Processing Speed, Working Memory, and Executive Functions: Independent or inter-related predictors of intelligence

The currently most discussed cognitive processes underling individual differences in intelligence are speed of information processing (Jensen, 2006; Schubert, Hagemann, & Frischkorn, 2017; Sheppard & Vernon, 2008), working memory capacity (Ackerman, Beier, & Boyle, 2005; Conway, Cowan, Bunting, Therriault, & Minkoff, 2002; Kane, Hambrick, & Conway, 2005), and executive functions (Friedman et al., 2006; Jewsbury, Bowden, & Strauss, 2016; Miyake, Friedman, Rettinger, Shah, & Hegarty, 2001). These three processing domains were often discussed separately or as independent predictors of individual differences in intelligence, focusing on the question which of the processes shows the largest relationship to individual differences in intelligence. Especially regarding processing speed and working memory capacity as predictors of intelligence, some researchers argued for them being independent predictors (Colom, Abad, Quiroga, Shih, & Flores-Mendoza, 2008), while others showed considerable correlations between these two processing domains (Ackerman, Beier, & Boyle, 2002; Kyllonen & Christal, 1990; Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007; Schmitz & Wilhelm, 2016).

Recent results indicated that the neural speed of information processing of higher order cognitive processes explains up to 80% of variance in intelligence (Schubert, Hagemann, & Frischkorn, 2017), matching the amount of variance in intelligence often explained by working memory capacity (Kyllonen & Christal, 1990; Oberauer, Schulze, Wilhelm, & Süß, 2005). This finding strongly suggests that these two processing domains cannot be independent predictors of individual differences in intelligence. Hence, it follows that speed of information processing and

the capacity of working memory have to be inter-related and might be constrained by similar features of the neuro-cognitive system (Dang, Braeken, Colom, Ferrer, & Liu, 2015). The aim of the present study is to bridge the gap between working memory capacity (WMC) and processing speed (PS) as predictors of intelligence. On the basis of current conceptions of working memory (Barrouillet, Portrat, & Camos, 2011; Cowan, 2017; Oberauer, 2002; Oberauer & Kliegl, 2006) that emphasize the role of attentional processes the present study explores in how far executive functions (i.e. attention regulation mechanisms sensu Miyake et al., 2000) may explain the inter-relation between WMC and PS as predictors of intelligence.

The relationship of processing speed with intelligence

Across a variety of different measures there is a consistent relationship between speed of information processing and intelligence (Jensen, 2006). A review of a broad variety of tasks reported an average correlation of $r = -.24$ of single task measures of PS and intelligence (Sheppard & Vernon, 2008). These correlations tend to increase ($r = -.40$ to $-.50$) when reaction times from different tasks are aggregated (Kranzler & Jensen, 1991; Schmitz & Wilhelm, 2016; Schubert, Hagemann, & Frischkorn, 2017), indicating that foremost variance shared between different measures for PS is related to intelligence. Moreover, the correlation between PS and intelligence increases even further, if measures specifically representing the speed of the decision process, such as the *drift rate* from the diffusion model, are used to represent processing speed (Schmiedek et al., 2007).

Separating encoding processes and motor execution from the actual decision process via cognitive modeling is a promising approach to further investigate the relationship between speed of information processing and intelligence (Frischkorn & Schubert, 2018). Specifically, the diffusion model (Ratcliff, 1978) has often been successfully used to separate the speed of

information accumulation, represented by the *drift rate*, from other processes included in

reaction times, such as encoding, motor execution or response caution. Results indicated that

drift rates show trait-like properties (Schubert, Frischkorn, Hagemann, & Voss, 2016) and show

consistent relationships with intelligence ranging from r = .50 to .90 (Ratcliff, Thapar, &

McKoon, 2010; Schmiedek et al., 2007; Schubert, Hagemann, Voss, Schankin, & Bergmann,

2015). This suggests that it is precisely the speed of information accumulation that is related to

intelligence and not speed of motor execution or encoding.

