

Time pressure affects the efficiency of perceptual processing in decisions under conflict

Michael Dambacher · Ronald Hübner

Abstract The negative correlation between speed and accuracy in perceptual decision making is often explained as a tradeoff, where lowered decision boundaries under time pressure result in faster but more error-prone responses. Corresponding implementations in sequential sampling models confirmed the success of this account, which has led to the prevalent assumption that a second component of decision making, the efficiency of perceptual processing, is largely independent from temporal demands. To test the generality of this claim, we examined time pressure effects on decisions under conflict. Data from a flanker task were fit with a sequential sampling model that incorporates two successive phases of response selection, driven by the output of an early and late stage of stimulus selection, respectively. The fits revealed the canonical decrease of response boundaries with increasing time pressure. In addition, time pressure reduced the duration of non-decisional processes and impaired the early stage of stimulus selection, together with the subsequent first phase of response selection. The results show that the relation between speed and accuracy not only relies on the strategic adjustment of response boundaries but involves variations of processing efficiency. The findings support recent evidence of drift rate modulations in response to time pressure in simple perceptual decisions and confirm their validity in the context of more complex tasks.

Introduction

A fundamental characteristic of human decision making is that its speed can be deliberately increased, but usually at the cost of precision. The generality of this relation – a joint increase of response times and accuracy – has been demonstrated across various domains, such as perceptual decisions (Miller, Sproesser, & Ulrich, 2008; Palmer, Huk, & Shadlen, 2005), visual search (Carrasco & McElree, 2001; McElree & Carrasco, 1999), memory retrieval (Doshier, 1976; Reed, 1973), or motor planning (Fitts, 1954; Harris & Wolpert, 1998). Accordingly, research on corresponding speed accuracy functions (SAFs) has greatly contributed to our understanding of mental information processing and decision making (Garrett, 1922; Wickelgren, 1977). A particularly relevant finding is that speed can be traded for accuracy simply by changing the decision criterion.

This speed accuracy tradeoff can be straightforwardly implemented in sequential sampling models, which not only account for performance in a wide range of perceptual tasks (Brown & Heathcote, 2005; Ratcliff & McKoon, 2008) but can also be plausibly linked to neurophysiological correlates of decision making (Bogacz, Wagenmakers, Forstmann, & Nieuwenhuis, 2010; Forstmann et al., 2008, 2010, 2011; Ho et al., 2012; Ivanoff, Branning, & Marois, 2008; Philiastides, Ratcliff, & Sajda, 2006; van Veen, Krug, & Carter, 2008). In general, decision making in sequential sampling models is based on the accumulation of evidence over time until a boundary (or criterion) is reached and an associated response is initiated (Brown & Heathcote, 2005, 2008; Busemeyer & Townsend, 1993; Diederich & Busemeyer, 2006; Hübner, Steinhauser, & Lehle, 2010; Ratcliff & Smith, 2004; Ratcliff, 1978; Usher & McClelland, 2001; White, Ratcliff, & Starns, 2011). The

M. Dambacher (✉) · R. Hübner
Department of Psychology (Box D29), Universität Konstanz,
Universitätsstr. 10, 78464 Constance, Germany
e mail: michael.dambacher@uni-konstanz.de

negative relation between decision speed and accuracy results from the lowering of decision boundaries when time pressure increases. Under high speed stress relatively little evidence suffices to cross a boundary, so that decision time is reduced. At the same time, though, the error rate increases because the wrong boundary is reached more frequently due to the generally noisy samples of evidence. Thus, adjusting the decision boundaries can increase speed at the cost of reduced accuracy, and vice versa. In fact, this mechanism has often been sufficient to simulate empirical SAFs, while other model components, such as the rate of evidence accumulation, were kept constant. This has led to the prevalent assumption that the joint increase of error rates and response speed in decision making only reflects a strategic tradeoff, whereas the efficiency of perceptual processing is unaffected by temporal demands (e.g., Ratcliff & McKoon, 2008; Ratcliff, Thapar, & McKoon, 2003).

Recent reports, however, suggest that the tradeoff account does not generally hold but that time pressure also affects the efficiency of evidence accumulation (cf., Heathcote & Love, 2012; Heitz & Schall, 2012; Starns, Ratcliff, & McKoon, 2012; Vandekerckhove, Tuerlinckx, & Lee, 2008). Indeed, a recent modeling study on several data sets revealed that an emphasis of speed over accuracy not only lowers response criteria but also comes with a reduction in the quality of perceptual processing (Rae, Heathcote, Donkin, Averell, & Brown, 2014). Further, an fMRI study indicated that the rate of evidence accumulation in an orientation discrimination task increased when the instruction emphasized accuracy and, therefore, reduced time pressure. The sensory processing rate under accuracy stress could be even linked to the optimality of orientation-selective activation patterns in V1 (Ho et al., 2012).

Evidence independent from model assumptions also indicates that speeding up responses does not necessarily come with a tradeoff in accuracy. Motivating factors, such as the prospect of incentives, can mobilize additional resources (e.g., effort) that speed up responding without a drop in performance. For instance, in a simple letter categorization task, response times were shorter on trials that held out a bonus for fast and correct responses, while error rates did not change. This effect was already present in the fastest responses, pointing to an overall increase of processing efficiency (Kleinsorge, 2001). Similarly, shifts of entire SAFs towards better performance in response to monetary (compared to symbolic) incentives demonstrated that it is possible to speed up responding without costs in accuracy (Dambacher, Hübner, & Schlösser, 2011; Dambacher & Hübner, 2013). The consideration of model-based theoretical SAFs suggests that this speed-up is indeed driven by an improved quality of perceptual

processing rather than a change of non-decisional operations, such as the acceleration of motor execution (Hübner & Schlösser, 2010).

