A Neurocognitive Psychometrics Account of Individual Differences in Attentional
Control

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Abstract

Attention control processes play an important role in many substantial psychological theories, but are hard to reliably and validly measure on the subject-level. Therefore, associations between individual differences in attentional control and other variables are often inconsistent. Here we propose a novel neurocognitive psychometrics account of attentional control that integrates model parameters from the dual-stage two-phase model (Hübner et al., 2010), a mathematical model of selective attention, with neural correlates of conflict processing in a multi-layer structural equation model framework. We analyzed data from 150 participants who completed the Eriksen Flanker task while their EEG was recorded and used the neurocognitive psychometric approach to distinguish between two sequential stages of information-processing – target selection and response selection. Model parameters and neural correlates showed convergent validity and could be meaningfully related to each other. Together, these neurocognitive process parameters jointly predicted 37 % of the variance in individual differences in higher-order cognitive abilities. Individuals with greater cognitive abilities were not only better at focusing their attention on the target stimulus, but also at subsequent response-selection. All in all, our results support the idea that individual differences in attentional control processes contribute to individual differences in cognitive abilities. Moreover, they provide hope that the measurement crisis of individual differences in attentional control can be overcome by integrating measurement approaches from related disciplines such as mathematical psychology and cognitive neuroscience.

Keywords: individual differences; attentional control; EEG; mathematical models; cognitive abilities

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Attentional control – also referred to as cognitive control, executive functions, executive control, or inhibitory control – is an umbrella term for self-regulatory cognitive processes. These processes are assumed to play a crucial role in everyday goal-directed behavior and facilitate the transformation and manipulation of mental representations in working memory by activating goal-relevant information and/or inhibiting irrelevant information (Diamond, 2013; Friedman & Miyake, 2017; Miyake et al., 2000; Miyake & Friedman, 2012; Smith & Jonides, 1999). Individual differences in attentional control have been related to cognitive abilities (Wongupparaj et al., 2015), cognitive development (Blakemore & Choudhury, 2006), age-related cognitive change (Hasher et al., 1991), academic success (Best et al., 2011), psychopathologies (Snyder et al., 2015), neurodegenerative diseases (Chambers et al., 2009), and many more life outcomes. In a recent consensus paper, attentional control was defined as the basic ability of “maintaining an operative goal, and goal-relevant information, in the face of distraction” (von Bastian et al., 2020, p. 8).

Despite their great relevance for process-theories of self-regulatory behavior, however, recent empirical and methodological contributions have challenged the idea that individual differences in attentional control can be reliably and validly measured (Draheim et al., 2020; Frischkorn et al., 2019; Hedge et al., 2018, 2020; Rey-Mermet et al., 2018, 2019; Rouder et al., 2019; Rouder & Haaf, 2019; Schubert & Rey-Mermet, 2019; von Bastian et al., 2020). The reasons for these psychometric problems are still debated and proposed solutions via statistical modeling have been achieving only limited success. In the present paper, we therefore suggest a novel neurocognitive psychometrics approach to overcome this problem by making use of generative process models and neural correlates of attentional control.

Problems in the measurement of individual differences in attention control

It has been argued that concerns about the psychometric properties of attentional control measures may arise from the use of tasks developed and validated by experimental psychologists in individual differences research (Draheim et al., 2020; Hedge et al., 2018). Attentional control tasks typically consist of at least two conditions, with a baseline condition demanding only a low amount of attentional control and an experimental condition demanding a great amount of attentional control. A typical example is the Eriksen flanker task (Eriksen & Eriksen, 1974), in which participants have to identify a central stimulus while ignoring irrelevant flanking stimuli. In the congruent condition, these flanking stimuli are identical to the central stimulus, demanding little attentional control, whereas in the incongruent condition, these flanking stimuli differ from the central stimulus, demanding substantial attentional control. These greater attentional control demands are reflected in longer response times (RTs) and higher error rates in the incongruent than in the congruent condition, constituting the experimental effect. To study how people differ in attentional control, it is therefore necessary to study individual differences in these experimental effects, which is complicated by the challenging psychometric properties of intraindividual differences.

Several factors contribute to these unfavorable psychometric properties of experimental effects. First, attentional control tasks such as the flanker task have been designed to produce reliable experimental (i.e., intraindividual) effects by minimizing interindividual variability in these experimental effects (Hedge et al., 2018). As a consequence, individuals differ only little in how they are affected by increased attentional control demands, whereas the interindividual variability in baseline performance is much larger. Second, the variances of experimental effects in attentional control tasks have been shown to be much smaller than the variances of unsystematic measurement errors (Rouder et al., 2019; Rouder & Haaf, 2019). Rouder et al. (2019) reanalyzed data from 15 attentional control studies and estimated that the

standard deviation of trial noise ranged from 100 to 250 ms, whereas experimental effects showed an average standard deviation of about 25 ms.

Together, these two factors contribute to the low reliabilities of attentional control measures. Ability measures of attentional control are typically calculated as performance differences between conditions with lower and higher attentional demands. These difference scores are calculated by subtracting performance (e.g., response times) in the condition with lower attentional control demands from performance in the condition with higher attentional control demands. Whereas response time in the condition with lower attentional control demands can be decomposed into participants' general processing speed τ_{speed} and unsystematic measurement error $\epsilon_{\text{demands-}}$ (i.e., $RT_{\text{demands-}} = \tau_{\text{speed}} + \epsilon_{\text{demands-}}$), response time in the condition with higher attentional control demands can be decomposed into participants' general processing speed τ_{speed} , an unsystematic measurement error $\epsilon_{\text{demands+}}$, and experimentally induced processing demands, $\delta_{\text{demands+}}$ (i.e., $RT_{\text{demands+}} = \tau_{\text{speed}} + \epsilon_{\text{demands+}} + \delta_{\text{demands+}}$). It can be easily demonstrated that variation in the resulting difference score largely reflects unsystematic measurement error if individual differences in the experimental effect are relatively small,

$$\begin{aligned} \sigma^2(RT_{\text{demands+}} - RT_{\text{demands-}}) &= \\ \sigma^2[(\tau_{\text{speed}} + \epsilon_{\text{demands+}} + \delta_{\text{demands+}}) - (RT_{\text{demands-}} = \tau_{\text{speed}} + \epsilon_{\text{demands-}})] &= \\ \sigma^2(\delta_{\text{demands+}} + \epsilon_{\text{demands+}} - \epsilon_{\text{demands-}}) &= \\ \sigma^2(\delta_{\text{demands+}}) + \sigma^2(\epsilon_{\text{demands+}}) + \sigma^2(\epsilon_{\text{demands-}}). \end{aligned}$$

Because performance in both conditions is largely determined by general processing speed τ_{speed} , this variance is no longer included in the resulting difference score $\sigma^2(RT_{\text{demands+}} - RT_{\text{demands-}})$, which then largely consists of unsystematic error variances $\sigma^2(\epsilon_{\text{demands+}})$ and $\sigma^2(\epsilon_{\text{demands-}})$ in addition to a small amount of condition-specific variance $\sigma^2(\delta_{\text{demands+}})$. Because the variance related to measurement error is typically about seven times larger than the variance related to the experimental effect, the resulting difference score variable contains

mostly unsystematic measurement noise, making it largely unreliable (Hedge et al., 2018; Miller & Ulrich, 2013; Salthouse & Hedden, 2002).

These problematic psychometric properties of difference scores can be remedied by statistical modeling. Hierarchical models can be used to distinguish between the true but small variability in experimental effects and measurement error caused by substantial trial-to-trial variability (see Figure 1A; Matzke et al., 2017; Rouder et al., 2019; Rouder & Haaf, 2019). Moreover, bifactor (see Figure 1B) and latent-change (see Figure 1C) models can be specified in such a way that the variance of experimental effects $\sigma^2(\delta_{\text{demands+}})$ is estimated on a latent level free of measurement error (Holzinger & Swineford, 1937; McArdle, 2009; Reise, 2012).