However, PS can not only be measured via behavioral indicators such as reaction times,

but also with neurophysiological indicators such as latencies of event-related potential

components (Verleger, 1997). The event-related potential (ERP) decomposes the stream of

neural information processing from stimulus onset until the response into distinct components

that can be linked to specific cognitive functions (Luck & Kappenman, 2011). Specifically,

individual differences in the latency of an ERP component may reflect individual differences in

the neural speed of information processing, meaning that a higher speed of information

processing results in shorter latencies of an ERP components. Moreover, the onset of an ERP

component may also serve as an indicator of its functionality. While ERP components occurring

early after stimulus onset are mostly related to stimulus encoding, ERP components with a later

onset are foremost connected to higher-order processing.

Despite rather weak and inconsistent results on the relationship between latencies of ERP

components and intelligence (Schulter & Neubauer, 2005), a number of empirical results showed

consistent negative relations between the latency of the P3 component or the mismatch

negativity (MMN) and intelligence (Bazana & Stelmack, 2002; McGarry-Roberts, Stelmack, &

Campbell, 1992). In detail, more intelligent people displayed shorter latencies of the P3 (Bazana

& Stelmack, 2002; McGarry-Roberts et al., 1992; Troche, Houlihan, Stelmack, & Rammsayer, 2009), which is an ERP component that is associated with stimulus evaluation and categorization, context updating, and context closure. Furthermore, this relationship of latencies of ERP components with intelligence is mediated via behavioral RTs (Schubert et al., 2015) suggesting that neural processing speed may functionally underlie faster information processing on a behavioral level.

The mostly inconsistent relationship of ERP latencies with intelligence can be attributed to different problems, such as (1) small sample sizes (N < 50), (2) questionable selection of electrode sites for the measurement of ERP latencies, and (3) quantification of relationships with single task measures that confound task-related fluctuations with the trait-like neural processing speed of a person. A recent study addressing these issues by measuring ERP latencies for three different tasks at two measurement occasions could demonstrate that the shared variance of later ERP components (P2, N2, & P3) explained up to 80% of variance in intelligence (Schubert, Hagemann, & Frischkorn, 2017). Moreover, the results of this study indicated that the variance of single task latencies of ERP components included a large proportion of task- and condition-specific variance, which may be irrelevant to the relationship of ERP latencies with intelligence, as well as substantial unsystematic error variance. This finding may explain the inconsistent results from earlier studies using only single task measures. Taken together, all these results from behavioral and neuro-psychological studies indicate that there is a strong relationship between speed of higher order information processing and intelligence.

The relationship of working memory capacity with intelligence

In addition to speed of information processing, also working memory capacity has been closely linked to individual differences in intelligence (Ackerman et al., 2005; Kane et al., 2005;

Oberauer et al., 2005). Comparable to cognitive ability tasks, measures of working memory

capacity (WMC) are highly correlated with each other (Engle, Tuholski, Laughlin, & Conway,

1999; Kane et al., 2004; Oberauer, Süß, Wilhelm, & Wittman, 2003; Unsworth, Fukuda, Awh, &

Vogel, 2014) and resemble a hierarchical structure, with a broad single factor at the highest level,

and more domain and process specific factors on the lower level (Bayliss, Jarrold, Gunn, &

Baddeley, 2003; Kane et al., 2004; Oberauer et al., 2003; Shah & Miyake, 1996). Correlations

between the broad factor of WMC and intelligence are very high, ranging from r = .70 to .90

(Conway et al., 2002; Kane et al., 2005; Kyllonen & Christal, 1990; Oberauer et al., 2005).

These high correlations have led to a vivid discussion in how far WMC and intelligence may be

isomorphic (Ackerman et al., 2005; Kane et al., 2005; Oberauer et al., 2005), ultimately resolved

by concluding WMC explains a large proportion of individual differences in intelligence.

