 (Cohen, 1992) or to a partial-Eta squared (η_p^2) of .059. Accordingly, we calculated the necessary sample size for the between-factor with the most factor levels (payoff condition) in a 2 × 4 between Analysis of Variance (ANOVA) with both factors. For α = .05 and an anticipated power of $1-\beta$ = .90 the program ss.2way in R's pwr2 library (Lu et al., 2017) revealed a necessary sample size of 231 participants. However, the balancing of our design required at least 232 participants, resulting in 29 participants per cell. To take the possibility into account that the data of some participants might have to be excluded from the experiment (e.g., because they have dropped out of the experiment), we increased the sample size to 32 participants per cell of the experimental design resulting in 256 participants overall. Accordingly, 256 participants were recruited via an online system (SONA) at the University of Konstanz. For their participation they could receive between 4 € and 20 €, depending on their performance. Actually, the participants received between 5.5 and 14.6 €.

The data of seven participants were excluded (three abandoned the experiment; two had to stop due to technical issues during the testing; two produced extreme data, compared to the rest of the participants: one had an error rate of 71% at a mean RT of 305 ms, while the other had an error rate of 52% at a mean RT of 890 ms). The final sample consisted of 249 participants (176 female), whose age ranged from 18 to 33 years (M_{age} = 22.7, SD_{age} = 3.08). Participants were informed that they are free to withdraw from the study at any point in time without any negative consequences. Informed consent in line with the 1964 Declaration of Helsinki and its later amendments, as well as in agreement with the ethics and safety guidelines at the University of Konstanz was obtained from all participants as check mark on a corresponding information page before the experiment started.

Apparatus

Participants were tested in groups of up to 10 at a time in a group lab. Stimulus presentation and response recording were controlled by personal computers. The stimuli were presented on 23.8-in. color monitors (Fujitsu B248T) with a resolution of 1,920 × 1,080 pixels and a refresh rate of 60 Hz. Each screen was located centrally on a desk in front of a participant with a viewing distance of about 60 cm. The experiment was programmed in JavaScript and ran in a Google-Chrome browser (Versions 64 to 70) under Windows 10. Responses had to be entered via clicking mouse buttons.

Stimuli and Task

Combinations of the letters *B*, *D*, *K*, and *H* served as stimuli, which were presented in white on a black background. They were divided into two categories (*B*, *K* and *D*, *H*), which were mapped to a mouse key, respectively, counterbalanced across participants. The stimuli were approximately 1.84° (width) by 2.49° (height) visual angle in size. On each trial, three horizontally arranged letters were presented, with the outer two always being identical (e.g., *B K B*). The distance (eccentricity) of the outer letters to the middle letter was about 2.62° visual angle (center to center).

The task of the participants was to identify the category of the central letter (target) by clicking the corresponding mouse button. The stimuli (letter combinations) could be congruent or incongruent, depending on whether the flankers were mapped to the same button as the target (e.g., *B K B*), or not (e.g., *B H B*).

Procedure

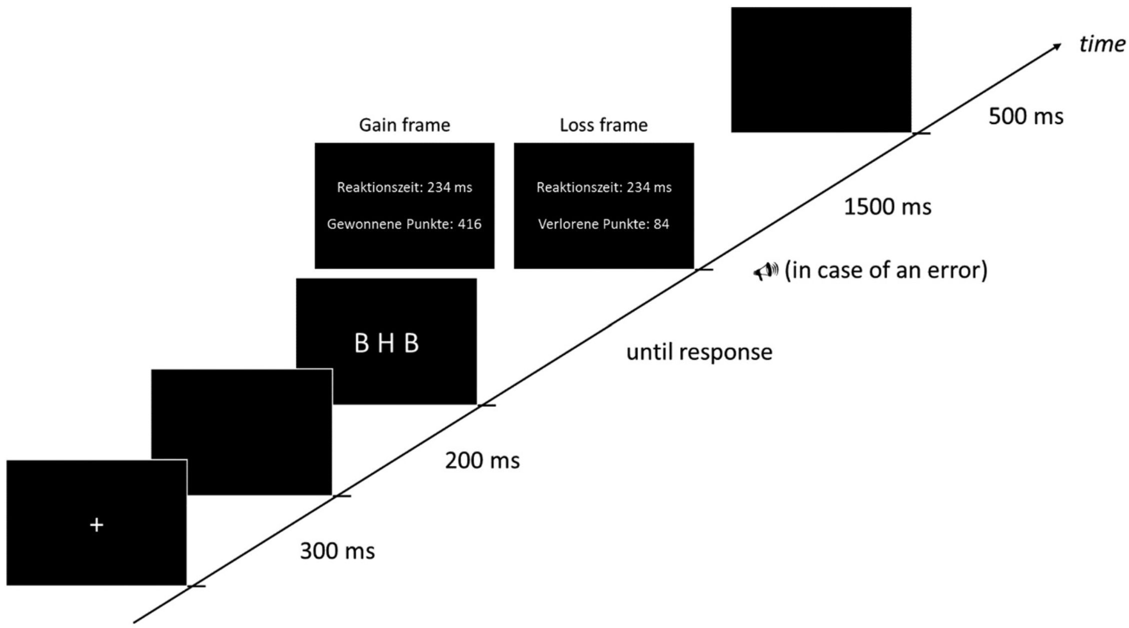
At the beginning of each trial a fixation cross was presented at the center of the screen for 300 ms (see Figure 1), followed by a blank screen for 200 ms. Then the stimulus appeared and remained on screen until a response was given. After the response, there was visual feedback for 1,500 ms about the response time and the gained or lost points (see below) on that trial. In case of an error, a tone was played concurrently for about 100 ms. Finally, a black screen appeared for 500 ms, before the next trial started.

Participants started the experiment with two short practice blocks of 16 trials each, in which they could not gain or lose any points. Then, participants ran through 20 test blocks of 32 trials, which resulted in 640 experimental trials overall. After each block, participants received summarized feedback about their performance (see below).

Conditions

There were four payoff conditions, to which different participants were assigned in sequential order. On each trial, participants could collect points, depending on the payoff condition and their performance (see Figure 2). Responses faster than 150 ms resulted in zero points. Correct responses with RTs between 150 and 650 ms resulted in 500–(RT–150) points, and those with RTs larger

Figure 1
Sequence of Events on a Trial of the Experiment



Note. In this example trial, the stimulus display consists of the target letter H and two copies of the flanker letter B. After the response, and depending on the framing, gained points (Gewonnene Punkte) or lost points (Verlorene Punkte) were displayed on the feedback screen, respectively, together with the response time (Reaktionszeit).

than 650 ms in zero points. Thus, for a correct response the participants received between 0 and 500 points, depending on RT.

Whereas the scheme for correct responses was identical in all four payoff conditions, it differed with respect to errors (see Figure 2). In Condition 1 (N = 63) errors with an RT between 150 and 650 ms resulted in 150−RT points, and errors slower than 650 ms in −500 points. Thus, the costs for an error increased with RT from 0 to a maximum of 500 points. In Condition 2 (N = 60) errors always led to zero points. In Condition 3 (N = 62) errors between 150 and 650 ms produced 400−RT points. Accordingly, errors between 400 and 650 ms produced costs from 0 to 250 points, while faster ones between 150 and 400 ms resulted in gains from 0 to 250 points. Errors slower than 650 ms resulted in −250 points. Finally, in Condition 4 (N = 64) errors between 150 and 650 ms produced 800 − 2·RT points. Consequently, slower errors between 400 and 650 ms produced costs from 0 to 500 points, while faster ones between 150 and 400 ms resulted in gains from 0 to 500 points. Errors slower than 650 ms resulted in −500 points.