Figure 1

Different statistical modeling approaches that account for the unreliability of individual differences in experimental effects: A) Hierarchical modeling; B) Bi-factor modeling; C) Latent-change modeling

These statistical models have recently been used to achieve more reliable estimates of individual differences in attentional control, with mixed success. Rouder et al. (2019) used

hierarchical models to estimate the true variability in experimental effects in four attentional control tasks, only to find that individual differences in these attentional control effects were rather weakly related. Several studies that used bifactor or latent-change models to estimate individual differences in attentional control reported that the resulting latent factors had small and sometimes non-significant variances and that they showed low convergent validities and even lower predictive validities (Frischkorn et al., 2019, 2020; Rey-Mermet et al., 2018, 2019). Taken together, these results illustrate that the psychometric problems of attentional control cannot be sufficiently addressed by statistical modeling procedures accounting for the unreliability of individual differences in experimental effects.

It is possible that true interindividual differences in experimental effects are simply too small to be measurable with sufficient resolution on a scale of milliseconds to covary meaningfully with each other, even when they are statistically modeled in a hierarchical or latent variable framework (Rouder et al., 2019; Rouder & Haaf, 2019). One reason for this may be that difference scores calculated from aggregate performance measures do not provide process-pure measures of attentional control, but rather a conglomerate of different cognitive processes varying across experimental conditions. In fact, previous research has shown that the assumption that a single cognitive process can be selectively inserted into an experimental task without affecting any other process is often not tenable, as experimental manipulations may interact with other task demands and tend to affect a number of cognitive processes simultaneously (Friston et al., 1996; Schubert et al., 2015; Smid et al., 2000). Hence, difference scores of aggregate performance measures cannot provide a process-pure measure of individual differences in attentional control, because they confound different sources of variance contributing to performance. In the present paper, we argue to instead use measures that more closely reflect the latent attentional control process by using a neurocognitive psychometrics account that combines generative process models of attentional control with neural correlates of inhibitory processes.

A neurocognitive psychometrics account of attentional control

Both generative process models and neural correlates of cognitive processes allow a process-purer measurement of individual differences in cognitive parameters than aggregate performance measures. Joint analyses of cognitive process models and neural correlates have been previously used to shed light on working memory processes (Trutti et al., 2021), processing speed (Schubert et al., 2019, 2020; Schubert & Frischkorn, 2020), mind wandering (Hawkins et al., 2015; Mittner et al., 2014), response inhibition (Sebastian et al., 2018), perceptual decision making (Nunez et al., 2017, 2019; Purcell et al., 2010, 2012), and reinforcement learning (Gläscher & O’Doherty, 2010; O’Doherty et al., 2007). The greatest benefit in the joint analysis of cognitive model parameters and brain data is that theories of how brain mechanisms and latent cognitive processes interact to give rise to observable behavior can be tested. Moreover, cognitive model parameters and neural correlates of cognitive processes can be used to mutually validate each other.

Cognitive models of attentional control

Different cognitive models have been developed to describe the latent cognitive processes involved in attentional control (Hübner et al., 2010; Ulrich et al., 2015; White et al., 2011). In the present study, we used the dual-stage two-phased model (DSTP; Hübner et al., 2010) as a generative processes model of selective attention to describe performance in the Eriksen flanker task, because DSTP model parameters can be theoretically mapped to neural correlates of selective attention. The DSTP model estimates a number of process parameters based on response time distributions of both correct and incorrect responses in congruent and incongruent trials. It assumes that response selection occurs in two distinct sequential stages. Decision making in each of the two stages is described by a random-walk evidence accumulation process that continues with a certain drift rate μ – the rate of evidence accumulation per time – until one of two response thresholds is reached. In addition, the model assumes that a parallel target selection process, which is also mathematically described

by a random-walk evidence accumulation process, determines how quickly individuals focus their attention on the target stimulus.

Figure 2

Illustration of the dual-stage two phase model

Note. Adapted from the image (<https://flic.kr/p/2hAdosN>) by Jim Grange (license used under CC BY-NC 2.0). μ_{TA} = target drift rate; μ_{FL} = flanker drift rate; μ_{SS} = stimulus selection drift rate; μ_{RS2} = response selection selection drift rate; A/B = upper/lower bound of threshold of the response selection process; C/D = upper/lower bound of threshold of the target selection process; t_{SS} = predicted time required for the target-selection stage; t_{RS2} = predicted time required for the response-selection stage

During the first stage (see the upper left part of Figure 2), attention is distributed evenly across the target and flanking stimuli and the drift rate of the evidence accumulation process for response selection process reflects a weighted average of target and flanker information, $\mu_{TA} \pm \mu_{FL}$. The distance between decision thresholds is specified by the threshold separation parameter a , with higher values indicating that more information needs to be accumulated before the response selection process is terminated. At the same time (see the lower left part of Figure 2), a parallel evidence accumulation process describes the process of visual target

selection with the drift rate μ_{ss} . If this target selection process reaches the upper decision threshold defined by the threshold separation parameter c before the response selection process is terminated, response selection enters its second stage. In this second stage (see the upper right part of Figure 2), the drift rate of the response selection process μ_{RS2} is entirely determined by the target stimulus selected in the previous target selection process. Typically, the termination of the target selection process reflects the successful focusing of selective attention on the target stimulus, although errors may occur. In addition, the model estimates a non-decision time parameter t_{er} , which summarizes the time required for all non-decision processes contributing to the observed behavior such as encoding and response execution (see Table 1 for an overview of all model parameters).

Hübner et al. (2010) conducted selective influence studies to empirically test the validity of these model assumptions. They demonstrated that experimental manipulations with high face validity selectively affected model parameters of the specific processing stages that specific experimental manipulations aimed at. They also demonstrated that the model provided an overall good account of the observed data, although subsequent parameter recovery studies identified challenges in the recovery of some model parameters (White et al., 2018). In the present study, we addressed these challenges by improving parameter reliabilities via structural equation modeling and by combining model estimates with neural correlates of selective attention.

Table 1
Overview and brief description of DSTP model parameters

Stage	Process	Parameter	Description
1	Response selection	t_{er}	Non-decision time
		a	Height of the response selection threshold
	Target selection	μ_{TA}	Target drift rate
		μ_{FL}	Flanker drift rate
		c	Height of the target selection threshold
		μ_{ss}	Stimulus selection drift rate
2	Response selection	a	Height of the response selection threshold
		μ_{RS2}	Response selection drift rate

Neural correlates of attentional control

There are plenty of neural correlates of attentional control, ranging from the default mode and salience networks over oscillatory dynamics of attention control to components of the event-related and lateralized readiness potentials (Cavanagh & Frank, 2014; Dosenbach et al., 2006; Fan et al., 2005; Gratton et al., 1988; Kopp et al., 1996; Mason et al., 2007; Pastötter & Frings, 2018; Posner & Rothbart, 2006; Seeley et al., 2007; Wascher et al., 1999; Willemsen et al., 2004). In the present study, we used the stimulus-locked lateralized readiness potential (sLRP) to describe conflict resolution in the Eriksen flanker task on a neural level. The sLRP is an event-related potential that can be observed at EEG recording sites over the motor cortex contralateral to the response hand (de Jong et al., 1988; Gratton et al., 1988). The functional interpretation of the sLRP is typically related to response activation processes and it has been used to study response preparation and response conflict and to distinguish between stimulus- and response-locked processes (Gratton et al., 1988; Hackley & Miller, 1995; Rinkenauer et al., 2004; Troche et al., 2015). It is assumed that the motor cortex and the parietal lobe contribute to its generation (Eimer, 1998; Leuthold & Jentzsch, 2002).

Figure 3

Illustration of the prototypical stimulus-locked lateralized readiness potential (sLRP) in the Eriksen flanker task

The sLRP consists of a large negative deflection about 300-500 ms after stimulus onset (see Figure 3), representing the activation of the response hand. In the Eriksen flanker task and other experimental tasks with a conflict between response alternatives, however, this large negative deflection is preceded by a smaller positive deflection about 200 ms after stimulus onset, which reflects the initial activation of the incorrect response hand induced by the irrelevant information (Gratton et al., 1988; Kopp et al., 1996; Wascher et al., 1999; Willemsen et al., 2004). This flanker-induced response activation (early sLRP) is followed by a subsequent target-induced response activation (late sLRP). Due to its early onset, it has been suggested that the early sLRP reflects an automatic response activation largely driven by the irrelevant flankers (Willemsen et al., 2004). If this automatic response activation crosses the response threshold, the resulting response is relatively fast but incorrect. If the automatic response is successfully inhibited before it crosses the response threshold, the resulting response is correct but relatively slow.