In addition to these correlational studies there are results from an experimental study

suggesting that overloading working memory while performing a matrix reasoning test affected

performance in the reasoning measure (Rao & Baddeley, 2013). In detail, participants were

asked to remember a set of three digits and count backwards while working on the matrix

reasoning task. Results showed that especially the time needed to solve an item increased

compared to a silent control and an articulatory suppression condition. Altogether these results

suggest that working memory is not only strongly related to individual differences in intelligence

but may actually causally underlie variations in it.

While this strong relationship between working memory and intelligence is undisputed,

researchers do not agree which process within working memory is central to the relationship of

working memory and intelligence. Some researchers argue that the relationship is best explained

by similar demands on short-term memory storage (Colom et al., 2008; Colom, Flores-Mendoza,

Quiroga, & Privado, 2005; Shahabi, Abad, & Colom, 2014), and others argue that processes specific to complex span tasks such as attention regulation are the reason for the strong association between working memory and intelligence (Conway et al., 2002; Unsworth et al., 2014). As there is robust evidence that the capacity of working memory is related to attentional processes (Chuderski, Taraday, Nęcka, & Smoleń, 2012; Kane & Engle, 2003; McVay & Kane, 2009, 2012; Meier & Kane, 2013) and current theories of working memory assume that attention plays a major role in maintenance of memory items regardless of concurrent processing (Oberauer, Farrell, Jarrold, & Lewandowsky, 2016; Souza & Vergauwe, 2018), it is plausible that both the capacity of short-term memory storage and additional demands in complex span tasks are strongly related to the same attentional processes within working memory (Barrouillet et al., 2011; Wilhelm, Hildebrandt, & Oberauer, 2013).

Executive Functions: Bridging the gap between processing speed and working memory?

Candidates for the attentional processes underlying both maintenance of items in short-term memory as well as additional demands of complex span tasks are executive functions. Executive functions (EFs) were initially defined as attentional control mechanisms within the central executive of working memory (Baddeley & Hitch, 1974; Jurado & Rosselli, 2007). However, in current research there is considerable heterogeneity and discussion with respect to the conception of executive functions[1] (Karr et al., 2018).

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[1] The term *executive functions* has been used to summarize either a very broad range of higher-order cognitive processes (Barbey et al., 2012; Diamond, 2013) or to describe a specific set of attention control mechanisms supposedly within the central executive of working memory (Jurado & Rosselli, 2007). The broad definition of executive functions subsumes a broad range of cognitive processes such as working memory, reasoning or fluency. Having this definition in mind, it is not plausible that executive functions mediate the relationship between working memory capacity and processing speed with intelligence. Therefore, the present article used the term *executive functions* in a more restricted sense, referring to attentional regulation mechanisms as conceptualized by Miyake et al. (2000). With respect to a broader definition of executive functions it may thus be reasonable to think of these processes as specific sub-components of executive functions that primarily involve attention.

Within the present manuscript we refer to EFs as a set of attention regulation mechanisms as described by Miyake et al. (2000) that are used to (a) focus attention on relevant information while ignoring irrelevant information (i.e. inhibition), (b) encode new information to memory while removing outdated and no longer relevant information (i.e. updating), or (c) switch between different tasks (i.e. shifting). While it is still under debate in how far these different EFs have to be separated or share common variance (Friedman & Miyake, 2017; Miyake & Friedman, 2012), the majority of results suggests that there is considerable overlap between the three EFs (Karr et al., 2018). Moreover, EFs have recently been subsumed within the hierarchical structure of intelligence (Jewsbury et al., 2016). In detail, updating was integrated within a general memory factor g_m, while shifting and inhibition were integrated in the general speed factor g_s, pointing towards relations of EFs with both memory and processing speed.

With respect to speed of information processing, the results from Schubert et al. (2017) support the proposal that executive functions may underlie the relationship of processing speed with intelligence as well. In detail, the latency of the P3 component showed the strongest association with intelligence. The P3 component has often been interpreted as an indicator of the efficiency of context-updating (Donchin, 1981; Polich, 2007), and thus shorter latencies of the P3 may reflect a faster inhibition of nonessential processes that in turn ease the transmission of information from attention and working memory regions located frontally in the brain to parietal memory storage processes (Polich, 2007). There is additional support for this hypothesis from behavioral studies showing strongest relations between inhibition and updating with intelligence (Wongupparaj, Kumari, & Morris, 2015).