The four payoff groups were randomly separated into a gain-frame and a loss-frame group, respectively, which received corresponding instructions and feedback. Participants in the gain-frame group were told that they start each trial with zero points, but that they gain one point for each millisecond they respond faster than 650 ms, given the response is correct. Participants in the loss-frame group were told that they start each trial with a balance of 500 points but will lose one point for each millisecond they respond slower than 150 ms, given the response is correct. The consequences of errors were framed accordingly. That is, participants in the gain-frame group received feedback stating that they "earned" minus X points, whereas those in the loss-frame group were told that they lost X points.

After each block, participants received feedback about their mean RT and accuracy (gain frame), or error rate (loss frame). Moreover, they were informed about the overall points gained (gain frame) or lost (loss frame) so far. At the end of the experiment, the collected points were summed up across all trials and multiplied by .005 €. The theoretical maximum number of points that could be collected during the experiment was 320,000 (500 points on each of the 640 trials), which corresponds to 16 €. Together with the 4 € base compensation, this would have resulted in a maximum overall payment of 20 €.

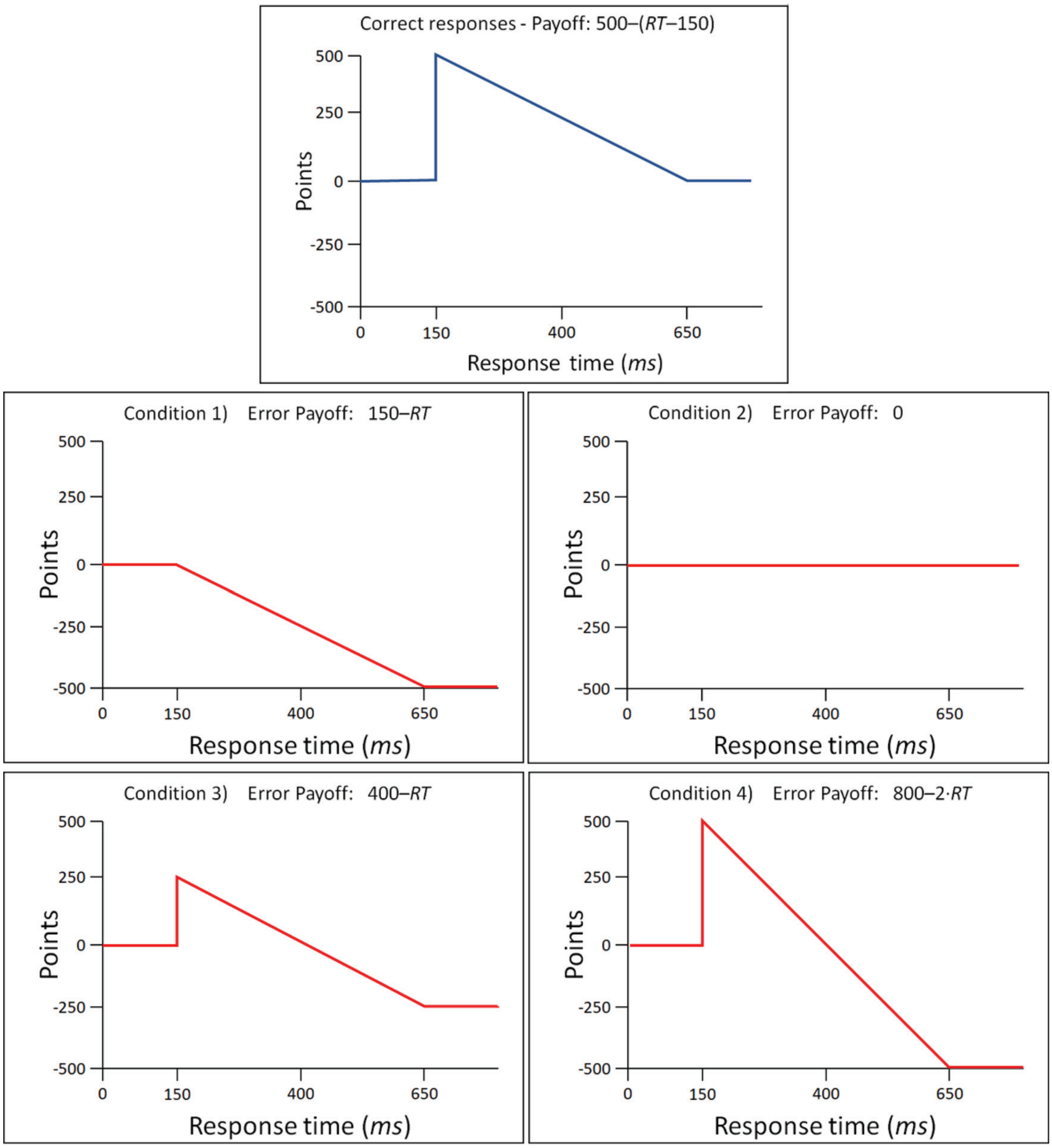
Results and Discussion

Less than 1 percent (.97%) of all RTs were smaller than 150 ms, and 4.94% were larger than 650 ms. RTs greater than 2 s were considered as outliers and excluded from the analyses (less than .001% of all data). Furthermore, errors (mean error rate: 13.3%) were excluded from RT analyses. Figure 3 shows the mean RTs and error rates observed in the eight main conditions and the two congruency conditions.

The program ezANOVA from the R library ez (Lawrence, 2016) was used for computing separate 4 × 2 × 2 ANOVAs with the between-participants factors *payoff condition* (1, 2, 3, and 4) and *framing* (gain and loss), and the within-participants factor *congruency* (congruent and incongruent) for the RTs and error rates, respectively. Posthoc t-tests were calculated to further examine differences between individual conditions.

The results of the ANOVAs are presented in Table 1. As can be seen, payoff produced a highly significant main effect in the error rates (9.49%, 11.4%, 13.7%, and 18.6%). Posthoc t-tests revealed

Figure 2
Payoff Schemes for Correct Responses and for Errors in the Four Payoff Conditions

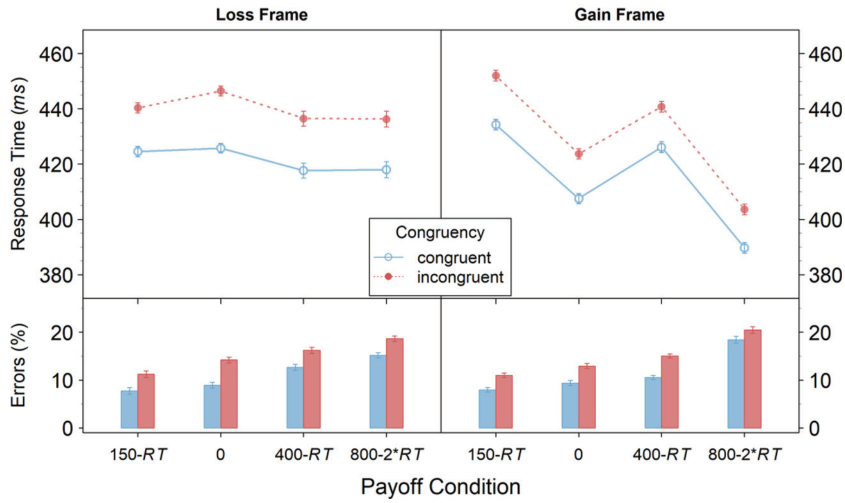


Note. The payoff formulas in the headings are valid only for RTs between 150 and 650 ms. See text for further details. See the online article for the color version of this figure.