This interpretation of the sLRP in conflict tasks mirrors the assumptions made by the DSTP model, thus allowing to relate model parameter to the sLRP. In particular, the duration of the early stages of the response-selection process, which corresponds to the duration of the target-selection process, should be closely related to the time at which the early sLRP component reaches its peak: Individuals who are very efficient at selecting the central target stimulus should show higher stimulus selection drift rates and shorter early sLRP peak latencies. Similarly, the duration of the second response-selection process should be closely related to the time at which the late sLRP component reaches its peak: Individuals who show higher response selection drift rates should also show shorter late sLRP peak latencies. A recent study reported a near one-to-one relationship between decision times and the timing of late sLRP peaks in a non-conflict decision task, suggesting that the LRP reflects an evidence accumulation process for response selection (Lui et al., 2020). Based on these findings, we extended this approach to decision making in the Eriksen flanker task and related model

parameters of the DSTP model to sLRP peak latencies to mutually validate model parameters and neural correlates of conflict resolution and response selection.

The present study

The goal of the present study was to propose a novel neurocognitive psychometrics approach to overcome problems in the measurement of individual differences in attentional control by making use of generative process models and neural correlates of attentional control. We used the DSTP model to describe individual differences in target selection (as reflected in the stimulus selection drift rate, μ_{SS} , and the height of the target selection threshold, c) and response selection (as reflected in the response selection drift rate stage 2, μ_{RS2} , and the height of the response selection threshold, a). For each of the two stages described by the DSTP model, we calculated the time required for these specific processing stage predicted by the model (see Figure 2) by dividing threshold separation parameters by drift rates. To calculate the predicted time required for the target-selection stage t_{SS} , we divided the threshold separation parameter c by the stimulus selection drift rate μ_{SS} . To calculate the predicted time required for the second response-selection stage t_{RS2} , we divided the threshold separation parameter a by the response selection drift rate μ_{RS2} . Moreover, we determined early and late sLRP peak latencies as neural correlates of the timing and efficiency of target and response selection processes. Model parameters and sLRP peak latencies were estimated twice based on an odd-even-split of the observed data, allowing us to overcome known issues regarding the reliabilities of model estimates and peak latencies by modeling them as latent variables free of measurement error (Cassidy et al., 2012; Schubert et al., 2017; White et al., 2018).

Integrating model parameters and neural correlates in a multi-layer structural equation model framework, we aimed to demonstrate the benefits of the proposed neurocognitive psychometrics approach for the measurement of individual differences in attentional control by demonstrating 1) that model parameters and neural correlates showed convergent validity

and could be meaningfully related to each other and 2) that neurocognitive process parameter showed construct-related validity by jointly predicting individual differences in higher-order cognitive abilities such as working memory capacity and fluid intelligence.

Methods

Participants

We recruited a sample of $N = 151$ participants between 18 and 60 years from different educational and occupational backgrounds via local newspaper advertisements, announcements on our website, distribution of flyers, and the departmental participant pool. One participant had to be excluded because of suspicious performance in the Eriksen flanker task (mean accuracy of 0.69 in congruent and of 0.30 in incongruent trials). The remaining 150 participants (97 females, 52 males, one other) had a mean age of $M = 31.79$ ($SD = 14.01$). Of these, 138 participants additionally completed a psychometric test battery of working memory and intelligence tests at a separate measurement occasion (see below).

A minimum sample size was $N = 84$ would be needed to the hypothesis of close fit ($H_0: \epsilon \leq .05$, $H_1: \epsilon \geq .10$) as suggested by Browne and Cudeck (1992) for the structural equation model with the fewest degrees of freedom ($df = 62$), an alpha error of $\alpha = .05$, and a power of $1 - \beta = .80$. We recruited more participants to increase power and the stability of parameter estimates.

All participants had normal or corrected to normal vision and no mental illness. Participants signed an informed consent form prior to their participation. They received 75 € and feedback about their intelligence test results as reward for their participation. The study was approved by the ethics committee of the faculty of behavioral and cultural studies, Heidelberg University. All procedures were conducted in accordance with the declaration of Helsinki.

Material

Eriksen flanker task

Participants had to decide if an arrow presented in the center of the screen (the target stimulus) pointed to the left or the right by pressing one of two response keys with their index fingers (Eriksen & Eriksen, 1974). The target stimulus was flanked by two arrow each on the left and the right. In congruent trials (50 % of all trials), these flankers pointed in the same direction as the target stimulus, whereas in incongruent trials (50 % of all trials), these flankers pointed in the opposite direction to the target stimulus. The trial order was randomized according to the rule that the same condition (congruent vs. incongruent) and the same direction of the target arrow (left vs. right) could occur a maximum of three times in a row. Participants completed 20 practice trials with feedback and 200 experimental trials without feedback.

Each trial began with a grey fixation cross shown on a black screen for 400-600 ms, followed by a blank screen presented for 400-600 ms. Next, five grey arrows 1.15° apart appeared horizontally aligned in the center of a black screen with a visual angle of 0.38° height and 0.89° width. The array of arrows was shown until participants pressed one of the two response keys, but at least for 1000 ms and at most for 3000 ms, followed by an inter-trial interval that consisted of a black screen and lasted 1000-1500 ms.

Working memory capacity

Participants completed the memory updating task, the operation span task, the sentence span task, and the spatial short-term memory task from the working memory test battery by Lewandowsky et al. (2010), and all except five participants additionally completed the location-letter binding task from the working memory test battery by Wilhelm et al. (2013). Due to a programming error, data from the short-term memory task had to be discarded because different participants had been shown different set sizes, confounding individual abilities with item difficulties. For each of the four remaining tasks, we calculated the mean

proportion of correctly solved items, averaged across set sizes, as a measure of working memory capacity. Four participants' operation span scores were removed from further analyses because they exceeded ± 2.5 *SDs* of the sample mean. Moreover, five participants did not complete the binding task. Participants had a mean updating score (accuracy) of $M = 0.63$ ($SD = 0.20$), a mean operation span score of $M = 0.78$ ($SD = 0.13$), a mean sentence span score of $M = 0.83$ ($SD = 0.15$), and a mean binding score of $M = 0.86$ ($SD = 0.11$). We subsequently transformed these variables into *z*-scores for further analyses. All working memory tasks showed high internal consistencies ranging from $\alpha = 0.79$ to $\alpha = 0.89$.

Fluid intelligence

Participants completed the short version of the Berlin Intelligence Structure Test (BIS; Jäger et al., 1997) as a measure of fluid intelligence. The short version of the BIS consists of 15 tasks, each of which is a combination of one operation-related component (processing capacity, processing speed, memory, creativity) with one content-related component (verbal, numerical, figural). Following the manual, participants' scores for each of the seven components were calculated by aggregating the normalized *z*-scores of all tasks measuring the respective component. Participants had a mean test score of $M = 97.22$ ($SD = 10.54$)¹, which is likely an underestimation of their true intelligence as the BIS norm sample contains data from senior high school students between 16 and 19 years. Participants had a mean processing capacity score of $M = 101.72$ ($SD = 7.02$), a mean processing speed score of $M = 101.13$ ($SD = 7.17$), a mean memory score of $M = 98.60$ ($SD = 7.19$), a mean creativity score of $M = 98.24$ ($SD = 6.92$), a mean verbal score of $M = 104.89$ ($SD = 5.89$), a mean numerical score of $M = 98.75$ ($SD = 7.26$), and a mean figural score of $M = 97.21$ ($SD = 6.67$). We transformed these variables into *z*-scores for further analyses. Both operation- and content-

¹ Please note that the BIS is normed to a mean value of 100 and a *SD* of 10.

related components showed low-to-moderate internal consistencies, ranging from $\alpha = 0.44$ to $\alpha = 0.75$ and from $\alpha = 0.49$ to $\alpha = 0.74$, respectively.

Procedure

During the EEG session, participants completed a demographic questionnaire and a number of cognitive tasks (data not reported here) in addition to the Eriksen flanker task while their EEG was recorded. Participants were seated in a dimly lit, sound-attenuated EEG cabin. During the psychometric testing session, participants completed the short version of the BIS, two brief highly speeded intelligence tests (data not reported here), a working memory test battery, a pretzel task (data not reported here), and a mind-wandering questionnaire (data not reported here) in groups of up to four participants. The two measurement sessions were scheduled to be about eight months apart, but had to be rescheduled for some participants due to a two-month break in data collection at the outbreak of COVID-19. One participant opted to complete the psychometric testing session via video chat due to the pandemic, which was only feasible for the pen-and-pencil tests but not the computer-based working memory tasks.