Beyond that, cognitive as well as neural theories of intelligence are in line with this theoretical perspective. The process-overlap theory (POT; Kovacs & Conway, 2016) assumes

that attentional control mechanisms are among the domain-general processes that act as a bottleneck constraining performance in a broad range of cognitive tasks. Moreover, the parieto-frontal integration theory (P-FIT; Jung & Haier, 2007) proposes that individual differences in the efficiency of information transmission from frontal association cortices and parietal brain regions may explain individual differences in g. P-FIT has been widely supported by results from structural and functional neuroimaging studies (Burgess, Gray, Conway, & Braver, 2011; Colom, Jung, & Haier, 2007; Colom & Thompson, 2013; Gläscher et al., 2010). Altogether, attention regulation mechanisms such as EFs may provide a theoretical account to bridge the gap between processing speed and working memory as predictors of individual differences in intelligence.

The present study

We conducted the present study to investigate in how far individual differences in executive functions (EFs) may underlie the relationship of processing speed and working memory capacity with intelligence. To that end, we administered three different EF tasks each tapping one of the executive functions (i.e. shifting, updating, and inhibition). While we recorded both behavioral responses and participants' EEG during the three EF tasks to further differentiate between behavioral and neurophysiological indicators of executive functions, we report only results for behavioral responses in this article.[2] Additionally, we assessed participants' intelligence, their working memory capacity, and speed of information processing to investigate in how far individual differences in EF tasks explain the relationship between these three constructs.

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[2] Preliminary analyses revealed an absence of experimental effects in ERP latencies and amplitudes, therefore EEG data were excluded from further analyses.

More specifically, we aimed to address two major points: First, we wanted to investigate in how far performance in the different experimental conditions of EF tasks measure performance specific to the manipulations that are related to the respective EFs, or performance that is unspecific with respect to the experimental manipulations. In addition, there still is a vivid discussion on the unity and diversity of the often separated EF: updating, inhibition, and shifting. Therefore, we were also interested whether inter-individual differences in intra-individual experimental effects within each EF were correlated. A substantial correlation would suggest unity in contrast to diversity of the three EF separated by Miyake et al. (2000). And second, we were interested how the two components of performance in EF tasks (manipulation specific vs. general) are related to processing speed, working memory capacity, and intelligence. All in all, joining the individual differences constructs of intelligence, processing speed, and working memory capacity with executive functions may provide insights in how far individual differences in EFs may explain the relationship between processing speed and working memory capacity as correlated predictors of intelligence.

Methods

Sample

We recruited a community sample of 107 participants via newspaper ads and flyers. The 101 participants[3] (53 ♀, 48 ♂) who attended both sessions of the experiment were on average 39.1 years (SD_{age} = 14.5, Min_{age} = 18, Max_{age} = 61), and were rewarded with 50€ for their participation. Although participants were recruited from the community, most of them were well

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[3] Only data from the participants who attended both sessions was analyzed and reported in the manuscript.

educated (42.6% university degree, 42.6% college degree, 10.9 % high school degree, 3.9% did

not report educational background). Nevertheless, average performance and individual

differences on the intelligence measures (M_{IQ} = 95.5, SD_{IQ} = 11.8) suggest slightly below

average cognitive ability, $t(100)$ = -3.85, p < .001, d_{Cohen} = .30 [.10, .51], compared to the

standardization sample[4] (M_{IQ} = 100) and no considerable restriction in variance. While the

overall sample size is comparably small for structural equation modeling, we secured that it had

sufficient power (1-β > .80) to assess model fit with the RMSEA (H0$_{RMSEA}$ =.05, H1$_{RMSEA}$ = .10,

df$_{Model}$ = 50, α = .05, N$_{Min}$ = 97).