that Conditions 1 and 2, and Conditions 2 and 3 did not differ significantly (see Table 2). In the RTs the main effect of payoff (443 ms, 431 ms, 435 ms, and 412 ms) was also significant. According to the posthoc tests, Conditions 1 and 4 differed significantly. The main effects of framing were not significant. The interactions with congruency were marginally significant. They reflect the tendency toward smaller congruency effects under a gain than under a loss framing. Moreover, the three-way interaction with congruency and payoff was significant in the error rates, which however, is difficult to interpret (see Figure 3). The main effect of congruency was significant in the RTs (congruent: 422 ms, incongruent: 439 ms) as well as in the error rates (congruent: 11.5%, incongruent: 15.1%). Furthermore, the interaction between congruency and payoff was significant in the error rates. The congruency effect (1: Δ 3.21%, 2: Δ 4.40%, 3: Δ 3.91%, and 4: Δ 2.59%) was smallest in Condition 4, and largest in Condition 2, where errors produced no costs. However, as indicated by the mentioned three-way interaction, this pattern was further modulated by the framing.

Together, our results show that varying the costs of response errors had little effect on mean performance. Across the different payoff conditions mean accuracy merely varied from 81% to 91%, while mean RTs varied from 412 ms to 443 ms. These results support

Figure 3
Average Performance in the Eight Main Conditions (Payoff Schemes and Framings) of the Experiment and the Two Congruency Conditions



Note. Error bars represent 95% within-participant confidence intervals (Loftus & Masson, 1994; Morey, 2008). See the online article for the color version of this figure.

the idea of an accuracy bias. Irrespective of the payoff scheme, most participants were reluctant to make errors, and, therefore, responded not as fast as required to optimize their monetary reward. However, up to now we only considered mean performance across participants. For examining to what extent participants differed in their SAT, we also analyzed individual performance.

To see which SAT participants used in the different conditions, we visualized the individual performance by placing mean RT and accuracy of each participant in a speed–accuracy space. Additionally, we color coded the sum of gained points (reward score) earned by each participant. The results for the different payoff conditions are shown in Figure 4. Because framing had only small effects, the data of both framing groups were merged.

By considering Figure 4 it becomes obvious that SAT varied across participants. Whereas some participants favored accuracy over speed, others responded faster at the cost of accuracy. However, it can also be seen that in the first three payoff conditions the range of SAT was rather restricted. Participants barely performed with an accuracy below 75%. Only in Condition 4, a substantial number of participants performed with a lower accuracy. Yet, even in this condition, many participants favored a relatively high accuracy. That is, they performed like the participants in the other conditions.

An interesting question is how much reward the individual participants achieved relative to the maximum possible reward. To approach an answer to this question, we entered the data from Condition 4 into linear regressions to estimate an average SATF.

Table 1
Result of the Overall ANOVAs

Predictor	df_N	df_D	F	p	η_p^2
			Response times		
Payoff (P)	3	241	2.93	<.05*	.035
Framing (F)	1	241	1.04	.301	.004
Congruency (C)	1	241	446	<.001***	.649
P × F	3	241	1.83	.142	.022
P × C	3	241	0.98	.405	.001
F × C	1	241	3.69	.06	.015
P × F × C	3	241	0.97	.406	.012
			Error rates		
Payoff (P)	3	241	11.2	<.001***	.112
Framing (F)	1	241	0.01	.956	.000
Congruency (C)	1	241	328	<.001***	.576
P × F	3	241	0.52	.669	.006
P × C	3	241	4.13	<.01**	.049
F × C	1	241	3.23	.074	.013
P × F × C	3	241	2.77	<.05*	.034

Note. ANOVA = Analysis of Variance.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2
Pairwise Comparisons Between the Payoff Conditions

Conditions	*df*	*t*	*p*	η_p^2
		Response times		
1 versus 2	121	–1.43	.16	.06
1 versus 3	123	–0.96	.34	.03
1 versus 4	94.3	–2.60	<.05*	.17
2 versus 3	120	–0.38	.70	.01
2 versus 4	105	–1.50	.14	.07
3 versus 4	109	–1.76	.08	.09
		Error rates		
1 versus 2	121	1.75	.08	.08
1 versus 3	103	3.11	<.01**	.24
1 versus 4	84.3	4.85	<.001***	.43
2 versus 3	120	−1.67	.09	.08
2 versus 4	87.6	3.80	<.001***	.32
3 versus 4	109	2.35	<.05*	.15

Note. When the assumption of homogeneous variances was violated, Welch two-samples *t*-tests were computed and *df*s corrected.
* $p < .05$. ** $p < .01$. *** $p < .001$.

As mentioned in the Introduction, SATFs are usually measured directly by varying speed pressure within participants. The individual SATFs then reflect the participants' abilities and strategies. With our between-participants design, however, this was not possible. Therefore, we used linear regression analyses to estimate a representative SATF from the SATs of the different participants. In addition to generally excluding RTs > 2 s, the data of very slow (mean-RT > 550 ms) participants (three) were excluded from the regression analyses to improve representativeness. The correlation between the remaining RTs and accuracies was .865, $t(59) = 13$, $p < .001$. The considered SATF ranges from 50% (RT 190 ms) to 100% accuracy (RT 515 ms). Because there was no reason to assume that the same SATs could not also have occurred in the other payoff conditions, we considered the fitted SATF as representative for all corresponding conditions. Accordingly, we plotted the regression line also in the panels of the other conditions (see Figure 4). As can be seen, the SATF estimated from the data in Condition 4 also fits the data in the other conditions rather well.

To compute the reward along the SATF, we needed a function that estimated for each payoff scheme the sum of points that is obtained for a given mean RT and mean accuracy (AC). As solution we constructed the function *sp*:

$$sp(RT, AC) = \left(AC \cdot po_c(RT) + (1 - AC) \cdot po_e(RT)\right) \cdot NT,$$

where po_c and po_e are our payoff functions that return, for a given RT, the payoff for a correct and incorrect response, respectively. *NT* is the number of trials in the experiments. If we apply this function to predict for each participant the sum of gained points in Condition 4, and correlate the results with the actually collected points, then we find a correlation of .97, $t(62) = 29$, $p < .001$. This shows that the function works very well.