EEG recording

The EEG was recorded with 32 equidistant Ag-AgCl electrodes, with aFz as a ground electrode. Impedances were kept below 5 k Ω . Electrodes were online referenced to Cz and later rereferenced to an average reference. The EEG signal was recorded continuously with a sampling rate of 1000 Hz (high-pass 0.1 Hz).

Data preprocessing

Behavioral data

We discarded any trials with RTs faster than 150 ms or with logarithmized RTs exceeding ± 3 SD of each participant's mean RT. The RT difference between experimental conditions was calculated by subtracting the individual mean RT of correct responses in congruent trials from the individual mean RT of correct responses in incongruent trials,

$$\Delta RT = \overline{RT}_{\text{incongruent}} - \overline{RT}_{\text{congruent}}.$$

EEG data

We preprocessed the EEG data with the open source toolbox EEGLAB (Delorme & Makeig, 2004) in MATLAB (The MathWorks Inc., Natick, Massachusetts). The data were filtered with a band-pass filter of 0.1-16 Hz. Bad channels were identified and subsequently removed based on probability and kurtosis of the channel data. The data were then rereferenced to an average reference. Segments were 1200 ms long and started 200 ms before stimulus onset. Artifact-containing segments were automatically detected and rejected with 1000 μ V as the threshold for detecting large fluctuations, 5 *SDs* as the probability threshold for the detection of improbable data, and 5 % as the maximum number of segments to be rejected per iteration. We then conducted independent-component analyses (ICA) of the data down-sampled to 200 Hz and filtered with a high-pass filter of 1 Hz to identify and remove artifacts and generic discontinuities with the ICLabel algorithm (Pion-Tonachini et al., 2019). Subsequently, we repeated the automatic detection and rejection of artifact-containing segments using the same specifications as before and interpolated any previously removed channels.

Data analysis***DSTP model estimation***

We fit the DSTP model to individual participant data – separately for odd and even trials to allow the estimation of reliabilities and the subsequent modeling of model parameters as latent variables – using the *R* package *flankr* (Grange, 2016). Models were fitted to trial-level RT and accuracy data (to cumulative distribution functions of correct response times and conditional accuracy functions) using the likelihood ratio chi-square statistic G^2 as an optimization criterion. Following the recommendations by Grange (2016) and based on our own experiences with the estimation procedure, we estimated model parameters in three steps. We first fitted the model with 50,000 iterations of the Nelder-Mead algorithm, using default starting values. We then used the resulting parameter estimates in the second step to

explore this general region of the parameter space by sampling 40 sets of starting values from a normal distribution with mean equal to the respective best-fitting parameter estimate and a standard deviation of 1/10 of the respective best-fitting parameter estimate. Each of the 40 sets of starting values was then used to estimate model parameters with 5,000 iterations of the Nelder-Mead algorithm. From these, we selected the best-fitting sets of resulting parameter estimates. In the third step, we used these best-fitting parameter estimates as starting values to fit the final model with 100,000 iterations of the Nelder-Mead algorithm.

We evaluated model fit by plotting model predictions against observed data. For each participant and separately for congruent and incongruent as well as for odd and even trials, we simulated response time and accuracy data predicted by the model using that participant's best-fitting model parameter estimates. We then calculated accuracy rates and the 25th, 50th, and 75th quantile of the correct response time distributions for each participant's observed and predicted data. As shown in Figure 4, model predictions closely corresponded to observed data for both congruent and incongruent trials. Correlations of accuracy rates ranged from .72 to .85, indicating that the models provided an acceptable account of accuracy rates despite their high absolute levels and small variance, and correlations of RT quantiles ranged from .97-.99, indicating that the models provided an excellent account of RT distributions.

Figure 4

QQ-plots for the assessment of model fit based on the comparison of statistics (accuracy rate, 25 %, 50 %, and 75 % quantile) of the observed and predicted data

Note. Each data point represents one participant. Diagonal lines indicate perfect model fit.

Subsequently, we calculated the time predicted by the model for each of the two processing stages by dividing threshold separation parameters by drift rates. To calculate the predicted time required for the target-selection stage t_{SS} , we divided the threshold separation parameter c by the stimulus selection drift rate μ_{SS} . To calculate the predicted time required for the second response-selection stage t_{RS2} , we divided the threshold separation parameter a by the response selection drift rate μ_{RS2} . Fewer than 1 % of all parameter estimates were removed from further analyses because they exceeded ± 2.5 SDs of the sample mean. We transformed all variables into z -scores for further analyses.

LRP latencies

We calculated difference waveforms – separately for odd and even trials to allow the estimation of reliabilities and the subsequent modeling of ERP latencies as latent variables – by subtracting electrophysiological activity at electrodes ipsilateral to the response hand from electrodes contralateral to the response hand. Because the equidistant electrode system used in the present study had no direct correspondence to C3 and C4 in the 10-20 system, we used two sets of electrodes slightly anterior and posterior of C3 and C4 in the 10-20 system. We then determined positive and negative sLRP peak latencies for incongruent trials separately for each of the two electrode positions and odd/even trials. The peak latency reflects the time-to-peak for an ERP component and indicates the time at which the amplitude of a component reaches its maximum. 3.96 % of all peak latencies were removed from further analyses because they exceeded ± 2.5 SDs of the sample mean. We transformed peak latencies into z-scores for further analyses.

Statistical analyses

We used structural equation models to evaluate the proposed relations between DSTP model parameters and sLRP peak latencies and to test if processing stages implied by the model could be mapped onto electrophysiological processing stages. Latent model parameters loaded onto model parameters that had been estimated separately for odd and even trials. Latent sLRP peak latencies loaded onto observed latencies that had been determined separately for each of the two electrode positions as well as for odd and even trials. In addition to the theoretically proposed model, we specified a number of alternative models with different relations between DSTP model parameters and sLRP peak latencies to demonstrate that the theoretically proposed model provided a better account of the data than alternative conceptions. Subsequently, we introduced a latent cognitive abilities factor into the best-fitting model to estimate the relationship of individual differences in DSTP model parameters and sLRP peak latencies with individual differences in cognitive abilities.

We also compared the results from the joint neurocognitive psychometric models to standard statistical modeling approaches to evaluate the added benefit of our novel modeling approach. First, we used structural equation models to evaluate the relationship of observed experimental effects (i.e., the RT difference ΔRT between experimental conditions) and estimated experimental effects (i.e., the hierarchically estimated individual posterior mean effect θ) with cognitive abilities. Second, we specified a bi-factor model to decompose the variance in mean RTs in experimental conditions into a common processing speed factor and an experimental effect factor that we related to cognitive abilities. Third, we estimated a latent-change model to generate a latent estimate of the experimental effect that we related to cognitive abilities.

Models were fitted with the *R* package *lavaan* (Rosseel, 2012) with the maximum likelihood algorithm with robust Huber-White standard errors and a scaled test statistic equal to the Yuan-Bentler test statistic to account for the nonnormality of some connectivity measures and possible deviations from multivariate normality. Individual posterior mean effects θ were estimated according to Rouder and Haaf (2020).

We evaluated goodness-of-fit based on the comparative fit index (CFI; Bentler, 1990) and the root mean square error of approximation (RMSEA; Browne & Cudeck, 1992) and compared model fits with the Akaike Information Criterion (Akaike, 1973) and based on Akaike weights (Wagenmakers & Farrell, 2004). We considered CFI values $> .90$ and RMSEA values $< .08$ to indicate acceptable model fit and CFI values $> .95$ and RMSEA values $< .06$ to indicate good model fit, as recommended by Browne and Cudeck (1992) and Hu and Bentler (1999). AIC differences ≥ 10 were interpreted to indicate a substantial advantage in relative model fit in direct model comparisons (Burnham & Anderson, 2002). The statistical significance of model parameters was assessed with the two-sided critical ratio test.

Transparency and Openness. The processed data supporting the findings of the study and the statistical analysis code needed to reproduce the analyses in the manuscript are available in the Open Science Framework repository at <https://osf.io/a96v7>. The raw data and study materials will be shared upon request with the exception of the Berlin intelligence structure test, which is commercially licensed. Neither the study nor the analyses were preregistered.