Yet, there is also evidence that speed pressure affects late motoric stages of the decision process. In several studies on lateralized readiness potentials (LRPs), the time from LRP onset to response execution (LRP-RT interval) was shorter under high than under low time pressure (Osman et al., 2000; Rinkenauer, Osman, Ulrich, Müller-Gethmann, & Mattes, 2004; van der Lubbe, Jaśkowski, Wauschkuhn, & Verleger, 2001). Since LRP-RT intervals are largely associated with operations following the selection of a particular response, these results indicate that also post-decisional processes, such as motor commands, are sensitive to temporal demands and hence contribute to the shape of SAFs. In contrast, sequential sampling accounts often do not pose time pressure effects on non-decisional components (e.g., Ratcliff & McKoon, 2008; Ratcliff, Thapar, & McKoon, 2003).

In sum, there is reason to believe that time pressure effects on response speed and accuracy do not generally result from shifts of decision boundaries alone but may involve changes in the efficiency of perceptual processing as well as in non-decisional operations. So far, however, model-based evidence comes mainly from studies on simple perceptual decisions (Ho et al., 2012; Rae et al., 2014). More complex tasks involving, for instance, response conflicts (e.g., Eriksen & Eriksen, 1974; Simon, 1990; Stroop, 1935) were hardly considered because the applicability of standard sequential models to such data is limited (Hübner et al., 2010; White et al., 2011). Thus, although there is ample evidence that also higher perceptual decisions follow the typical function of speed and accuracy, the exact underlying mechanisms are insufficiently understood. Conceptually, it appears possible that enhanced task complexity results in an augmented involvement of response strategies. Accordingly, corresponding SAFs may be largely based on strategic shifts of response criteria, compatible with the classic assumption of the speed accuracy tradeoff. In fact, results from recent simulations of data from a flanker task support this view (White et al., 2011). Yet, it is also possible that time pressure in complex decisions affects other processes, such as the efficiency of perceptual processing. In line with recent reports from simple tasks (e.g., Ho et al., 2012; Rae et al., 2014), one may then expect a modulation of drift rates as a function of time pressure. Likewise, also non-decisional operations may play a role for the shape of SAFs.

Fortunately, recent developments brought forth computational models that are able to delineate the processes of complex perceptual decisions (Hübner et al., 2010; White et al., 2011). While these accounts make some additional

assumptions relative to simple decisions, models from the sequential sampling family generally permit comparable conclusions since they share basic components and mechanisms. The present study, therefore, aimed at broadening the current perspective on the relation of speed and accuracy and examined the nature of SAFs in more complex decisions.

We used a flanker task (Eriksen & Eriksen, 1974), which is susceptible to speed and accuracy demands as are simple perceptual decisions: response times as well as accuracies decrease with increasing time pressure. Compared to simple decisions, though, the flanker task involves the resolution of response conflicts, providing additional potential targets for time pressure effects. In particular, participants have to categorize a central target stimulus in the presence of task-irrelevant flankers. These flankers modulate the overall item difficulty as they can be incongruent (i.e., response incompatible) or congruent (i.e., response compatible). A standard finding is a robust congruency or flanker effect, i.e., slower and more error-prone responses for incongruent than for congruent stimuli. The flanker effect often shows a characteristic course over SAFs: under high time pressure, reduced performance for incongruent compared to congruent (or neutral) stimuli is predominantly expressed in accuracy differences, which successively turn into response time effects as time pressure is relaxed (Dambacher & Hübner, 2013). The source of the

flanker effect lies in the co-processing of irrelevant flankers that together with the target fall into the initial spatial focus of attention. Co-processing of congruent flankers increases evidence in favor of the correct response, whereas co-processing of incongruent flankers produces evidence for the incorrect response. Importantly, the presence of incongruent flankers requires advanced mechanisms of selective attention. Conditional accuracy functions (CAFs), that are also considered in the present study (see below), demonstrate that accuracy for incongruent stimuli improves with response time. It is, therefore, possible that stimulus selectivity (i.e., the ability to restrict perceptual processing to the response-relevant item) is relatively low after stimulus onset, but advances with processing duration (cf., Gratton, Coles, & Donchin, 1992). The first sequential sampling model that was able to account for this increase in accuracy is the dual-stage two-phase (DSTP) model (Hübner et al., 2010).

Comparable to other sequential sampling models for binary choices, the DSTP model implements response selection as a diffusion process, which accumulates evidence until one of two response boundaries are reached (see Fig. 1). The first phase of response selection is based on sensory information from an early stimulus selection stage (e.g., sensory filtering) that provides initial perceptual evidence as input for the diffusion process. Because the quality of early stimulus selection is often relatively poor, a

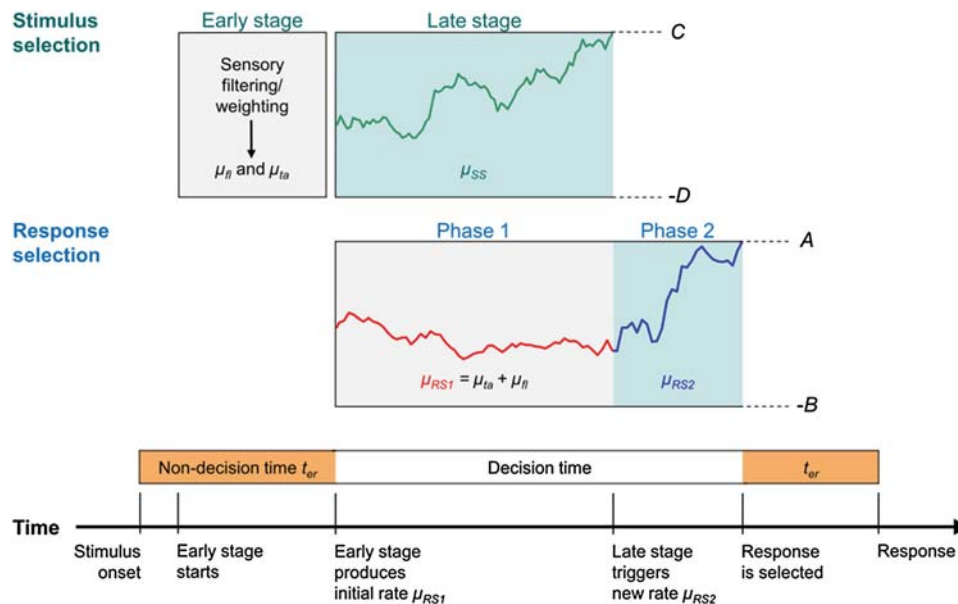


Fig. 1 The dual stage two phase (DSTP) model. An early stage of stimulus selection (i.e., sensory filtering/weighting) provides parameters for target (μ_{ta}) and flanker (μ_n) processing. They sum up to the drift rate μ_{RS1} in Phase 1 of response selection. In parallel, a late stage of stimulus selection (SS) runs with rate μ_{SS} until it reaches one of two boundaries C and D that reflect the selection of either the target or a flanker for selective processing. On completion of the late stimulus