General Procedure

The study consisted of two sessions that were approximately four months apart. In the

first occasion, participants completed three executive functioning tasks – a Switching task, an *N*-

Back task, and the Attention Network Test – while an EEG was recorded. For this occasion,

participants were seated in a dimly lit, sound-attenuated EEG cabin and tested individually. In

the second session, participants' intelligence, working memory capacity, and processing speed

were measured with paper-pencil tests and computerized tasks. In addition, participants

completed three knowledge tests and two personality questionnaires not reported here. This

session was conducted in groups of up to four participants. Both sessions took approximately 3

hours, and the sequence of tasks within the two occasions was the same for all participants.

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[4] It is important to note that the standardization sample of the BIS consisted of adolescents between the

ages of 18 to 20 and therefore likely represents an above average sample with respect to cognitive abilities.

Measures

        Executive Functions. The three executive functions sensu Miake et al. (2000) – shifting,

updating, and inhibition – were each assessed with one task. To additionally asses in how far all

executive functions rely on the same attention process conceptualized as executive attention by

Posner and Petersen (1990), a flanker manipulation was implemented in each of the three tasks

(Eriksen & Eriksen, 1974).

        Switching Task. The Switching task was adapted from Sauseng et al. (2006). An

illustration of the trial procedure can be found in Figure 1A (p. 42). In this task, participants saw

a digit from 1 to 9 (except the number 5) colored red or green that was presented centrally on a

black screen. Participants either had to decide whether the digit was smaller or larger than five or

whether it was odd or even, depending on the color of the presented number. Prior to the onset of

the target stimulus, a light grey fixation cross was presented centrally on the screen for 400-

600ms. Between onset of the target stimulus and the fixation cross, an inter-stimulus interval

(ISI) consisting of a blank screen was shown for 400-600ms that was presented until participants

responded and stayed on the screen for another 500ms to avoid offset potentials in the EEG due

to perceptual changes on the screen. Participants responded via keypresses on the keyboard by

pressing a left key "d" if the digit was smaller than five or odd, and a right key "l" if the number

was larger than five or even. Before the next trial started, there was an inter-trial interval (ITI) of

1000-1500ms.

        The switching task consisted of four different blocks. In the first two blocks, participants

had to decide whether the number was less or more than 5 in one block, or odd or even in the

other block, irrespective of the stimulus color. These *control blocks* consisting of 48 trials (8

digits x 2 colors x 3 repetitions) did not require any task switching and were used to quantify

global switch costs in comparison to the two switching blocks. In the third block, participants

were instructed to decide whether the digit was smaller or bigger than 5 for red stimuli and odd

or even for green stimuli. This *shifting* block consisted of 96 trials (8 digits x 2 tasks x 2 shifting

x 3 repetitions) of which the to-be-conducted task switched in half of the trials. In the last block,

additional flanker stimuli that were congruent, neutral, or incongruent to the target stimulus were

added to the task and participants were instructed to ignore the flankers while completing the

same task as in the *shifting* block. This *shifting flanker* block consisted of 288 trials (8 digits x 2

tasks x 2 shifting x 3 flanker x 3 repetitions). The color of flanker and target stimuli was always

the same, therefore congruency of the flankers was only manipulated on the content level (i.e. the

numerical information), but not on the task cue level. Incongruent flankers were always a

different digit than the target stimulus, but could indicate the same response as the target

stimulus (e.g., red 8 as flankers and a red 6 as target are both larger than 5).

All participants completed 16 practice trials per block. The experimental trials within all

blocks were pseudo-randomly sorted following some constraints: In all blocks, digits were not

allowed to repeat more than three times in a row. Likewise, stimulus color, and thus tasks in the

switching blocks, and responses were not allowed to repeat more than three times in a row.

N-Back Task. Participants completed a 2-Back task that was adapted from Scharinger et

al. (2015). The trial procedure of the *N*-Back task can be seen in Figure 1B (p. 42). Participants

saw a series of light grey letters (H, C, F, or S) shown centrally on the screen one after the other.