Results

Descriptive statistics and reliabilities of error rates, RTs, model parameters, and sLRP latencies are shown in Table 2. The grand average of the ERP is shown in Figure 5. We confirmed the expected experimental effect on participants' performance and sLRP peak latencies. Participants responded slower in incongruent than in congruent trials, $F(1,149) = 301.92, p < .001, \eta_p^2 = .67$, and also committed more errors in these trials, $F(1,149) = 42.83, p < .001, \eta_p^2 = .67$. Positive sLRP peak latencies $F(1,132) = 15.10, p < .001, \eta_p^2 = .10$, and negative sLRP peak latencies, $F(1,127) = 65.21, p < .001, \eta_p^2 = .34$, were slower when flankers were incongruent than when they were congruent to the target stimulus.

Figure 5

Grand average of the lateralized readiness potential averaged across both electrode sites

Table 2*Means (SDs in italics) and reliabilities of accuracy rates, response times, model parameters, and sLRP latencies*

	ACC	RT	Δ RT	θ RT	t_{er}	a	μ_{TA}	μ_{FL}	c	μ_{SS}	μ_{RS2}	t_{SS}	t_{RS2}	early sLRP	late sLRP
odd			0.02	0.02	0.25	0.17	0.19	0.12	0.07	0.56	1.27	0.14	0.14		
congruent	1.00	0.49	0.02	0.00	0.04	0.09	0.09	0.08	0.03	0.15	0.19	0.10	0.08	0.18 ¹ 0.06	0.36 ¹ 0.06
	0.01	0.09												0.17 ² 0.05	0.34 ² 0.06
incongruent	0.98	0.51												0.19 ¹ 0.06	0.40 ¹ 0.08
	0.03	0.10												0.19 ² 0.06	0.36 ¹ 0.07
even			0.02	0.02	0.26	0.17	0.18	0.12	0.07	0.56	1.29	0.13	0.13		
congruent	1.00	0.49	0.02	0.01	0.05	0.07	0.08	0.07	0.03	0.14	0.19	0.08	0.07	0.18 ¹ 0.05	0.37 ¹ 0.08
	0.02	0.09												0.17 ² 0.05	0.34 ² 0.06
incongruent	0.98	0.51												0.19 ¹ 0.06	0.39 ¹ 0.07
	0.03	0.10												0.18 ² 0.06	0.37 ² 0.07
reliability			.52 ^a	.55 ^a	.43 ^a	.70 ^a	.52 ^a	.44 ^a	.66 ^a	.72 ^a	.56 ^a	.92 ^a	.75 ^a		
congruent	.70 ^a	.99 ^a												.64 ^b	.80 ^b
incongruent	.81 ^a	.99 ^a												.71 ^b	.83 ^b

Note. ^aReliability estimated based on Spearman-Brown corrected odd-even correlation; ^breliability estimated with Cronbach's α across odd/even trials and anterior/posterior electrode positions; ¹more anterior electrode position; ²more posterior electrode position. ACC = accuracy rate; RT = mean response time; Δ RT = observed experimental effect; θ RT = hierarchically estimated experimental effect; t_{er} = non-decision time; a = height of the response selection threshold; μ_{TA} = target drift rate; μ_{FL} = flanker drift rate; c = height of the target selection threshold; μ_{SS} = stimulus selection drift rate; μ_{RS2} = response selection drift rate; t_{SS} = predicted time required for the target-selection stage; t_{RS2} = predicted time required for the response-selection stage; early sLRP = latency of the early positive peak in the lateralized readiness potential; late sLRP = latency of the late negative peak in the lateralized readiness potential.

Joint models of DSTP model parameters and sLRP latencies

We used structural equation models to assess the relations between model parameters and sLRP peak latencies (see Table 3 for zero-level correlations between all variables). The a-priori theoretically proposed joint model, in which sLRP latencies were regressed on model-predicted times for the stimulus- and response-selection stage (see Figure 6A), provided an acceptable account of the data, $\chi^2(62) = 96.19$, $p = .004$, CFI = 0.93, RMSEA = 0.06 (95% CI = [0.04; 0.08]). On the one hand, the speed with which participants finished the stimulus-selection process t_{SS} (as implied by the DSTP model) predicted the latency of the early sLRP peak, $\beta = 0.35$, $p = .029$, 95% CI = [0.13; 0.58]. On the other hand, the speed with which participants finished the response-selection process t_{RS2} (as implied by the DSTP model) predicted the latency of the late sLRP peak, $\beta = 0.55$, $p < .001$, 95% CI = [0.36; 0.74].

We specified a number of alternative joint models to test if any other structural relations between model parameters and sLRP peak latencies provided a better account of the data (see Figure 6B-F), but found that all alternative models showed an inferior model fit to the theoretically proposed joint model (all $\Delta AICs \geq 7.13$). Three of those alternative models provided a significantly worse ($\Delta AICs$ ranging from 14.99 to 33.42) and two models (see Figure 6B and 6E) provided only a marginally inferior ($\Delta AICs$ ranging from 7.13 to 9.60) account of the data. A direct comparison of the theoretically proposed model shown in Figure 6A to the two alternative models based on Akaike weights indicated that the candidate model was 35.28 times more likely to be the true model in terms of Kullback-Leibler discrepancy than the model shown in Figure 6B and 121.44 times more likely to be the true model than the model shown in Figure 6E. This preference for the theoretically proposed model was also supported by a normalized probability ratio of 100 % over all competing models calculated based on Akaike weights. Taken together, of all the joint models tested, the theoretically proposed model provided the best account of the data.

Table 3*Pearson correlations between all measures*

Operation Span	-0.16	-0.1	-0.16	0	-0.22	-0.19	0.02	0.09	-0.03	-0.09	-0.05	-0.15	0.37	0.21	0.23	0.07	0.5	0.58	0.65
Sentence Span	-0.06	-0.06	-0.3	-0.19	-0.15	-0.26	-0.18	-0.13	-0.03	-0.18	-0.04	-0.24	0.44	0.37	0.36	0.14	0.44	0.59	
Mmemory Updating	-0.24	-0.21	-0.32	-0.1	-0.17	-0.27	-0.21	-0.11	-0.19	-0.28	-0.24	-0.36	0.58	0.44	0.34	0.11	0.7		
Binding	-0.2	-0.15	-0.39	-0.17	-0.15	-0.21	-0.21	-0.08	-0.19	-0.26	-0.18	-0.33	0.53	0.44	0.34	0.19			
Creativity	-0.16	-0.02	-0.07	-0.07	-0.1	-0.12	-0.27	-0.23	0	0.08	0.12	0.01	0.33	0.35	0.13				
Memory	-0.15	-0.15	-0.06	-0.03	-0.14	-0.21	-0.19	-0.03	-0.15	-0.23	-0.08	-0.22	0.43	0.43					
Processing Speed	-0.17	-0.13	-0.33	-0.24	-0.3	-0.33	-0.34	-0.24	-0.2	-0.18	-0.16	-0.32	0.52						
Processing Capacity	-0.2	-0.09	-0.25	-0.15	-0.22	-0.28	-0.28	-0.27	-0.14	-0.16	-0.11	-0.27							
late sLRP (even, pos)	0.37	0.29	0.45	0.14	0.23	0.3	0.16	0.12	0.49	0.56	0.69								
late sLRP (even, ant)	0.41	0.3	0.42	0.07	0.09	0.23	0.16	0.14	0.54	0.44									
late sLRP (odd, pos)	0.22	0.21	0.27	0.22	0.32	0.42	0.06	0.13	0.65										
late sLRP (odd, ant)	0.2	0.22	0.31	0.12	0.23	0.26	0.13	0.17											
early sLRP (even, pos)	0.18	0.26	-0.03	0.06	0.23	0.34	0.58												
early sLRP (even, ant)	0.12	0.23	0.08	0.04	0.22	0.3													
early sLRP (odd, pos)	0.27	0.24	0.17	0.11	0.63														
early sLRP (odd, ant)	0.13	0.1	0.1	0.15															
tRS2 (even)	0.08	-0.03	0.43																
tRS2 (odd)	0.15	0.09																	
tSS (even)	0.79																		
	tSS (odd)	tSS (even)	tRS2 (odd)	tRS2 (even)	early sLRP (odd, ant)	early sLRP (odd, pos)	early sLRP (even, ant)	early sLRP (even, pos)	late sLRP (odd, ant)	late sLRP (odd, pos)	late sLRP (even, ant)	late sLRP (even, pos)	Processing Capacity	Processing Speed	Memory	Creativity	Binding	Mmemory Updating	Sentence Span

Note. tSS = predicted time required for the target-selection stage; tRS2 = predicted time required for the response-selection stage; early sLRP = latency of the early positive peak in the lateralized readiness potential; late sLRP = latency of the late negative peak in the lateralized readiness potential; ant = anterior; pos = posterior.