selection SS, response selection enters Phase 2, which is characterized by a transition of the drift rate from μ_{RS1} to μ_{RS2} . A decision is completed as soon as the response selection process (either during Phase 1 or Phase 2) hits one of two response boundaries A and B reflecting the choice alternatives. The duration of the non decision time (e.g., sensory encoding and filtering, motor commands) is captured in parameter t_{er} .

late stimulus selection stage also implemented as diffusion process runs in parallel with response selection and has the function to categorize the response-relevant stimulus component, i.e., the central target among the irrelevant flankers. Once the late stimulus selection process has finished, and given that no response has been selected yet, response selection enters the second phase, in which only the selected stimulus component (either the target or a flanker) drives response selection. As a consequence, response selection changes its processing rate: if the late stage of stimulus selection has chosen the target, the rate of evidence in favor of the correct response increases relative to Phase 1. This efficiency enhancement of response selection in Phase 2 usually occurs on a substantial proportion of trials and explains why accuracy is higher for slow than for fast responses. Finally, pre- and post-decisional processes like stimulus encoding and response execution, respectively, are jointly captured as non-decisional component. A more formal description of the DSTP parameters is given below (see also Hübner et al., 2010).

Present study

We used the DSTP model to identify processes that modulate response speed as a function of time pressure in the flanker task. Participants had to indicate the parity of a central target digit before a given deadline (450, 550, or 650 ms) exceeded. In line with previous studies on simple perceptual decisions, we expected a decrease of response selection criteria with increasing time pressure. Further, and more critically, a modulation of drift rates would indicate that time pressure also affects evidence accumulation (Heitz & Schall, 2012; Ho et al., 2012; Rae et al., 2014). Specifically, it is conceivable that the quality of sensory filtering (i.e., early stage of stimulus selection, captured as non-decision parameter in the DSTP model) suffers from high time pressure. A short deadline may, therefore, result in reduced non-decision time as well as in a lower drift rate in the first phase of response selection. In addition, impaired early stimulus selection may also translate in a reduced rate of the late stage of stimulus selection (cf. Fig. 1).

Methods

Participants

Data were recorded from 16 students (13 female; mean age: 21.6 years, SD: 3.6 years) at the Universität Konstanz. All had normal or corrected-to-normal vision. The experiment was performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki

and its later amendments. In agreement with the ethics and safety guidelines at the Universität Konstanz, we obtained a verbal informed consent statement from all individuals prior to their participation in the study. Potential participants were informed of their right to abstain from participation in the study or to withdraw consent to participate at any time without reprisal.

Stimuli

Numerals from 2 to 9 served as target items in a parity-judgment task. On either horizontal side of the target, two flankers, that were identical to each other, set up stimulus congruency. For incongruent stimuli, flankers consisted of response-incompatible numerals, i.e., flankers and targets differed in parity. Congruent stimuli were composed of a target and flankers of the same parity. The target was always presented at screen center. Each character extended a visual angle of approximately 0.9° horizontally and 1.27° vertically and the spacing between characters (center to center) was 1.27° of visual angle. Stimuli were congruent on half of the trials and incongruent on the other half. They were presented in white on a black background on a 19" color monitor with a resolution of $1,280 \times 1,024$ pixels and a refresh rate of 60 Hz. A USB computer mouse registered the responses.

Procedure

Participants were seated at a distance of approximately 50 cm from the monitor and received written instruction. Prior to each block of trials, one of three deadlines (i.e., 450, 550, and 650 ms) indicated the level of time pressure in the block. Every trial started with a central fixation cross (400 ms plus 600 ms blank), followed by a stimulus array for 165 ms and a blank screen until participants' response. The task was to signal the parity of the target numeral by pressing the corresponding mouse button with the index or middle finger of the right hand prior to deadline expiration. After each trial, feedback signaled whether the response was correct ("Korrekt", green color), incorrect ("Fehler!", red color), too slow ("Schneller antworten!", red color), or too fast, i.e., before stimulus onset ("Zu früh!", red color). At the end of a block, participants indicated the level of effort they sensed during the block on a five-point scale (not reported here). Then, they had the opportunity to take a short break while the mean response time and the proportion of errors of the previous block were presented together with the balance of earned points (see below). The experiment comprised three practice blocks and twelve main blocks of 64 trials, and it took approximately 1 h.

Performance-contingent payment

Participants received a base payment of 6 EUR and, depending on their performance, earned an additional amount of up to 8 EUR. For performance-contingent payment, each trial was rewarded with 10 points for a correct response before the deadline, while errors, too fast, or too slow responses were not incentivized. In addition, participants received a bonus of 500 points after each block if they reached a pre-specified accuracy level (i.e., 70, 80, and 90 % for the deadlines of 450, 550, and 650 ms, respectively). Points were converted into money after the experiment. Written instructions explained that accuracy, and hence the overall profit, increases with the time spent for stimulus processing. Participants were, therefore, advised to exploit the available interval for accurate decisions, but at the same time to put effort in meeting time demands.

Behavioral results and discussion

Responses faster than 100 ms or slower than 1,200 ms were excluded from data analysis (<0.5 % of all data). SAFs are shown in Fig. 2.