For each letter, participants decided whether or not it was identical to the letter presented two

steps before. Between subsequent letters, there was an ISI consisting of a blank screen that was

shown for 1000-1500ms. The letters were always shown for 2500ms irrespective of the time

participant needed to respond. This way we ensured that all participants had the same time to

encode the new letter and decide whether it matched the letter two steps back. Additionally, by not changing the perceptual input after participants' responses, we avoided offset potentials in the EEG. Participants responded via keypress, pressing a left key "d" if the current letter did not match the letter two steps back, and pressing a right key "l" if the current letter matched the letter two steps back.

The *N*-Back task consisted of two blocks. In the *2-back* block, participants completed 96 trials (4 letters x 2 match x 12 repetitions) of the 2-Back task, preceded by two introductory trials requiring no response as there were no letters two steps prior to presentation. In the *2-back flanker* block, participants completed 384 trials (4 letters x 2 match x 4 flanker x 12 repetitions) of the 2-Back task with additional flanker stimuli. Unlike in the Shifting Task, there were four levels of the flanker manipulation within this block. There either were no flanker stimuli – like in the 2-back block – or flanker stimuli that were either congruent, neutral or incongruent. Moreover, the flanker block was separated into three sub-blocks consisting of 128 trials, in order to give participants short breaks. Like in the 2-back block, the experimental trials of all sub-blocks were preceded by two introductory trials requiring no response.

Participants completed 16 practice trials that were repeated until participants' average accuracy in these 16 practice trials was above chance. Experimental trials were pseudo-randomly sorted with the constraint that responses and thus the match conditions were allowed to repeat a maximum of two times. Additionally, flanker congruency was not allowed to repeat more than two times in the flanker block.

Attention Network Test (ANT). In the Attention Network Test (Fan et al.), participants had to decide whether an arrow pointed left or right (see Figure 1C for the trial procedure). The arrow (i.e., the target stimulus) could appear above or below a fixation cross that was located

centrally on the screen. Furthermore, the centrally presented arrow was flanked by two more arrows to the left and right. The flanking arrows were either pointing in the same direction (congruent), in the other direction (incongruent), or were without arrow heads indicating any direction (neutral).

Each trial started with a light grey fixation cross presented centrally on the black screen for 400-1600ms, followed by a short cue stimulus presented for 100ms. There were four different cue options: (1) There was no cue and the fixation cross remained on the screen, (2) there was a central cue at the position of the fixation cross, (3) there was a double cue above and below of the fixation cross, or (4) there was a spatial cue located either above or below the fixation cross validly cueing the position of the following target stimulus. Between the cue stimulus and the target stimulus there was an ISI of 400ms with the fixation cross being presented centrally on the screen. Then the target stimulus, i.e. the central arrow, and flanker arrows appeared above or below the fixation cross on the screen and participant had to decide whether the central arrow pointed right or left. Participants responded via key press, pressing the left key "d" if the arrow pointed left, and the right key "l" if the arrow pointed right. The target stimulus and flanker stimuli remained on-screen for 1700ms, irrespective of the speed of the response. Before the next trial started, there was an ITI again consisting of the light grey fixation cross presented centrally on the screen that lasted 1700ms.

The ANT consisted of three blocks of 96 trials each (2 direction x 2 location x 4 cue x 3 flanker x 2 repetitions) that were pseudo-randomly sorted. Specifically, all of the four experimental factors were allowed to repeat a maximum of three times in subsequent trials. 24 practice trials were conducted prior to the first experimental block. In between blocks, participants took short breaks and read a short reminder of the task instructions.

Intelligence. Intelligence was measured with the short-version of the Berlin Intelligence Structure test (BIS; Jäger, Süß, & Beauducel, 1997). The BIS is based on the bimodal Berlin Intelligence Structure model (Jäger, 1982). According to this model, the 15 tasks of the BIS short version are grouped into four operation-related (processing capacity, memory, processing speed, and creativity) and three content-related (verbal, numerical, and figural) components of intelligence (for a detailed review and replication of the BIS structure see Bucik & Neubauer 1996). Each task combines one operation-related component with one content-related component of intelligence. The standard scores of the five tasks with verbal, numerical, and figural content were aggregated across operations and used as separate indicators of intelligence.