Figure 6*Graphical illustration of the joint models*

Note. Standardized regression weights, correlation coefficients, and residual variances are shown next to paths. Non-significant correlations or regressions are grayed out. AIC differences show differences in model fit in comparison to the best-fitting model shown in A. t_{SS} = predicted time required for the target-selection stage; t_{RS2} = predicted time required for the response-selection stage; early sLRP = latency of the early positive peak in the lateralized readiness potential; late sLRP = latency of the late negative peak in the lateralized readiness potential.

Relations with higher-order cognitive abilities

To test if model parameters and sLRP latencies jointly predicting individual differences in higher-order cognitive abilities, we specified a latent variable model in which individual differences in higher-order cognitive abilities were predicted by the DSTP model parameters. We then tested if any associations between model parameters and cognitive abilities were mediated by sLRP latencies.

The first model (see Figure 7A), in which cognitive abilities were regressed on the times required for the two distinct processing stages, provided an acceptable account of the data, $\chi^2(66) = 96.79, p = .008$, CFI = 0.95, RMSEA = 0.06 (95% CI = [0.03; 0.08]). Participants with higher cognitive abilities finished both the stimulus-selection process, $\beta = -0.21$, $p = .035$, 95% CI = [-0.39; -0.02], and the response-selection process, $\beta = -0.45$, $p = .001$, 95% CI = [-0.71; -0.19], faster than those with lower cognitive abilities. These results indicate that both stages of processing described by the DSTP model – the stimulus-selection stage and the subsequent response-selection stage – were related to cognitive abilities.

We then extended this model by introducing sLRP latencies as mediators of the association between DSTP model parameters and cognitive abilities (see Figure 7B). This joint mediation model provided an acceptable account of the data, $\chi^2(186) = 285.17, p < .001$, CFI = 0.90, RMSEA = 0.06 (95% CI = [0.03; 0.07]). The association between the speed with which participants finished the stimulus-selection process t_{ss} (as implied by the DSTP model) and their cognitive abilities was fully mediated by individual differences in latencies of the early sLRP peak, as indicated by the non-significant direct effect between t_{ss} and cognitive abilities, $\beta_c = -0.02$, $p = .845$, 95% CI = [-0.24; 0.20], and a significant indirect effect, $\beta_{ab} = -0.10$, $p = .033$, 95% CI = [-0.20; -0.01]. The association between the speed with which participants finished the response-selection process t_{RS2} and their cognitive abilities was not mediated by individual differences in latencies of the late sLRP peak, as indicated by the non-significant indirect effect, $\beta_{ab} = -0.04$, $p = .608$, 95% CI = [-0.21; 0.12]. Taken together, the

moderate association between cognitive abilities and attentional-control processes related to stimulus selection could be accounted for by the neurocognitive psychometrics model, whereas the joint model could not shed any further light on the association between cognitive abilities and cognitive processes related to response-selection. Together, the neurocognitive process parameters accounted for 37 % of the variance in the latent cognitive ability variable.

Figure 7

Graphical illustration of the joint models predicting cognitive abilities

Note. Standardized regression weights, correlation coefficients, and residual variances are shown next to paths. Non-significant correlations or regressions are grayed out. To account for the moderate sample size, we reduced the complexity of measurement models by constraining residual variances of DSTP model parameters to be equal in odd and even trials and by constraining residual variances of sLRP latencies to be equal across electrode sites. g = cognitive abilities; WMC = working memory capacity; t_{ss} = predicted time required for the target-selection stage; t_{RS2} = predicted time required for the response-selection stage; early sLRP = latency of the early positive peak in the lateralized readiness potential; late sLRP = latency of the late negative peak in the lateralized readiness potential.

Comparison to standard statistical modeling approaches

We compared the results from the joint neurocognitive psychometric models to standard statistical modeling approaches (see Figure 1) to evaluate the added benefit of our novel modeling approach (see Table 4 for zero-level correlations between all variables).

Table 4

Pearson correlations between standard measures and cognitive abilities variables

Operation Span-	-0.27	-0.24	-0.26	-0.22	0	0.01	-0.02	-0.01	0.37	0.21	0.23	0.07	0.5	0.58	0.65
Sentence Span-	-0.26	-0.26	-0.28	-0.23	-0.11	-0.04	-0.14	-0.06	0.44	0.37	0.36	0.14	0.44	0.59	
Mmemory Updating-	-0.42	-0.41	-0.41	-0.39	-0.19	-0.04	-0.22	-0.07	0.58	0.44	0.34	0.11	0.7		
Binding-	-0.42	-0.41	-0.39	-0.4	-0.17	-0.08	-0.21	-0.11	0.53	0.44	0.34	0.19			
Creativity-	-0.13	-0.14	-0.11	-0.14	-0.04	-0.06	-0.06	-0.08	0.33	0.35	0.13				
Memory-	-0.2	-0.21	-0.21	-0.21	-0.06	-0.1	-0.08	-0.12	0.43	0.43					
Processing Speed-	-0.42	-0.44	-0.39	-0.41	-0.08	-0.02	-0.11	-0.05	0.52						
Processing Capacity-	-0.3	-0.31	-0.27	-0.26	0	0.06	-0.03	0.04							
θ RT (even)-	0.29	0.25	0.35	0.45	0.34	1	0.37								
θ RT (odd)-	0.25	0.31	0.41	0.36	0.99	0.35									
Δ RT (even)-	0.23	0.19	0.29	0.39	0.33										
Δ RT (odd)-	0.17	0.24	0.34	0.29											
RT incongruent (even)-	0.97	0.97	0.98												
RT incongruent (odd)-	0.97	0.97													
RT congruent (even)-	0.99														

correlation:
Pearson

1.0
0.5
0.0
-0.5
-1.0

RT congruent (odd) RT congruent (even) RT incongruent (odd) RT incongruent (even) Δ RT (odd) Δ RT (even) θ RT (odd) θ RT (even) Processing Capacity Processing Speed Memory Creativity Binding Mmemory Updating Sentence Span

Note. Δ RT = observed experimental effect; θ RT = hierarchically estimated experimental effect.

First, we calculated the individual difference between mean RTs in incongruent and congruent trials as a measure of attentional control demands and modeled these differences scores as a latent factor across odd and even trials to predict individual differences in cognitive abilities (see Figure 8A). The resulting model provided a good account of the data,

$\chi^2(43) = 47.57, p = .292, CFI = 0.99, RMSEA = 0.03$ (95% CI = [0.00; 0.06]). Individual differences in the experimental effect, however, did not explain any variance in individual differences in cognitive abilities, $r = -0.13, p = .346, 95\% CI = [-0.39; 0.14]$. We then repeated this analysis, fitting the same structural equation model, but this time used hierarchically estimated individual posterior mean effects θ as indicators of the latent factor. In comparison to raw RT differences, these estimated effects reflect only true individual variation in the experimental effect by statistically accounting for trial noise. The resulting model provided a good account of the data, $\chi^2(43) = 48.55, p = .259, CFI = 0.99, RMSEA = 0.03$ (95% CI = [0.00; 0.06]). Although we observed a larger latent correlation between individual posterior mean effects θ and cognitive abilities than we did between the observed experimental effect and cognitive abilities, this correlation did still not reach statistical significance, $r = -0.19, p = .144, 95\% CI = [-0.44; 0.07]$. On a descriptive level, both analyses converged by showing that participants with higher cognitive abilities tended to be less affected by additional attentional control demands introduced by incongruent flankers. A Bayes Factor of $BF_{10} = 190$ comparing the positive-effect to the common-effect model indicated that there was decisive evidence for true individual variation in the experimental effect (Haaf & Rouder, 2017; Rouder & Haaf, 2020).