Mean response times and error rates

Latencies of correct responses were analyzed in a two-way repeated measures ANOVA on the factors deadline (450,

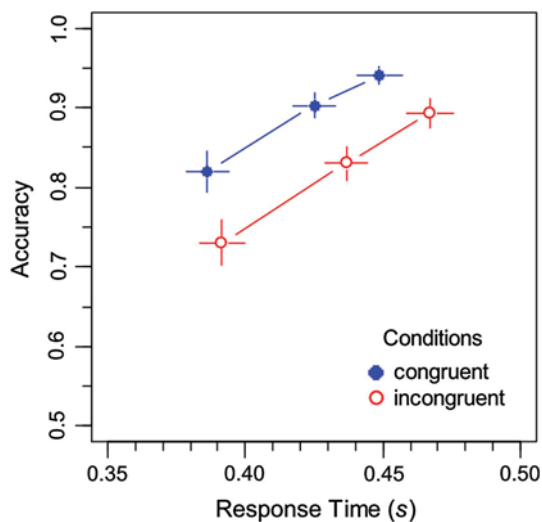


Fig. 2 Speed accuracy function (SAF) for congruent (filled symbols) and incongruent (open symbols) stimuli. The three data points in each congruency condition reflect mean response times and accuracies that gradually increase with the three deadlines of 450, 550, and 650 ms, respectively

550, 650), and congruency (congruent, incongruent). The results revealed significant main effects of deadline, $F(2, 30) = 48.1$, $p < 0.001$, $\eta_p^2 = 0.762$, and congruency, $F(1, 15) = 36.4$, $p < 0.001$, $\eta_p^2 = 0.708$. Response times decreased with shorter deadlines (458, 431, 389 ms), and they were faster for congruent than for incongruent stimuli (420 vs. 432 ms). In addition, the interaction between the two factors, $F(2, 30) = 5.30$, $p < 0.01$, $\eta_p^2 = 0.272$, indicated that the congruency effect in response times increased with deadline.

An analogous ANOVA on accuracies revealed significant main effects of deadline, $F(2, 30) = 44.0$, $p < 0.001$, $\eta_p^2 = 0.746$, and congruency, $F(1, 15) = 80.0$, $p < 0.001$, $\eta_p^2 = 0.842$. Error rates increased with decreasing deadlines (8.28, 13.4, 22.5 %), and they were lower for congruent than for incongruent stimuli (11.2 vs. 18.2 %). Further, the interaction of deadline x congruency, $F(2, 30) = 4.60$, $p < 0.05$, $\eta_p^2 = 0.235$, attested that the congruency effect in error rates decreased with increasing deadline.

In summary, the data showed the expected SAF, i.e., a drop in accuracy as response speed increased with time pressure. Further, the results confirmed the common pattern of a progressive shift of the congruency effect from accuracies to response times as responses became slower (see also Fig. 2) (cf., Dambacher & Hübner, 2013).

Distributional data

Cumulative distribution functions (CDFs) for correct responses were computed from quantile-based (0.1, 0.3, 0.5, 0.7, and 0.9) averages of response times. That is, correct responses from each participant, congruency condition (congruent, incongruent), and deadline (450, 550, 650 ms) were sorted into six bins comprising 10, 20, 20, 20, 20, and 10 % of the data, respectively (Ratcliff & McKoon, 2008; Ratcliff, 1979). The resulting empirical CDFs are represented as points in Fig. 3. Except for the first quantile under the shortest deadline, they consistently show a right shift of the response time distribution for incongruent compared to congruent items.

Because several participants made fewer than five errors in at least one condition, analogous CDFs for error response times could not be computed. Instead of excluding these data sets, we considered error data by means of CAFs that can be calculated even for conditions with few or no errors. We, therefore, were able to take into account data from all participants for the model fits (see below). Beyond that, CAFs are more informative for our objective than error CDFs because they directly reflect the increase of accuracy (and hence selectivity) with response time (cf., Gratton et al., 1992). We calculated CAFs as mean response time and proportion of correct answers in

Fig. 3 Cumulative density functions (*CDFs*). Panels illustrate correct empirical responses (*symbols*) and model fits (*lines*) for congruent (*filled, solid*) and incongruent (*open, dashed*) stimuli across three deadlines of 450, 550, and 650 ms

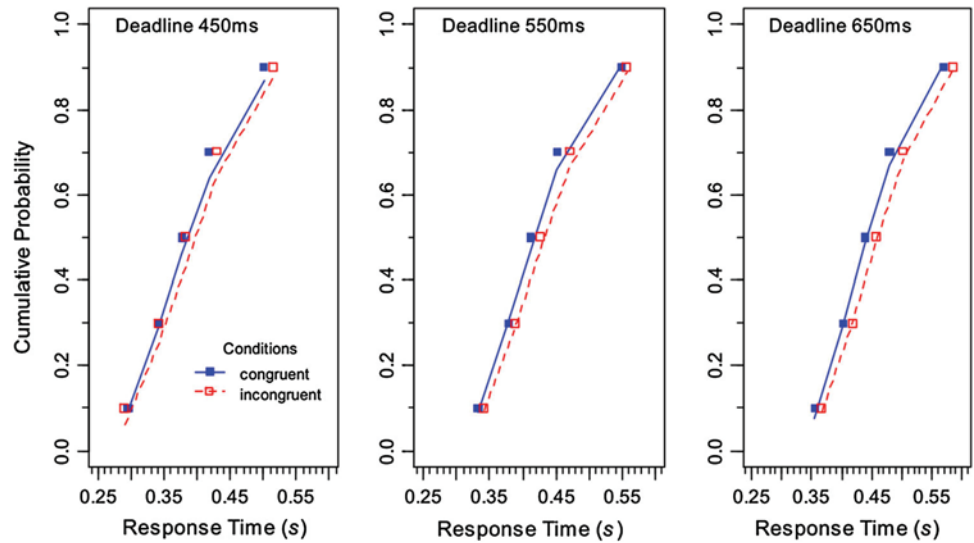
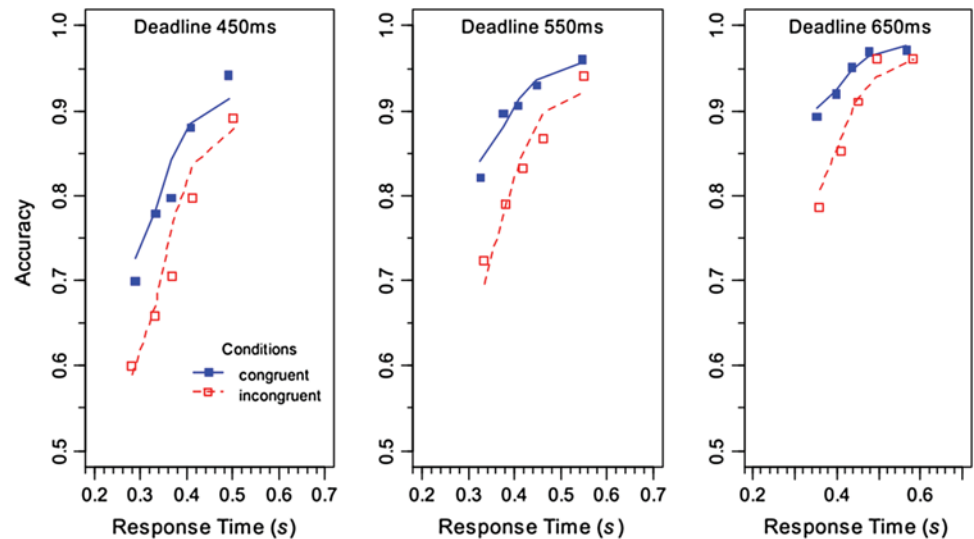