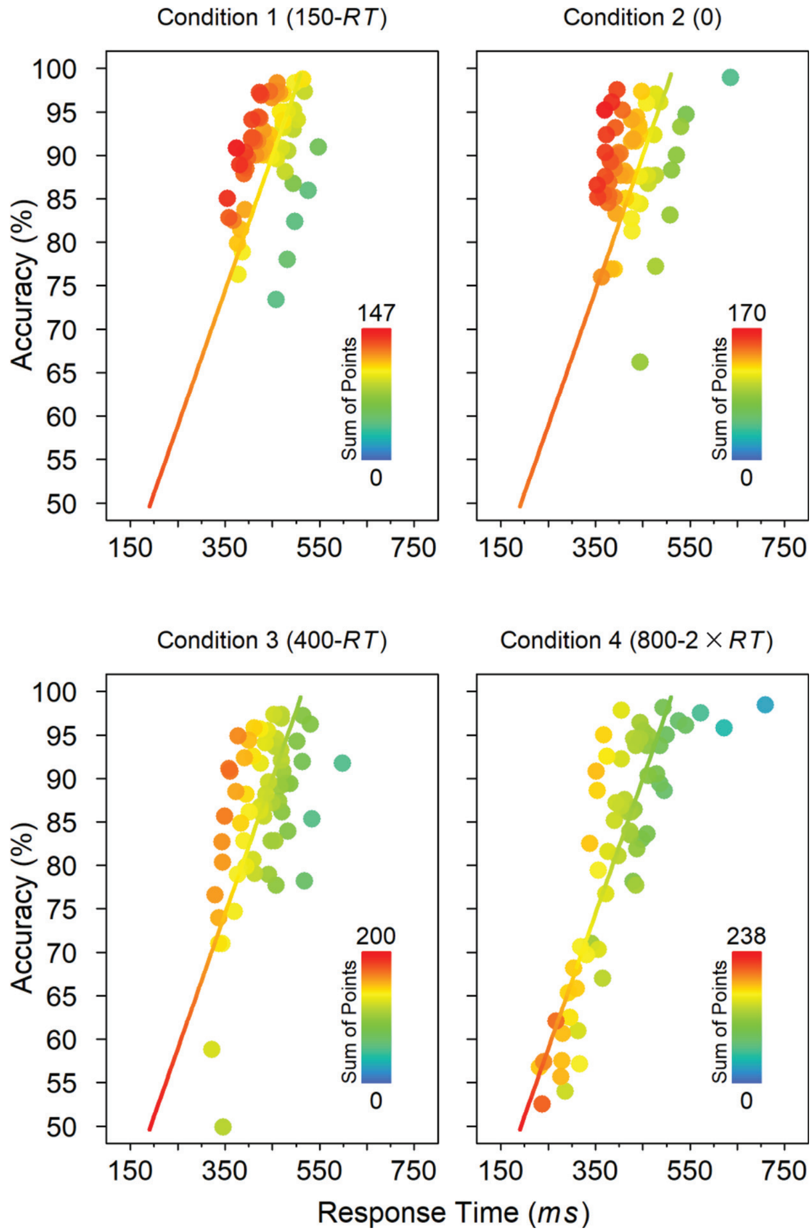
With the function *sp* it was possible to compute the sum of points that could have been gained for the different SATs along the SATF. In Figure 4 the corresponding sums along the SATF are coded by color (for details see below). Although this gives a first impression how the reward increases with response speed, the exact relations are difficult to see. Therefore, we also computed detailed reward functions showing how reward changes with SAT along the SATF. Figure 5 shows the functions for the four payoff conditions. As can be seen, for Condition 2, where errors have no costs, the reward function is slightly concave. For the other conditions, however, the reward score increases monotonously with speed along the SATF. The increase is smallest for Condition 1 and steepest for Condition 4. The reward functions show that, except in Condition 2, responding very fast would have increased the reward despite the reduced accuracy. Thus, these functions are generally informative for assessing the chosen payoff schemes in the present experiment.

The SATF estimated from Condition 4 in combination with the reward functions can be used to examine to what extent our participants optimized their reward in the different payoff conditions. Comparing the absolute reward across conditions makes little sense, because it largely depends on the payoff scheme. However, we can compare the obtained reward within each condition relative to the possible maximum in that condition. In Figure 4 the different sums of points are coded by color in such a way that the color changes from dark red (light gray) representing the maximum reward in a condition, either obtained by a participant or present along the SATF, to dark blue (black), which indicates zero reward. Thus, the range of reward along a SATF represents only part of the whole range. It largely coincides with the range of the corresponding reward function in Figure 5. For instance, the reward in Condition 1 along the SATF ranges from 93,132 points for 100% accuracy to 133,515 points for 50% accuracy. Obviously, in this condition reward could be increased only slightly by responding very fast. This could have been one reason why no participant was motivated to respond very fast. The maximum number of points (146,658) in this condition, however, was achieved by an efficient participant, who performed relatively fast (375 ms) with an accuracy of 91%. Despite the relatively high reward, the performance nevertheless indicates an accuracy bias. It is highly likely that this participant could have responded faster and thereby increased the reward.

The situation was similar in Condition 2, where errors were not punished. However, because of the concave reward function (see

Figure 4

Participants' Mean RT and Accuracy for the Four Payoff Conditions

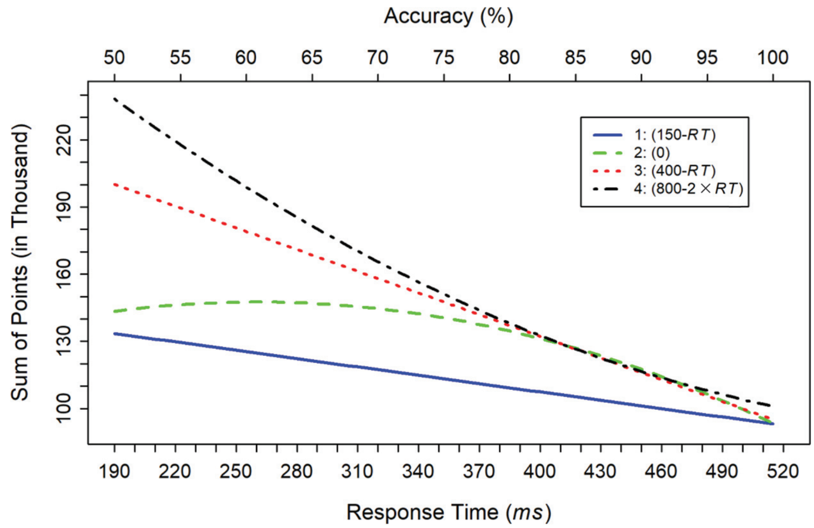


Note. Colors represent the sum of gained points (in thousands) collected by the individual participants. The lines show the SATF estimated from the data in Condition 4. RT = response time. See the online article for the color version of this figure.

Figure 5), performance can be considered as somewhat closer to optimal compared to Condition 1. For Condition 3 the maximum reward (200,121 points, 50% accuracy, RT 190 ms) lies on the SATF (obtained minimum reward: 53,054 points, 92% accuracy, RT 599 ms). Accordingly, if a participant, represented by the SATF, had responded very fast, she/he would have received a higher reward than the most successful participant (172,124 points, 91% accuracy, RT 361 ms).

It should be noted that our estimated SATF represents the SATF of a person with average information-processing capacity and motoric skills. Accordingly, all participants, whose data point lies above or below the SATF in Figure 4, are more or less efficient, respectively. That is, for a given RT, more efficient participants were more accurate than an average participant. The opposite holds for less efficient ones. What we do not know, is to what extent the SATF of more or the less efficient participants run parallel to the fitted SATF over the whole range and whether all participants would have been able to deliberately realize any SAT along their SATF from perfect accuracy to almost guessing. However, from what has been observed in other SAT studies, it is likely that this would have

Figure 5
Example Speed–Accuracy Reward Functions for the Four Payoff Conditions



Note. The functions are based on SATF fitted to the data of Condition 4 (see the text for details). This SATF also determines the shown RT range. See the online article for the color version of this figure.

been possible. In any case, it is reasonable to assume that efficient participants who performed for a given accuracy faster than average (i.e., high-accuracy persons left of SATF) could have responded even much faster and thereby increased their reward, at least in most payoff conditions. Moreover, in Condition 4, where the obtainable reward increased along the SATF from a minimum of 100,951 points to a maximum of 238,224 points, at least some participants responded very quickly. The most successful participant, whose SAT is located close to the SATF, achieved 211,545 points (accuracy 53%, RT 238 ms). This demonstrates that fast responding was principally possible, and we see no reason why not all people, at least those with high capacity, should be able to do so.