Second, we estimated a bi-factor model to decompose the variance in mean RTs in experimental conditions into a common processing speed factor and an experimental effect factor (see Figure 8B). This bi-factor model provided a good account of the data, $\chi^2(61) = 79.18, p = .059, CFI = 0.99, RMSEA = 0.05$ (95% CI = [0.00; 0.07]). Factor loadings on the latent experimental effect were very low, $\beta = 0.13, 95\% CI = [0.08; 0.19]$. Moreover, the unstandardized variance of the experimental effect $\Delta, \sigma^2 = 0.01, p = .016, 95\% CI = [0.00; 0.02]$, was 56 times smaller than the variance of the common processing speed factor, $\sigma^2 = 0.67, p < .001, 95\% CI = [0.54; 0.81]$. Participants with higher cognitive abilities showed a higher general processing speed than participants with lower cognitive abilities, $r = -0.51,$

$p < .001$, 95% CI = [-0.67; -0.36]. We again found no evidence for ability-related differences in the experimental effect, $\beta = 0.05$, $p = .723$, 95% CI = [-0.20; 0.29].

Third, we estimated a latent-change model to generate an alternative latent estimate of the experimental effect (see Figure 8C). This latent-change model provided an even slightly better account of the data than the bi-factor model, $\chi^2(64) = 77.50$, $p = .120$, CFI = 0.99, RMSEA = 0.04 (95% CI = [0.00; 0.06]), $\Delta AIC = 5.8$. Again, the unstandardized variance of the experimental effect Δ , $\sigma^2 = 0.01$, $p = .014$, 95% CI = [0.00; 0.02], was much smaller than the variance of the non-experimental RT factor, $\sigma^2 = 0.68$, $p < .001$, 95% CI = [0.54; 0.81]. Individual differences in cognitive abilities were yet again only predicted by the non-experimental RT factor, $r = -0.51$, $p < .001$, 95% CI = [-0.66; -0.36], but not by individual differences in the experimental effect, $\beta = 0.05$, $p = .710$, 95% CI = [-0.20; 0.29].

Figure 8

Graphical illustration of the standard statistical models of the experimental effect predicting cognitive abilities

A

B

C

Note. Standardized regression weights, correlation coefficients, and residual variances are shown next to paths. Non-significant correlations or regressions are grayed out. g = cognitive abilities; WMC = working memory capacity; Δ = experimental effect; RT = reaction time.

Do age differences in our sample account for the results?

To assess if the age heterogeneity in our sample of individuals between 18 and 60 years accounted for the results, we repeated the main correlational analyses correcting for age. The a-priori specified joint model (see Figure 6A) still provided an acceptable account of the data, $\chi^2(71) = 119.80, p < .001$, CFI = 0.91, RMSEA = 0.07 (95% CI = [0.05; 0.08]). Age differences were related to the speed with which participants finished the response-selection process t_{RS2} (as implied by the DSTP model), $\beta = 0.63, p < .001$, 95% CI = [0.47; 0.78], but not to any of the other latent variables, all $\beta \leq 0.19$, all $ps \geq .211$. Accounting for age differences did not affect the relations between cognitive model parameters and sLRP peak latencies, which indicates that the proposed neurocognitive process model holds across different age groups.

Controlling for age differences affected the relationship between neurocognitive process parameters and cognitive abilities. The age-controlled version of the regression model shown in Figure 7A showed an acceptable account of the data, $\chi^2(75) = 127.09, p < .001$, CFI = 0.93, RMSEA = 0.07 (95% CI = [0.05; 0.09]). The relationship between the speed with which participants finished the stimulus-selection process and their cognitive abilities remained significant, $\beta = -0.19, p = .033$, 95% CI = [-0.37; -0.02], but the speed with which participants finished the response-selection process was no longer related to their cognitive abilities, $\beta = -0.19, p = .256$, 95% CI = [-0.51; 0.14]. The age-controlled version of the mediation model shown in Figure 7B showed an acceptable account of the data, $\chi^2(201) = 340.75, p < .001$, CFI = 0.88, RMSEA = 0.07 (95% CI = [0.06; 0.08]). Individual differences in positive sLRP peak latencies still mediated the association between the speed with which participants finished the stimulus-selection process t_{SS} and their cognitive abilities after controlling for age differences, as indicated by the non-significant direct effect between t_{SS} and cognitive abilities, $\beta_c = -0.05, p = .668$, 95% CI = [-0.27; 0.17], and a significant indirect effect, $\beta_{ab} = -0.11, p = .031$, 95% CI = [-0.20; -0.01].

Discussion

We developed a neurocognitive psychometrics approach to overcome problems in the measurement of individual differences in attentional control by making use of cognitive process models and neural correlates of attentional control. Integrating model parameters of the DSTP model and sLRP peak latencies in a multi-layer structural equation model allowed us to reliably and validly measure individual differences in attentional control on a latent level. Individual differences in these neurocognitive process parameters were related to each other in a theoretically meaningful manner, mutually underlining their validity. Moreover, they jointly predicted about 37 % of the variance in individual differences in higher-order cognitive abilities.

Benefits of the neurocognitive psychometrics account

The greatest benefit of our neurocognitive psychometrics account of attentional control lies in the fact that it does not require the calculation of difference scores between aggregate performance measures in experimental conditions. Because individuals differ only little in how they are affected by experimentally induced attentional control demands and because the reliability of difference scores is typically low if baseline performance in the two conditions is strongly correlated, difference scores tend to show unfavorable psychometric properties (Hedge et al., 2018; Rouder et al., 2019; Rouder & Haaf, 2019). Moreover, their validity has been repeatedly questioned, as experimental manipulations often affect a number of other cognitive processes in addition to the targeted processes (Friston et al., 1996; Schubert et al., 2015; Smid et al., 2000). Therefore, difference scores of aggregate performance measures (e.g., mean RTs) do not allow a process-pure measurement of individual differences in attentional control. We observed the same issues of difference scores in the present study, in which we failed to find any association between individual differences in experimental effects and cognitive abilities despite numerous attempts to model these individual effects with

statistical modeling approaches controlling for unsystematic measurement error and trial noise (Holzinger & Swineford, 1937; McArdle, 2009; Rouder & Haaf, 2019).

The neurocognitive psychometrics account proposed in the present study addresses these issues by using cognitive process models and neural correlates of attentional control. The joint analysis of cognitive model parameters and brain data uses psychological theories of how latent cognitive processes and brain mechanisms interact to give rise to observable behavior to measure individual differences in these processes. Because cognitive models consist of latent parameters that are directly estimated from the full intraindividual distribution of observed behavior, there is no need to calculate unreliable difference scores. Although we transformed model parameters into ratio scores when we calculated the time predicted by the model for the two sequential processing stages, the resulting ratio scores did not suffer from low reliabilities because the two model parameters (drift rates and threshold heights) were not highly correlated. In the present study, DSTP model parameters and their neural correlates showed moderate to high reliabilities. We further improved their reliabilities via structural equation modeling, allowing us to measure individual differences in attentional control virtually free of measurement error.

The joint analysis of cognitive model parameters and brain data allowed us to mutually validate both sets of neurocognitive process parameters in a multi-layer structural equation model. We proposed that the time required for each of the two processing stages defined in the DSTP model would predict the latencies of the two consecutive sLRP peaks. By comparing this multi-layer model with a number of alternative models, we confirmed a close link between the stimulus-selection stage and the positive sLRP component and between the response-selection stage and the negative sLRP component. The DSTP model assumes that timing of the stimulus-selection stage reflects the speed with which individuals successfully focus their attention on the target stimulus to subsequently ignore the irrelevant flankers

(Hübner et al., 2010). This assumption was confirmed by the close link between the time required for the stimulus-selection stage and the positive sLRP peak latency. In addition, the DSTP model assumes that the subsequent response-selection stage reflects an evidence accumulation process that terminates after crossing a decision threshold and precedes response execution (Hübner et al., 2010). This assumption was also confirmed by a close link between the time required for the response-selection stage and the negative sLRP peak latency. This close link is consistent with previous research that found a near one-to-one relationship between the duration of the readiness potential and the decision time predicted by the diffusion model in an action selection task (Lui et al., 2020). Moreover, it fits the interpretation that the negative sLRP peak reflects the crossing of a decision threshold, but that is also echoes the process of evidence accumulation in decision making (Spencer & Coles, 1999; van Vugt et al., 2014). Taken together, these results support the validity of the neurocognitive process measures used in the present study.