Fig. 4 Conditional accuracy functions (*CAFs*). Panels illustrate empirical quantile means of the response time distributions (*symbols*) and model fits (*lines*) for congruent (*filled, solid*) and incongruent (*open, dashed*) stimuli across three deadlines of 450, 550, and 650 ms



each of five 20 % bins of the entire response time distribution (correct and error responses) from each participant, congruency condition, and deadline. Empirical CAFs are shown as points in Fig. 4. The figure illustrates characteristic courses of the functions across all deadlines. The overall level of accuracies gradually increases as deadlines become longer (cf., also Fig. 2). Further, within each deadline, accuracies are low for the fastest responses and approach an asymptote as responses become slower. The fastest responses show a large congruency effect in accuracy that diminishes with increasing response times. This attenuation of the flanker effect is in accordance with the view that stimulus selectivity improved over time. Besides these visual similarities of the overall pattern the model fits revealed also differences between the deadline conditions.

Modeling

The DSTP (Hübner et al., 2010) model was used to fit the empirical data. As briefly outlined in the introduction, the core of the model is response selection, which is divided into a first and a second phase (Phase 1 and Phase 2), each represented by a diffusion process (Ratcliff, 1978; Voss, Nagler, & Lerche, 2013), RS1 and RS2, respectively (see Fig. 1). Basically, a diffusion process is characterized by a drift rate parameter reflecting the evidence available for responses A and B, and by two corresponding boundary parameters A and $-B$. Noisy samples of evidence are accumulated over time, beginning at state X_0 until boundary A or $-B$ is reached, which then triggers the corresponding response. Here, we assume that $X_0 = 0$, and that A and B represent the correct and incorrect button press, respectively.

In the first phase of response selection, perceptual evidence (for RS1) is provided by an early stage of stimulus selection, which filters the sensory input and weights task-relevant stimulus components (Hübner et al., 2010; Logan & Gordon, 2001). For instance, in our flanker task, the central stimulus component was always the target. The attentional weights for the central position are, therefore, higher than those for the other locations. This translates into distinct component rates μ_{ta} and μ_{fl} for the relevant and irrelevant stimulus components, respectively, which result from the product of bottom-up sensory input and attentional weights. The parameter μ_{ta} represents the rate of evidence provided by the target in favor of the correct response, whereas μ_{fl} stands for the evidence contributed by information from the flankers. Both rates sum up to the total rate μ_{RS1} for Phase 1 of response selection (process RS1), i.e., $\mu_{RS1} = \mu_{ta} + \mu_{fl}$. The value of μ_{fl} is positive if the stimulus is congruent, and negative if it is incongruent. Thus, the overall rate for RS1 is reduced for incongruent compared to congruent stimuli, and can even be negative.

If response selection relied on process RS1 alone there would be no qualitative improvement over time, and accuracy for incongruent stimuli would remain at a relatively low level. It has been shown that such a mechanism is too simple and insufficient to account for distributional data in the flanker task (Hübner et al., 2010). Instead, a more sophisticated stimulus selection process SS, also implemented as diffusion process in the DSTP model, is assumed to run in parallel with RS1. When this stimulus selection with rate μ_{SS} hits one of its boundaries C or $-D$, the target C or a flanker D , respectively, is selected for further processing, whereas unselected stimulus components are henceforth ignored. From that point onwards, response selection enters Phase 2 and continues as process RS2 (see Fig. 1). There are two possible scenarios for Phase 2 in the flanker task: the first is that the target was selected by SS. In that case, the rate μ_{RS2} is usually higher than μ_{RS1} in Phase 1, especially for incongruent stimuli. As a second scenario, the flanker was selected by SS. If the flanker is incongruent to the target, μ_{RS2} is negative and leads with high probability to an error. For congruent stimuli, the selection of a flanker results in a positive μ_{RS2} . Of course, response selection can also complete in Phase 1, i.e., when RS1 hits one of its boundaries earlier than process SS finishes. In this case, the selected response is initiated without entering Phase 2.

Finally, while Phases 1 and 2 of response selection reflect the duration of the central decision process, non-decisional operations are represented by parameter t_{er} . This parameter captures the duration of pre-decisional processes, such as stimulus encoding or sensory filtering (i.e., the early stage of stimulus selection), as well as of post-

decisional processes, such as motor planning or response execution.