Working Memory Capacity (WMC). Working memory capacity was measured with four tasks from the working memory test battery by Lewandowsky et al. (2010). Specifically, we used the memory updating task, two complex span tasks, and a spatial short-term memory task. Following the scoring script provided by Lewandowsky et al. (2010), performance was measured by the mean proportion of correctly remembered items for each task separately.

Processing Speed (PS). We measured participants' processing speed with two elementary cognitive tasks (ECTs), the Posner letter matching task and the Sternberg memory scanning task. These tasks are commonly used as an indicator of basic information processing speed.

Posner Letter Matching Task. In the Posner Letter Matching task (Posner & Mitchell, 1967), participants decided whether two letters were physically or semantically identical. The experimental procedure was adapted from Schubert et al. (2017). Specifically, the participants completed two different blocks, first a physical identical and second a name identity block. Each of the two blocks consisted of 40 trials preceded by 10 practice trials, in half of which the two

letters matched physically or semantically corresponding to the block instructions. The two

letters comprising the target stimulus were selected from a pool of five letters (a, b, f, h, q) that

could be capitalized or not. Each trial started with a fixation cross presented centrally on the

screen for 1000-1500ms. Immediately after that, the letter pair was shown on the screen.

Participants then responded via key press, pressing either a right or left key with their index

fingers, indicating whether the two letters were physically or semantically identical. Response

mapping of the keys was counterbalanced across participants. After the response, the trial ended

and the next trial started after an ITI of 1000-1500ms. We used the mean logarithmized RT of

correct responses in the two blocks (physical vs. semantic identity) as two separate indicators of

processing speed.

   Sternberg Memory Scanning Task. In the Sternberg Memory Scanning task (Sternberg,

1969), participants saw a memory set of digits from zero to nine and had to decide whether a

subsequently presented probe digit was contained in the memory set or not. Again, the

experimental procedure was adapted from Schubert et al. (2017). Participants completed two

blocks, first one block with memory set size three and second one block with set size five, each

consisting of 40 trials, preceded by 10 practice trials. In each block, the probe digit was

contained in the memory set in half of the trials. Each trial started with a fixation cross presented

centrally on the screen for 1000-1500ms. Then the digits comprising the memory set were

presented sequentially on the screen for 1000ms with an ISI of 400-600ms. After the last digit, a

question mark was presented for 1800-2200ms, followed by the probe digit. Participants then

responded via key press, pressing either a left or right key with their index finger. The response

mapping of keys was counterbalanced across participants. After the response, the trial ended and

the next trial started after an ISI of 1000-1500ms. Again, we used the mean logarithmized RT of

correct responses in the two experimental blocks (set size three vs. five) as separate indicators of processing speed.

Data Analyses

Pre-Processing: Behavioral data. To ensure that intra-individual outliers in reaction times measured in EF tasks and ECTs did not distort our results, we discarded trials with RTs shorter than 150ms or longer than 3000ms. Then, we discarded any incorrect trials and trials in which the logarithmized reaction times of correct responses deviated more than 3 SD from the mean logarithmized reaction time of each participant within the different conditions in each task. Finally, we calculated the mean logarithmized reaction time as the dependent variable. As accuracies were very high ($M > .90$) and showed little to no variation in all EF tasks and ECTs (see Table 1), we refrained from analyzing accuracy measures.