Relations between individual differences in attentional control and cognitive abilities

Individuals with higher cognitive abilities completed both the stimulus-selection and the response-selection stage described by the DSTP model faster than individuals with lower cognitive abilities. Hence, smarter individuals were better at focusing their attention on the target stimulus (reflected in drift rates and decision thresholds during the stimulus-selection stage) and at selecting the appropriate response once their attention was focused on the target stimulus (reflected in drift rates and decision thresholds during the second response-selection stage). This result has important implications for process theories of higher-order cognitive abilities, which propose that individual differences in attentional control contribute to individual differences in intelligence and working memory capacity (Engle, 2018; Kovacs & Conway, 2016, 2019; Shipstead et al., 2016). In particular, they are consistent with process overlap theory, which states that different domain-general executive processes act as

bottlenecks in information processing (Kovacs & Conway, 2016, 2019). Based on our results, process overlap theory would predict that some individuals struggle with certain cognitive tasks because they experience problems in selectively focusing their attention on elements of the tasks, whereas other individuals struggle with the same tasks because they show deficits in response-selection processes. The performance of yet other people may be constrained by cognitive processes not assessed in the present study. Hence, our results are consistent with the idea that different elementary cognitive process parameter contribute to cognitive ability test performance in an independent manner (Kovacs & Conway, 2016, 2019; Thomson, 1916). Moreover, our results are consistent with the idea that individual differences in processes that facilitate the disengagement from and inhibition of irrelevant information give rise to individual differences in cognitive abilities (Engle, 2018; Shipstead et al., 2016). All in all, our results empirically support the starring role that many process theories of intelligence give to attentional control (Schubert & Rey-Mermet, 2019) as individual differences in attentional control predicted 37 % of the variance in individual differences in higher-order cognitive abilities.

Further analyses revealed that the association between individual differences in the stimulus-selection stage and cognitive abilities was fully mediated by sLRP correlates of stimulus selection. To the degree that smarter individuals were better at focusing their attention on the target stimulus than less intelligent ones, they were also faster to neurally inhibit the incorrect response hand in incongruent trials (Gratton et al., 1988; Kopp et al., 1996; Wascher et al., 1999; Willemsen et al., 2004). Although strong causal claims are not warranted due to the correlational design of the present study, we nevertheless think that this full mediation underlines the role of selective attention in cognitive abilities. Several neuroimaging studies have suggested that the anterior cingulate cortex and the lateral prefrontal cortex are involved in conflict monitoring and resolution in the flanker task (Fan et al., 2003, 2005; Posner & Rothbart, 2006). Moreover, theta power increases in the anterior

cingulate cortex have been shown to constrain automatic response priming in cognitive control tasks and have been associated with a slowing of response times in congruent trials and a reduction of response errors in incongruent trials (Pastötter et al., 2010). Structural and functional properties of these brain areas have been repeatedly linked to individual differences in cognitive abilities (Basten et al., 2015; Jung & Haier, 2007) and the frontal control system has even been suggested to be the neural basis of general intelligence (Duncan et al., 2000). We do not think that the moderate associations between the neurocognitive process parameters of attentional control and cognitive abilities found in the present study warrant such a particularly strong claim. Nevertheless, we hope that our results help to ensure that the role of attentional control in cognitive abilities is not prematurely dismissed just because the measurement of individual differences in attentional control poses a methodological challenge.

We found no evidence that the association between individual differences in the response-selection stage and cognitive abilities was mediated by sLRP correlates of response selection. Hence, the variance shared between model parameters of the response-selection stage and cognitive abilities did not overlap with the variance shared between model parameters of the response-selection stage and negative sLRP peak latencies. Moreover, we found that the relationship between the time participants required for response-selection (as predicted by DSTP model parameters) and their cognitive abilities was fully accounted for by age differences in our sample. Taken together, this inconsistency in correlations across measurement layers of the neurocognitive psychometrics model and the age-dependency of the relationship may indicate that the link between cognitive abilities and response-selection processes involved in selective attention is less consistent than the link between individual differences in stimulus-selection processes and cognitive abilities.

Limitations

Although the sample size of the present study was chosen to provide sufficient power to test the hypothesis of close fit for the model with the smallest degrees of freedom and although it was substantially larger than typical sample sizes in ERP studies (Browne & Cudeck, 1992; Clayson et al., 2019), it was still relatively small considering the complexity of the estimated multi-layer structural equation models. For this reason, parameter estimates (i.e., estimated variances, factor loadings, correlation estimates, and regression weights) of these models showed a substantial degree of estimation uncertainty that was reflected in the width of their confidence intervals (Kretzschmar & Gignac, 2019). To account for this problem, we reduced the number of estimated parameters in the most complex structural equation models (i.e., those that assessed relations between model parameters, sLRP latencies, and cognitive abilities) by introducing constraints into measurement models. In particular, we constrained the residual variances of DSTP model parameters to be equal in odd and even trials and the variances of sLRP latencies to be equal across electrode sites. Not introducing these constraints did not affect any of the main conclusions but resulted in even larger estimation uncertainty. Given that the neurocognitive psychometrics approach proposed in the present paper offers a promising perspective to solving the measurement crises of individual differences in attentional control, a replication of the core findings in an independent and ideally larger sample is necessary.

Another limitation of the present study lies in the fact that the first positive sLRP peak was not very pronounced and that no systematic differences in peak amplitude were visible between congruent and incongruent trials (see Figure 5). Although participants showed significantly longer peak latencies in incongruent trials ($\omega^2 = .03$), we would have expected to see a larger effect of flanker congruency on the positive sLRP peak. Previous research has shown that the effect of congruency on the early sLRP peak is determined by the temporal displacement between flanker and target stimuli, with greater effects on both behavioral

performance and peak amplitudes being seen if the flankers are presented before the target (Kopp et al., 1996; Wascher et al., 1999). Future studies examining individual differences in the flanker task should therefore consider to present the irrelevant flankers immediately before the onset of the target stimulus to maximize the effects of response priming. However, such offset presentation would complicate the integrability of the electrophysiological correlates with mathematical model parameters, because the DSTP model assumes a parallel onset of the target and the irrelevant flankers.

Finally, the present study did not address the issue of convergent validity between different measures of attentional control. In their recent review, von Bastian et al. (2020) identified the convergent validity of inhibition measures as an open research question, because several studies failed to identify a coherent latent inhibition factor (e.g., Hedge et al., 2018; Rey-Mermet et al., 2018, 2019), whereas others identified such a factor (albeit with a low unique variance) that was substantially related to real-world behaviors (e.g., Friedman et al., 2007; Young et al., 2009). The current study does not add to this debate, because the DSTP model has only been validated for the Eriksen flanker task. While it has been discussed that parameters of the late response-selection stage of the DSTP model could be mapped onto parameters of late selection processes described by computational models of the Stroop task and that the DSTP model may even be used to model performance in the Stroop task (Hübner et al., 2010; White et al., 2018), such an application of the model would first need to be validated. More broadly applicable models of decision making in conflict tasks such as the Diffusion Model for Conflict Tasks (DMC) may instead be better suited to address the question of convergent validity between different measures of attentional control, because they have not been tailored to specific experimental tasks (Ulrich et al., 2015). In a recent reanalysis of seven datasets from previously published studies, Hedge et al. used the DMC to describe performance in the Eriksen flanker, Stroop, and Simon tasks (2020). They found no substantial between-task correlations of model parameters reflecting conflict processing, but

only of model parameters reflecting general processing speed, the speed of non-decisional processes, and decision cautiousness. All in all, more research will be needed to address the question of criterion validity of attentional control in a comprehensive manner.

Conclusions

We proposed a neurocognitive psychometrics account of attentional control to overcome problems in the reliable and valid measurement of individual differences in attentional control. Integrating parameters of a cognitive process model and neural correlates of attentional control in a multi-layer structural equation model framework, we demonstrated that model parameters and neural correlates showed convergent validity and could be meaningfully related to each other. Together, these neurocognitive process parameters jointly predicted 37 % of the variance in individual differences in higher-order cognitive abilities. Individuals with greater cognitive abilities were not only better at focusing their attention on the target stimulus, but also at subsequent response-selection. All in all, our results support the idea that individual differences in attentional control processes contribute to individual differences in cognitive abilities. Moreover, they provide hope that the measurement crisis of individual differences in attentional control can be overcome by integrating measurement approaches from related disciplines such as mathematical psychology and cognitive neuroscience.

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