Fit procedure

A computer version of the DSTP model was fit to the distributional data (cf., Hübner et al., 2010). Specifically, the PRAXIS algorithm (Brent, 1973; Gegenfurtner, 1992) was applied to find parameter values that minimized the G^2 statistics (Wilks likelihood ratio Chi square; cf., Ratcliff & Smith, 2004):

$$G^2 = 2 \sum_{i=1}^J N p_i \ln \left(\frac{p_i}{\pi_i} \right),$$

where N is the number of observations, J is the number of bins, p_i is the proportion of observations in the i th bin, and π_i is the proportion in this bin predicted by the model. For N , we used the average number of valid trials per person in the corresponding fit condition. This was uncritical, because G^2 was inappropriate for significance testing and merely served as goodness-of-fit measure (cf., Ratcliff & Smith, 2004).

The DSTP model was fit to the proportions of correct responses in the CDF bins, and to the error proportions in the CAF bins. Because the congruent and incongruent conditions were fit simultaneously for each deadline, we had $J = 22$ for each fit (6 bins for correct responses in the congruent condition, 5 bins for errors in the congruent condition, 6 bins for correct responses in the incongruent condition, and 5 bins for errors in the incongruent conditions). The degrees of freedom (df) of the goodness-of-fit statistics were computed as

$$df = (J_c - 1) + (J_i - 1) - M,$$

with J_c and J_i reflecting the number of bins for the congruent and incongruent conditions, respectively, and M representing the number of model parameters.

The following assumptions were made to restrict the number of parameters in the model. First, we assumed symmetric boundaries for both response and stimulus selection. Second, the value of parameter μ_{RS2} , reflecting the rate of response selection in Phase 2 after stimulus selection, has the same magnitude irrespective of whether the target or a flanker was selected. However, if a flanker was selected, its sign depends on stimulus congruency: the rate is μ_{RS2} for congruent, but $-\mu_{RS2}$ for incongruent stimuli.

The resulting DSTP model has seven parameters: boundaries $A = B$ for response selection; component rates for target and flanker, μ_{ta} and μ_{fl} ; rate μ_{RS2} for response selection in Phase 2; rate μ_{SS} for late stimulus selection; boundaries $C = D$ for late stimulus selection; and finally, a

Table 1 Parameter estimates from DSTP model fits to distributional data of the three deadlines (DL of 450, 550, and 650 ms)

Parameters									
DL	μ_{ta}	μ_{fl}	A/B	μ_{SS}	C/D	μ_{RS2}	t_{er}	G^2	df
450	0.0672	0.0311	0.0459	0.3523	0.0768	0.0982	0.2360	0.3128	13
550	0.1194	0.0438	0.0481	0.3846	0.0770	0.0933	0.2740	1.6806	13
650	0.1683	0.0386	0.0510	0.4211	0.0813	0.0891	0.2989	2.1891	13

Drift rates reflect the increase of accumulated evidence per second

μ_{ta} drift rates for the target in Phase 1, μ_{fl} drift rates for flankers in Phase 1, A/B response selection boundaries, μ_{SS} drift rates for the late stage of stimulus selection, C/D boundaries for the late stage of stimulus selection, μ_{RS2} drift rates for response selection in Phase 2, t_{er} mean non decision time (in seconds), G^2 Wilks likelihood ratio Chi square, df degrees of freedom

non-decision parameter t_{er} . Accordingly, for this model $df = (11-1) + (11-1) - 7 = 13$.

Because the signal-to-noise ratio in single participants is very low, fitting the model to individual data is rather difficult. We, therefore, performed global fits to quantile averages across all participants. Using different sets of parameter start values to avoid local minima, every fit ran until G^2 was minimized. Each of the required several hundred cycles comprised the simulation of 8×10^5 trials.

To estimate the variability of these global parameters, we applied a jackknife procedure (e.g., Gray & Schucany, 1972; Jackson, 1986; Mosteller & Tukey, 1977), where a set of parameter values P_i is computed for each participant i ($i = 1 \dots n$) by temporarily omitting participant i and fitting the model to the quantile-averaged data from the remaining $n-1$ participants; the global parameters thereby served as start values for the individual jackknife fits. Hence, we obtained one parameter set for each participant, providing a basis for statistical tests of time pressure effects.

Specifically, the jackknifed values were used to compute standard errors for parameter difference scores between the longest (650 ms) and the shortest deadline (450 ms) (Abdi & Williams, 2010). The corresponding confidence intervals (CIs) provided a test criterion for time pressure effects in the global parameters. That is, if increasing time pressure from the long to the short deadline reliably affected a particular model parameter, the associated difference score between the long and short deadline would lie outside the confidence band (95 % CI as one-sided test, 97.5 % CI as two-sided test).

For comparison, we also submitted the jackknifed parameters to ANOVAs on the within-subject factor deadline including all three levels of time pressure (450, 550, 650 ms); the artificially large F values due to the reduction of error variance of the jackknifing procedure were corrected as $F_c = F/(n-1)^2$. To our knowledge, the validity of ANOVAs on jackknifed data has yet only been confirmed in the context of onset latencies of LRPs (Ulrich & Miller, 2001). It was, therefore, interesting to test

Table 2 Jackknife and ANOVA results

	$\Delta_{DL650 DL450}$	$CI_{0.95}$	$CI_{0.975}$	$ \Delta_{DL650 DL450} > CI$	p_{ANOVA}
μ_{ta}	0.1011	0 ± 0.0263	0 ± 0.0320	**	<0.001
μ_{fl}	0.0075	0 ± 0.0184	0 ± 0.0224		0.399
A/B	0.0051	0 ± 0.0046	0 ± 0.0056	*	0.011
μ_{SS}	0.0688	0 ± 0.0213	0 ± 0.0259	**	<0.001
C/D	0.0045	0 ± 0.0100	0 ± 0.0121		0.528
μ_{RS2}	0.0091	0 ± 0.0183	0 ± 0.0222		0.500
t_{er}	0.0629	0 ± 0.0187	0 ± 0.0228	**	<0.001

$\Delta_{DL650 DL450}$ difference scores between global DSTP parameters of the longest (650 ms) and the shortest (450 ms) deadline (cf. Table 1), $CI_{0.95}$ and $CI_{0.975}$ jackknife based 95 and 97.5 % confidence intervals of the DSTP difference scores, respectively, $|\Delta_{DL650 DL450}| > CI$ DSTP difference score is outside the 95 % (*, one sided test) or the 97.5 % (**, two sided test) confidence interval, p_{ANOVA} corrected p values of one way repeated measures ANOVAs on jackknife based parameters for the three deadlines (450, 550, 650 ms)

whether its application to model parameters produces similar results as the jackknife-based CIs.