Overall, our analyses indicate that people can deliberately choose their SAT from a wide range. However, accuracy is sacrificed for speeding up responding only when the increase in reward is rather large. And even in such conditions only some participants overcome their accuracy bias. What we still do not know is how participants controlled their SAT. Did they merely adjust their response threshold or also adapt other mechanisms? To answer this question, we modeled part of our data.

Modeling and Identifying Possible Strategies

To examine how our participants realized their individual SAT, we modeled the data of Condition 4. In this condition, where fast errors even produced a large reward, the range of SATs was most extended across participants and includes the SATs observed in the other conditions. Thus, results obtained with the data of Condition 4 can be generalized. The obtained model parameters were then entered into a cluster analysis to identify possible strategies applied.

As models, we considered current sequential-sampling models for conflict tasks: the Dual-Stage Two-Phase (DSTP) model (Hübner et al., 2010), the Diffusion Model for Conflict tasks (DMC, Ulrich et al., 2015), and the Shrinking-Spotlight (SSP) model (White et al., 2011). Modeling revealed that for each model there were some participants whose data could only be fitted very poorly. Therefore, we decided to exclude participants with an estimated average deviation of 5% per data point from further analyses. The application of this threshold led to the exclusion of seven participants for the DSTP model, of 15 participants for the DMC model, and of 25 participants for the SSP model. Moreover, a cluster analysis computed on the model parameters to identify common strategies resulted in three clusters for the DSTP model, and two clusters for each of the other two models. Because the DSTP model revealed the most complete picture of possible strategies, we will only report the results of this model.

The DSTP Model

As the other models for conflict tasks, the DSTP model is based on a response-selection mechanism, implemented as diffusion process (cf. Ratcliff, 1978). This process is characterized by a drift rate μ, reflecting the change in evidence available for response A relative to response B during a prespecified time interval, and by two corresponding thresholds of evidence A and B, with separation a and $B < A$. Responses A and B usually represent a correct and a wrong response, respectively. Noisy samples of the evidence are accumulated beginning at starting time t_0 with starting value X_0, until threshold A or B is reached. The duration of this process is the decision time. It is assumed that the observed response time is the sum of this decision time and some nondecisional time T_{er}, representing the duration of processes such as stimulus encoding, response execution, and so forth The complexity of the diffusion process can further be increased by assuming that the starting value, the nondecisional time, and/or the rate vary randomly across trials according to specific distributions (Ratcliff & Rouder, 1998).

Here, for simplicity, these assumptions were dropped. Moreover, we generally assumed that the thresholds are symmetrical around 0, that is, B = –A, with $A > 0$ and $X_0 = 0$. In this special case, where the separation a is 2·A, a will also be called *response criterion*. Thus, in this simple form the drift-diffusion model has three parameters: μ, a, and T_{er}.

The specific characteristics of the DSTP model are the differentiation of two discrete stages of information selection (early, late) and of two corresponding phases of response selection. The first phase starts with the rate of evidence provided by the early stage of information selection. This stage is already selective, for instance by applying perceptual (e.g., spatial) filters, although selectivity is far from perfect. For the first phase of response selection (RS1) it is assumed that the corresponding drift rate, μ_{RS1}, is composed of two component rates, μ_t and μ_f, which are the result of the early stage of stimulus selection. The components represent the evidence provided by the target and the flankers in favor of the correct response A, respectively. Both components sum up to the total rate $\mu_{RS1} = \mu_t + \mu_f$. The component μ_f is positive, if the flankers are response compatible, but negative, if they are incompatible. Thus, the rate μ_{RS1} is usually smaller for incongruent than for congruent stimuli and can even be negative.

To account for the fact that accuracy for incongruent stimuli usually improves with RT, an additional and more effective late stage of information selection is assumed. This late stage is also implemented as a diffusion process, which runs in parallel with RS1 and represents a late categorical stimulus-selection process (SS). It has its own evidence thresholds C and D with separation c, $C > D$, and drift rate (μ_{SS}). If this process reaches one of its thresholds, it initiates a transition of RS1 into a second phase RS2 of response selection by shifting the drift rate from μ_{RS1} to μ_{RS2}. For the flanker task, terminating in C or D is linked to target or flanker selection, respectively. When the target was selected, then μ_{RS2} is usually higher compared to μ_{RS1}. When the flanker was selected, then the size of μ_{RS2} depends on the congruency of the stimulus. Selecting a congruent or incongruent flanker leads to $\mu_{RS2} = \mu_{RS2C} > 0$ or $\mu_{RS2} = \mu_{RS2D} < 0$, respectively. However, it can also happen that a response is already selected during RS1, that is, before *SS* finishes.

In this study, we assumed symmetric thresholds for response selection as well as for information selection (i.e., B = –A, and D = –C). Furthermore, we assumed that target and flanker selection (i.e., SS terminating in C or D) leads to the same absolute magnitude of the drift rate in RS2 (i.e., $\mu_{RS2D} = -\mu_{RS2C}$, and $|\mu_{RS2D}| = |\mu_{RS2C}| = |\mu_{RS2}|$). Thus, altogether, the model has seven parameters: μ_t, μ_f, a, μ_{SS}, c, μ_{RS2}, and T_{er}.

Fitting Method

The models were fitted to the data by using a similar method as in Hübner and Pelzer (2020). First, the correct responses of each participant were summarized by five RTs resulting from five percentiles (.1, .3, .5, .7, .9) of the cumulative distribution function (CDF). Because errors are often rare in congruent conditions, accuracy was, as recommended by Hübner (2014), represented by so-called *conditional accuracy functions* (CAFs; De Jong et al., 1994). A CAF is usually constructed by first dividing the distribution of all RTs (correct and error RTs) by means of quintiles (i.e., .2, .4, .6, .8) into five equally sized intervals: {[0, .2), [.2, .4), [.4, .6), [.6, .8), [.9, 1.0]} for each congruency condition, respectively. Accuracy in each interval is then plotted against the mean RT in that interval. CAFs are an informative data representation, especially for conflict tasks, because they visualize how accuracy varies with RT. Whereas accuracy for congruent stimuli is usually constantly high across RT, that for incongruent stimuli is usually low for fast responses, but increases with RT.

Thus, in all, there were 30 data points for each participant (2 × 5 RTs from the CDFs, 2 × 5 RTs from the CAFs, and 2 × 5 accuracies from the CAFs). Next, a grid was spanned for each model across 10 equally spaced values per model parameter domain. Because we expected fast RTs due to the high time pressure in our experiment, the parameter ranges were extended to the lower end, compared to Hübner and Pelzer (2020). Then, data were simulated for each grid point with 10,000 trials per condition. The grid was used to find optimal sets of starting values for 20 subsequent optimization processes using the SIMPLEX algorithm (Nelder & Mead, 1965), and for which also 10,000 trials were simulated per condition at each iteration. The two resulting best fitting parameter values were then used as starting values for two further SIMPLEX runs. Finally, the best fitting set of parameter values for each participant were taken as result.