Fit results and discussion

Figures 3 and 4 illustrate that the DSTP model (lines) fit the data (symbols) rather well. Table 1 shows the DSTP parameters from fits to averaged data from all participants. Table 2 lists the parameter difference scores together with the jackknife-based CIs as well as the p values of the ANOVAs.

As expected, the parameters for response boundaries A and B decreased as deadlines were reduced. The effect was significant on the level of the 95 % CI as well as in the ANOVA [$F_c(2, 30) = 5.24, p = 0.011$]. This result reflects the canonical speed accuracy tradeoff as it is described in numerous SAF simulations (Ratcliff & McKoon, 2008).

Critically, deadlines also affected the drift rate μ_{ta} for the target, which gradually decreased with increasing time pressure [97.5 % CI; $F_c(2, 30) = 28.59, p < 0.001$]. In contrast, the component rate μ_{fl} for flankers was not

significant. Overall, the summed rate μ_{RS1} (i.e., $\mu_{ta} + \mu_{fl}$) dropped substantially: with decreasing deadline, respectively, μ_{RS1} amounted to 0.2070, 0.1632, and 0.0983 for congruent stimuli (i.e., $\mu_{fl} > 0$) and to 0.1297, 0.0756, and 0.0361 for incongruent stimuli (i.e., $\mu_{fl} < 0$). Thus, compatible with recent evidence that the rate of perceptual processing is sensitive to time pressure (Ho et al., 2012; Rae et al., 2014), early stimulus selection in the flanker task is less efficient under speed stress and hence results in an attenuated response selection RS1.

Furthermore, the rate for late stimulus selection μ_{ss} decreased with time pressure [97.5 % CI; $F_{c(2, 30)} = 22.27, p < 0.001$], whereas the threshold parameter C/D was not reliably affected. As a consequence, the mean duration of Phase 1 became longer under shorter deadlines, which in turn increased the probability that response selection completed already in this first phase. In fact, our simulations revealed that for decreasing deadlines the proportion of terminated decisions in Phase 1 was 0.54, 0.55, and 0.57 for congruent, and 0.47, 0.49, and 0.55 for incongruent stimuli, respectively. Thus, besides lower rates of response selection in Phase 1, also the decreasing number of decisions entering the more reliable Phase 2 contributed to impaired performance under time pressure.

The rate μ_{RS2} for Phase 2 of response selection yielded no reliable deadline effect. Yet, in contrast to the other parameters, μ_{RS2} numerically increased with time pressure. This illustrates that the efficiency of response selection in Phase 2 is not necessarily directly proportional to Phase 1. Instead, once the late stage of stimulus selection has chosen an item (i.e., target or flanker), evidence accumulation for response selection enters Phase 2 and proceeds on the basis of this categorical stimulus representation. This is even the case when the efficiency of preceding processes was low, for instance, due to poor sensory filtering.

Finally, shorter deadlines also caused a decrease in parameter t_{er} [97.5 % CI; $F_{c(2, 30)} = 24.42, p < 0.001$], which reflects non-decisional portions of response times, such as stimulus encoding and the early stage of stimulus selection. A shortening of t_{er} can, therefore, result in a low quality of sensory filtering, which is in line with the smaller rates in the subsequent Phase 1 of response selection and the late stage of stimulus selection (see above). In addition, t_{er} comprises the time from response selection to execution; hence its shortening may also point to the acceleration of motor programs. This is compatible with a time pressure-induced reduction of post-decision motor intervals as revealed by LRPs (e.g., Rinkenauer et al., 2004). Note that different temporal effects of t_{er} (e.g., sensory filtering, motor commands) are neither mutually exclusive nor exhaustive, since processes underlying t_{er} are generally underspecified in current implementations of sequential sampling models.

General discussion

The assumption that the inverse relation between speed and accuracy reflects a tradeoff resulting from (strategic) adjustments of response criteria is widely accepted. Recent studies on simple perceptual decisions, though, suggest that, in addition to response criteria, the rate of evidence accumulation is also affected by time pressure (Heathcote & Love, 2012; Heitz & Schall, 2012; Ho et al., 2012; Rae et al., 2014; Vandekerckhove, Tuerlinckx, & Lee, 2008). The present results of a more complex flanker task support this view as they demonstrate that modulations of drift rates and the duration of non-decision processes co-determine SAFs. In particular, fits of the DSTP model revealed that sensory filtering, and therefore, the efficiency of early response selection suffered from time pressure. We discuss the implications of these findings in the following.

As expected, time pressure generated a SAF: response times as well as accuracy decreased with shorter deadlines. The data also showed a pronounced flanker effect with better performance for congruent than for incongruent items across all deadlines, an effect that progressively moved from accuracy to response times. Overall, the data pattern is consistent with results from previous flanker tasks (e.g., Dambacher et al., 2011; Dambacher & Hübner, 2013; Hübner & Schlösser, 2010).

The data were fit with the DSTP model that is able to decompose processes of perceptual decisions under conflict. Similar to other dual-process accounts (Evans & Stanovich, 2013), the DSTP model permits the separation of an early stage of attentional stimulus selection from a later stage of high selectivity (Hübner et al., 2010; Hübner & Töbel, 2012). For the present data, this account provided decent fits across all levels of time pressure. The observed decrease of decision boundaries with deadlines is in line with numerous previous studies fitting single-stage sequential sampling models to data from simple perceptual decisions (e.g., Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998; Ratcliff & Smith, 2004). Accordingly, time pressure engages a tradeoff of speed against accuracy that permits faster responses via the reduction of the required evidence for response selection.