The optimization processes minimized the sum of squared percentage errors (SPE) between observed and predicted summary values (Hübner & Pelzer, 2020):

$$SPE = \sum \left(\frac{o_i - s_i}{o_i} \right)^2,$$

where o_i is an observed value from the population sample, and s_i the corresponding value obtained by simulation. The goodness-of-fit criterion SPE was computed for each participant over all 30 data points.

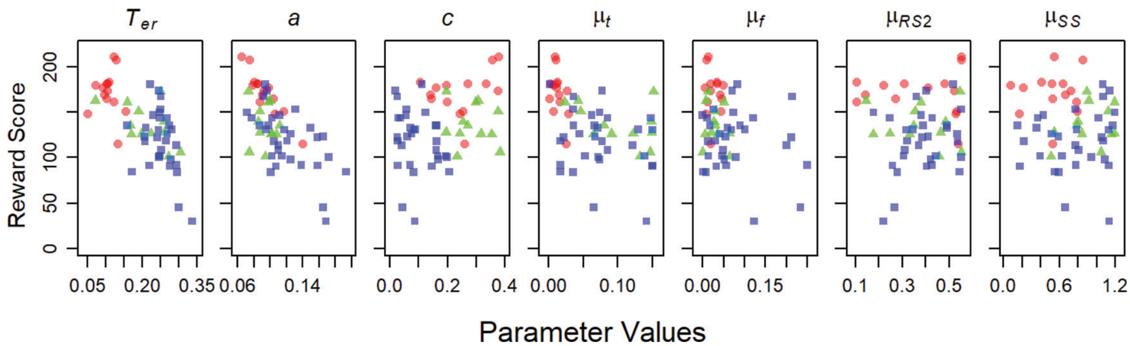
Results and Discussion

We first computed a one-way ANOVA across the modellable participants with framing as independent variable (gain and loss) and reward score as dependent variable. This revealed no significant difference, $F(1, 55) = 1.14$, $p = .29$, $\eta_p^2 = .02$. The same was the case for mean RT and accuracy as dependent variable, respectively. Therefore, the data from the two framing groups were collapsed for all subsequent analyses.

As we have seen in Figure 4, the performance and the corresponding gained points varied largely across participants in Condition 4. This suggests that they applied different SAT strategies. To examine the extent to which these strategies can be categorized, we conducted an Agglomerative Hierarchical Clustering (cf. Ketchen & Shook, 1996). It was based on the Euclidean distance in the hyperspace spanned by all model parameters and the reward score. The reward score was included to ensure that groups of participants, who obtained similar scores with a similar strategy, were identified. If only the parameter values had been clustered, then the clustering could also have been based on variance unrelated to the scores. It is important to note that our approach did not produce a bias, because clustering could still have failed. The number of clusters was determined by a combination of the Elbow and Average Silhouette Method (cf. Bholowalia & Kumar, 2014).

As a result, three clusters were identified. A graphical illustration of the relations between the reward scores and the parameter

Figure 6
Result of the Cluster Analysis for the Parameter Values of the DSTP-Model



Note. The red (black) circles, green (light gray) triangles, and blue (dark gray) squares indicate how the reward score (in thousand) and parameter values of the DSTP model are related for Group (cluster) 1, 2, and 3 of participants, respectively. DSTP = Dual-Stage Two-Phase. See the online article for the color version of this figure.

values for each cluster is shown in Figure 6. The average scores and parameter values for the corresponding groups are provided in Table 3, where group numbering reflects the order of the average reward score. For comparison, the table also provides the mean values of the unmodellable (UM) group.

We then computed posthoc contrasts between the performance measures and parameter values adjusted by a Monte-Carlo simulation of the multivariate *t*-distribution. The analyses revealed that Groups 1 and 2 differed significantly ($p < .05$) in score, accuracy, and RT. Moreover, they differed in the parameters T_{er}, μ_t, μ_{fl}, and μ_{SS}. The same differences were significant between Groups 1 and 3. Additionally, parameter *a* differed. Finally, Groups 2 and 3 differed significantly in RT and accuracy (but not in score), and in the parameters T_{er}, *a*, and *c*. These results indicate that the groups applied specific strategies.

For assessing the performance of each group and the corresponding model fit, CDFs and CAFs were computed by percentile averaging across group members. The results are shown in Figure 7. If we consider the CDFs of the different groups, it is obvious that Group 1 was the fastest. Because mean accuracy (64%) was close to chance level, this indicates that this group traded accuracy for speed to a high degree. That this was a successful strategy under the given payoff scheme can be seen by the fact that they collected the most points (see Table 3). When we consider the parameter values, then we see that the high speed was not only due to a very low response criterion, but also to a small T_{er}, compared to the other groups. The short nondecisional time indicates that little time was spent for perceptual encoding, which also explains the small rate μ_t, reflecting little evidence extracted from the target. Furthermore, members of Group 1 used little effort for early selection, as indicated by the fact that μ_{fl} was much larger than μ_t. However, the absolute values are rather small so that the resulting congruency effect should be negligible. Indeed, as can be seen in Figure 7, the effects are hardly visible, and, if at all, mainly present in accuracy (CAFs). Finally, late information selection was relatively slow (small μ_{SS}). Although, altogether, these parameter values indicate that information and response selection were largely reduced, these processes were by no means absent. As can also be seen by considering the CAFs, fast guessing played, if at all, only a minor role.

Group 2 was more cautious. Its members spent more time on stimulus encoding (larger T_{er}) than those in Group 1. Moreover, they had an efficient early selection, that is, the flankers had a much smaller impact (μ_{fl}) than the target (μ_t). Late selection was also relatively fast (larger μ_{SS}). Together, these parameter values produced a high level of accuracy (81%) at a respectable speed. Nevertheless, this strategy was less successful in collecting points than that of Group 1. Obviously, this group tried hard to respond quickly without sacrificing much accuracy.

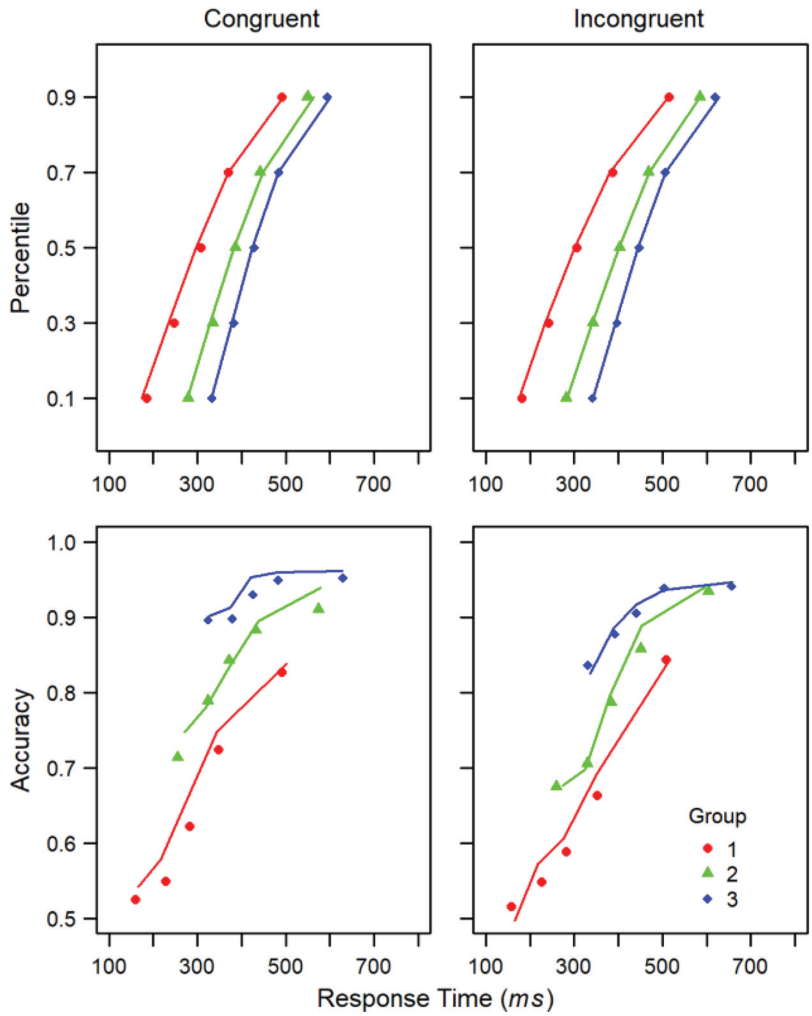
Table 3
Descriptive Statistics (Mean Values, Standard Deviations in Parentheses) for the Groups Resulting From the Cluster Analysis the Unmodellable (UM) Group Consists of Participants, Whose Data Could Not Satisfactorily Be Modeled

	Parameter										
Group (*N*)	T_{er}	*A*	*c*	μ_t	M_{fl}	μ_{RS2}	μ_{SS}	Reward score	SPE	RT (ms)	Accuracy
1 (14)	.105	.093	.243	.013	.024	.375	.527	172,003	.144	304	.641
	(.026)	(.019)	(.091)	(.009)	(.016)	(.177)	(.242)	(24,093)	(.078)	(53)	(.097)
2 (12)	.210	.093	.285	.100	.029	.373	.915	136,357	.059	399	.810
	(.064)	(.012)	(.065)	(.048)	(.022)	(.134)	(.236)	(22,161)	(.036)	(42)	(.060)
3 (31)	.250	.121	.095	.075	.078	.389	.766	118,427	.024	457	.912
	(.037)	(.031)	(.060)	(.046)	(.072)	(.104)	(.330)	(33,634)	(.026)	(76)	(.068)
UM (7)								142,965	.386	361	.731
								(47,283)	(.081)	(109)	(.156)

Note. SPE = sum of squared percentage errors; RT = response time; UM = unmodellable.

Figure 7

Visualization of the Performance and Goodness-of-Fit of the DSTP Model for the Three Groups Identified by the Cluster Analysis



Note. Top panel: Cumulative distribution functions (CDFs) of the response times. Bottom panel: conditional accuracy functions (CAFs). The points show the data, whereas the lines represent the model predictions. DSTP = Dual-Stage Two-Phase. See the online article for the color version of this figure.

Group 3, the largest group, was even more cautious. They used much time for stimulus encoding and had a relatively high response criterion (a). Early stimulus selection was moderate, while the criterion (c) for late stimulus selection was low. These parameter values produced a very high accuracy (91%) at the cost of speed. Consequently, this group collected the fewest points. It seems that its members had a large accuracy bias and, therefore, completely ignored the payoff scheme.

How the members in the different clusters are located in the speed–accuracy space is shown in Figure 8. As can be seen, the SATs of the members in Group 1 are located around the lower end of the SATF, whereas those of Group 3 cluster around the upper end. The SATs of the members in Group 2 are in between. The SATs representing the unmodellable participants are widely distributed along the SATF.

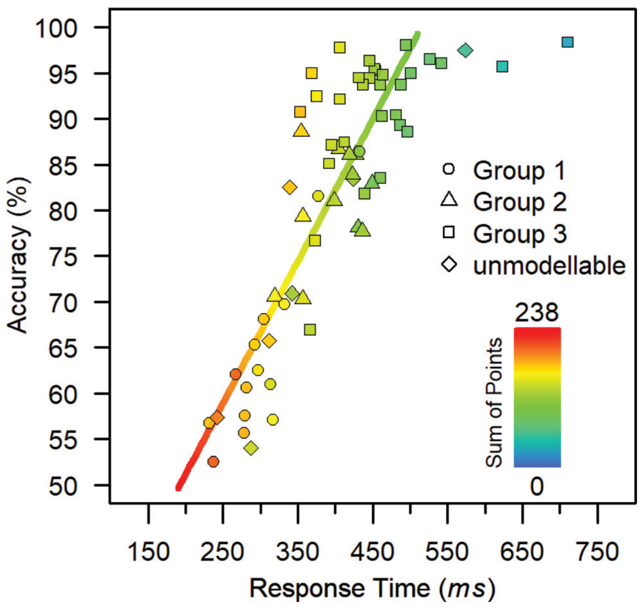
Taken together, the cluster analysis identified three groups of participants that are systematically ordered along the SATF. The modeling also shows that the different SATs were not obtained by merely adapting the response criterion accordingly. Rather, several mechanisms were adapted to speed up responding or to achieve a high accuracy. Although the different SATs represent individual performance, it is reasonable to assume that each participant would also have been able to realize different SATs.

General Discussion

The aim of the present study was to investigate the accuracy bias in decision making under time pressure. Responding quickly is usually only possible with reduced accuracy, that is, there is a SAT (for an overview see Heitz, 2014). Therefore, an important

Figure 8

Location of the Members in the Three Groups and of the Unmodellable Participants in Speed–Accuracy Space



Note. Data are from Condition 4. Sum of points in thousands. See text for details. See the online article for the color version of this figure.

question is, which SAT people apply under specific payoff conditions. One might think that they choose a SAT that optimizes their reward. However, evidence indicates that this is rarely the case. Rather, most people exhibit an accuracy bias (cf. Bogacz et al. 2006). That is, they try to avoid errors, even if this is disadvantageous for their reward. A possible reason for this bias is that errors have a negative connotation (Fiedler et al., 2020) and, therefore, elicit negative emotions (e.g., Dignath et al., 2020). Thus, it seems that, rather than optimizing reward, people try to optimize or, at least, maintain their wellbeing, that is, to gain some reward while limiting error-related negative emotions.

To investigate the role of errors and their costs for reward optimization under time pressure, we conducted a flanker-task experiment with different payoff and framing conditions. In all conditions, the reward for correct responses increased continuously with their speed in the range between 650 and 150 ms. While the scheme for correct responses was identical in our four payoff conditions, it differed for errors (see Figure 2). In Condition 1, errors could produce costs between 0 and 500 points, depending on their RT. In Condition 2, errors had no costs at all. In Condition 3, errors slower than 400 ms produced speed-dependent costs between 0 and 250 points, while faster errors between 150 and 400 ms resulted in gains between 0 and 250 points. Finally, in the most extreme Condition 4, errors slower than 400 ms produced speed-dependent costs from 0 to 500 points, while fast errors between 150 and 400 ms resulted in gains from 0 to 500 points. Thus, from Condition 1 to Condition 4, except Condition 2, it was increasingly advantageous to respond quickly. A further exception were responses faster than 150 ms, which resulted in zero points.