Importantly, we also found modulations of the rate of evidence accumulation. As time pressure increased, the component rate for target processing μ_{ta} decreased by around 60 % from the longest to the shortest deadline. Also the drift component for flanker processing μ_{fl} , although not significant, was numerically lowest under the shortest deadline. The consequence of this inferior output of early stimulus selection is a substantial drop in the overall drift rate μ_{RS1} (i.e., $\mu_{ta} + \mu_{fl}$) in Phase 1 of response selection. These results corroborate findings on simple decisions showing that the integration of perceptual evidence is

reduced under time pressure (Ho et al., 2012; Rae et al., 2014). They, therefore, suggest that SAFs in complex tasks are not solely based on strategic shifts of response criteria.

Interestingly, the finding is at odds with another recent modeling study of data from a flanker task, in which participants were instructed to emphasize speed or accuracy in different blocks of trials (White et al., 2011). Fits of several models confirmed the typical decrease of response criteria in speed vs. accuracy blocks, but against the authors' expectations, modulations of drift rates did not appreciably improve the fits. One possible reason is that the effects escaped observation because the speed instruction did not impose an explicit deadline, which may have resulted in a relatively low level of time pressure. Likewise, the accuracy instruction presumably posed a moderate challenge as it simply asked participants to avoid errors even if this is at the cost of speed. White et al. suggested that this task description was well compliant with capacity-saving criterion shifts, without an effort-demanding increase of attentional resources. In contrast, the present deadlines set up clear temporal limits that entailed error feedback for too late responses. Arguably, this encouraged participants to meet temporal demands. At the same time, they were motivated to exploit the available time under long deadlines to increase accuracy and, therefore, to maximize their profit. Indeed, our performance-contingent payment reflects another difference to White et al.'s method and may have additionally motivated the investment of attentional effort to optimize performance. Other reports of improved efficiency in response to performance-contingent compared to flat payments in flanker tasks support this conclusion (Dambacher et al., 2011; Hübner & Schlösser, 2010). Together, the data suggest that changes of perceptual processing rates rely on clear, priorly known levels of time pressure and high commitment of participants to the task.

In addition to the rate of response selection in Phase 1, the rate μ_{SS} of the late stage of stimulus selection decreased with time pressure. Consequently, the mean duration of Phase 1 increased with shorter deadlines, leading to a higher proportion of responses that were already triggered in Phase 1 and, accordingly, had a lower accuracy.

A plausible reason for the drift rate modulations in Phase 1 of response selection and late stimulus selection is expressed in parameter t_{er} . Its decrease with time pressure indicates that less time was allocated to non-decision processes, such as stimulus encoding and sensory filtering. As a result of impaired filtering, we would expect a decrease of the drift rate for targets relative to that for flankers. In fact, we observed a drop of the ratio of target vs. flanker rate from a value of around 4:1 (i.e., 0.1683 vs. 0.0386) under the long to around 2:1 (i.e., 0.0672 vs. 0.0311) under the short deadline (see Table 1). This indicates that the

quality of sensory filtering under higher time pressure was indeed reduced.

Variations of t_{er} may also point to deadline effects on other non-decisional components. Yet, current sequential sampling accounts (including the DSTP model) conflate different pre- and post-decisional components in one parameter, so that their unique contribution remains covert. One of the contemporary challenges is, therefore, to refine the models to disentangle non-decisional processes that have been shown to play a role for the time course of decision making. For instance, LRP studies attested the speed-up of post-decisional processes in response to time pressure (Osman et al., 2000; Rinkenauer et al., 2004; van der Lubbe et al., 2001). These results suggest that temporal demands can also affect the duration of motor operations, a finding that broadens the traditional view of threshold modulations as determinant of SAFs. Further, empirical evidence suggests that advanced temporal preparation for the occurrence of an imperative stimulus affects the onset rather than the rate of evidence accumulation (Bausenhart, Rolke, Seibold, & Ulrich, 2010; Seibold, Bausenhart, Rolke, & Ulrich, 2011). Sequential sampling models uniquely capturing the duration of pre-decisional operations could further delineate distinctive effects of decision onset and accumulation rate. Thus, the decomposition of non-decisional components would foster a more fine-grained view on the dynamics of decision making.

As a note on statistical analyses, we took advantage of the jackknifing procedure to draw inferences about parameter variability between different levels of time pressure. While resampling techniques such as jackknifing or bootstrapping are well established as powerful analysis tools (Efron, 1979, 1982), they have hardly been considered for the evaluation of model parameters. As shown in this study, though, resampling can be useful to determine the reliability of effects on one or more free parameters. This is especially helpful when single-participant data are too noisy for individual fits. Moreover, resampling statistics enrich commonly reported goodness of fit measures (e.g., G^2 , AIC, BIC), which do not provide significance tests of model results. We demonstrated the feasibility of the jackknife approach by computing CIs for simple effects between the two extreme deadlines as well as ANOVAs including all three deadline levels. Notably, the pattern of results was the same in both analyses. We stress, however, that a formal generalization from CIs to ANOVAs has yet been described for LRPs (Miller, Patterson, & Ulrich, 1998; Ulrich & Miller, 2001) but is missing in the domain of model parameters. Future applications and simulations may hence disclose further advantages and limits of resampling techniques for statistics on model parameters.

In conclusion, the present flanker task provides evidence that adjustments of response criteria are not sufficient to

account for SAFs in decisions under conflict. Instead, formal modeling shows that time pressure reduces the duration of non-decisional processes and impairs early sensory filtering, which lowers processing efficiency in decision making. Our results add to recent reports of speed-induced modulations of processing rates (e.g., Ho et al., 2012; Rae et al., 2014) and expand their validity from simple to more complex perceptual decisions involving selective attention and response conflict.

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Conflict of interest The authors declare that no competing interests exist.

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