Each payoff condition applied to a corresponding group of participants. Furthermore, each group was separated into two subgroups, of which one was instructed according to a gain frame, whereas the other read a loss framed instruction (Tversky & Kahneman, 1981). The idea behind this manipulation was that the accuracy bias might be easier to overcome in a condition where even gains are framed as losses. However, the loss framing did not have the expected effect. There was merely the tendency of a larger congruency effect under a loss than under a gain framing, and a difficult to interpret three-way interaction with payoff and congruency.

Concerning the different payoff schemes, our results show that, on average, the different costs of errors had only a small effect on performance. From Condition 1 to Condition 4, response speed increased only by 31 ms, while accuracy decreased only by about 10%. Moreover, the congruency effect in the error rates was somewhat smaller in Condition 4 than in the other conditions. This, however, was presumably not due to an increased attentional selectivity (Hübner et al., 2010), but rather to a generally reduced time spent for stimulus encoding. Evidence for this interpretation is provided by our modeling results.

Thus, increasing the advantage of fast responses by reducing the costs of fast errors did, on average, not substantially speed up responding. Consequently, performance was largely suboptimal with respect to monetary reward. This confirms the notion that people have an accuracy bias, that is, are unwilling to make errors. However, analyzing the individual data revealed a considerable variability across participants (see Figure 4), especially in Condition 4, where not only fast correct responses but also fast errors produced large benefits. Under this payoff scheme, at least some participants overcame their bias and largely sacrificed accuracy for speed. At this point it should be noted that we cannot exclude that some of the slower participants did not fully comprehend the payoff scheme and its implications for optimizing reward. Furthermore, as one reviewer noted, some participants might have tried to avoid errors to prevent opportunity costs, which play some role in economic decision making (e.g., Hoskin, 1983). In the present case opportunity costs of errors are the loss of gains that could have been obtained in case of a correct response. Indeed, correct responses always produced more benefits than errors, even in Condition 4. Although we cannot exclude these alternative accounts, we think that they, if at all, did not substantially affect our data. Rather, our results are largely in line with an accuracy bias that has been shown to persist even if detailed feedback and hints are provided (e.g., Fiedler et al., 2020).

We used the large range of individual differences in Condition 4, which also encompassed the SATs observed in the other conditions, to estimate a representative SATF for our task. Usually, SATFs are estimated from SATs obtained by varying time pressure within participants (e.g., Dambacher & Hübner, 2015). In our case, each SAT was based on the performance of an individual participant. Nevertheless, we think that it is reasonable to assume that the fitted SATF represents the range of SATs potentially realizable by a participant with average performance capacity.

The fitted SATF enabled us to compute speed–accuracy reward functions for the different payoff schemes (see Figure 5). These functions show that for all conditions, except Condition 2, where errors had no costs, reward increased with an increasing response speed. Whereas the increase was relatively small in Condition 1, it was much larger in Condition 3, because of the reward for fast errors. However, this potential increase was obviously not large enough for motivating the participants to overcome their accuracy bias. Only in Condition 4, where fast errors were rewarded almost as much as fast correct responses, at least some participants substantially sacrificed accuracy for speed and optimized their reward this way.

The large range of performance in Condition 4 raised the question, how the different SATs were achieved. To find an answer, we modeled the corresponding data.

To examine the processes and mechanisms that our participants used to realize their SAT, we modeled the data from Condition 4, which produced the largest intraindividual differences in performance. Moreover, the range of performance also included that observed in the other conditions. Because we used the flanker paradigm as task, we considered current diffusion models for conflict tasks (Hübner et al., 2010; Ulrich et al., 2015; White et al., 2011) as potential models. For the present objective, that is, to identify groups of participants who applied a similar strategy, the DSTP model (Hübner et al., 2010) proved to be the most suitable. Accordingly, we used the parameter values obtained with this model for a cluster analysis, which identified three groups for 57 modellable participants.

Group 1 comprised 14 participants, who performed very fast but with a low accuracy. The corresponding mean parameters (see Table 3) indicate that the strategy was to spend little time and effort for stimulus encoding and early selection, and to implement a very low threshold. The reduced early selection did not produce large congruency effects, because the rate of evidence generally had little effect. However, as can be seen by considering the CAFs in Figure 7, a congruency effect was still present. In any case, applying this SAT strategy led to a relatively high reward.

Because in Condition 4 fast errors led to a similar reward as fast correct responses, fast guessing might also have been a good strategy. However, when we consider the CAFs for this condition (see Figure 7), then we see little evidence that a substantial number of participants mainly relied on fast guessing. One reason for avoiding fast guesses might have been that the participants were afraid to respond faster than 150 ms, the lower limit of the payoff scheme, although we suspect that such thoughts probably occurred rather rarely, if at all. It is also unlikely, that a high proportion of fast guesses was responsible for the fact that the data of the excluded participants could not be modeled. Obviously, the accuracy of these participants was higher than that of Group 1.

Group 2 (12 participants) put much effort in responding quickly while maintaining a relatively high level of accuracy. Finally, the members of Group 3 (31 participants) responded relatively slowly, presumably, to attain high accuracy. It seems that they largely ignored the payoff scheme or were unwilling to tolerate errors. Thus, our modeling revealed that of the 57 modellable participants in Condition 4, only the 14 in Group 1 seriously tried to optimize their monetary reward.

Taken together, our results support the notion that the performance of people is largely guided by an accuracy bias. Although the observed SATs varied to some extent in all of our four payoff conditions, only in the most extreme condition, where fast errors resulted in large reward, a minority of participants were willing to substantially sacrifice accuracy for speed in order to optimize their reward. This clear evidence of an accuracy bias was presumably due to our continuous payoff scheme. For the mostly applied payoff schemes with a fixed deadline, reward is usually all or nothing, which makes timeout errors rather salient and unpleasant. The only way to avoid timeout errors is to speed up responding, which, however, increases the risk of response errors. Thus, participants trade one error type for another one (Dambacher et al., 2011). This suggests that a payoff scheme with a short deadline and costly timeout errors are a better way to get people to overcome their accuracy bias than a continuous payoff scheme or loss framing. However, if one wants to investigate the accuracy bias, a scheme with a continuous reward function is more appropriate.

Our modeling revealed that the extreme SATs in Condition 4 were not achieved by merely lowering the response threshold, but also by other mechanisms, such as reducing the time spent on stimulus encoding, which, in turn, also affects the rate of evidence accumulation (see also Dambacher & Hübner, 2015; Ho et al., 2012). However, despite the high-speed pressure, we found little evidence for fast guessing. Accordingly, the DSTP model (Hübner et al., 2010) was flexible enough to account for most of the data, even for those close to guessing.

The modeling further provides insights into how our participants realized their SAT and produced the great variability in performance. Although some of this variability was certainly due to individual differences in information-processing capacity, most of the variability resulted from the application of different strategies. However, as our study also shows, the participants hardly used strategies that enabled them to earn as much money as possible. In most conditions, this would have required to respond very quickly and, accordingly, to accept many errors. That errors were largely avoided in our experiment, although this lowered the reward, supports the hypotheses that people have an accuracy bias. A plausible reason for this bias is the negative connotation of errors (Fiedler et al., 2020), which evokes negative emotions after each response error (Johnson et al., 2017). Accordingly, it seems that the strategy of most participants was to optimize their well-being during the experiment rather than their monetary reward.

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