For all measures, we conducted additional uni- and multi-variate outlier analyses on the between-person level. First, univariate outliers deviating more than 3 SDs from the mean were deleted, resulting in 0.0 % to a maximum of 2.3 % of subjects being excluded across the different measures. Second, multi-variate outliers on the different measures within each cognitive process were identified. Only in the ANT did the Mahalanobis distance for one participant exceed the critical value of $\chi^2(12) = 39.9$. This subject was excluded case wise for the ANT. Finally, multivariate outliers across the measures of different cognitive processes were again identified via the Mahalanobis distance. As no subject exceeded the critical value of $\chi^2(23) = 49.7$, no data was discarded in this final step.

Statistical analyses. As an initial manipulation check, we analyzed whether the experimental manipulations in the EF tasks showed the usual effects on behavioral response times. This ensured that the EFs supposed to be required by specific experimental manipulations

were actually demanded within the respective task. For all ANOVAs, we corrected violations of sphericity by adjusting the degrees of freedom with the Greenhous-Geisser correction. For post-hoc comparisons, *p*-values were corrected with the Tukey method.

Following these experimental analyses, we estimated structural equations models addressing the two main research questions of the present study: 1) does performance across conditions in EF tasks represent mainly general or manipulation-specific aspects, and 2) how are these different variance components in EF tasks related to intelligence, working memory capacity, and processing speed. Therefore, we first established separate measurement models for the EF tasks. All of these models were set up as bi-factor models with all indicators across the different blocks and experimental manipulations loading on a general speed factor, and factors specific to the experimental manipulations or blocks within each EF task. Due to the rather small sample for SEM, we kept the number of freely estimated parameters in these models as low as possible to ensure stable parameter estimates and therefore either fixed loadings to one or constrained them to be equal. In addition, fixing or constraining the loadings on both manipulation specific and general factors more closely resembles latent change score models (Kievit et al., 2018; Steyer, Eid, & Schwenkmezger, 1997), mimicking the often used difference scores used to measure EFs.

This bi-factor approach allowed us to separate task-general and manipulation-specific variance in the EF tasks, with the manipulation-specific factors capturing individual differences in executive functions associated with specific experimental manipulations. These bi-factor models will answer the first of the two major points we wanted to investigate within the present study, namely, in how far performance within one condition of an EF task represents general performance, or performance specific to the manipulation that is linked to the respective EF.

The best fitting bi-factor models for the EF tasks were then merged and the three covariates were entered into the model. In a first step, we analyzed the three covariates – intelligence, processing speed, and working memory capacity – separately; in a second step, we included all covariates simultaneously to additionally assess the inter-relations between covariates and answer the second of the two major points we wanted to investigate in the present study: How is general and manipulation-specific variance from EF task related to WMC, PS, and intelligence, and do these relationships provide evidence that individual difference in EF might represent the missing link between WMC and PS as a predictor of intelligence?

We assessed model fit of all structural equation models using the comparative fit index (CFI; Bentler, 1990) and the root mean square error of approximation (RMSEA; Browne & Cudeck, 1992). We considered model fit as acceptable with CFI > .90 and RMSEA < .10 (Bentler, 1990; Browne & Cudeck, 1992; Hu & Bentler, 1999). When model evaluation diverged between the two fit criteria, we evaluated model fit with the more favorable fit index, because previous research has shown that goodness-of-fit statistics tend to underestimate absolute model fit in small samples (Kenny, Kaniskan, & McCoach, 2015; Schubert, Hagemann, Voss, & Bergmann, 2017). For comparisons of two models, we required more complex models to show a lower AIC than more parsimonious models with an AIC difference $\Delta^{AIC} > 10$ to retain the more complex model (Burnham & Anderson, 2002). Finally, we assessed statistical significance of model parameters with the two-sided critical ratio test. If parameters did not differ significantly from zero, we fixed them to zero and estimated the SEM again. Thus, only parameters significantly different from zero are reported in the results section.

Results

Manipulation Check: EF tasks

To ensure that experimental manipulations within the EF tasks demanded the respective attentional control mechanisms, we ran within-subject ANOVAs for the three EF tasks. The mean reaction time and proportion of correct responses across the different experimental conditions within the three tasks are displayed in Table 1. For brevity, we only report the effect size estimates of the critical manipulations in the text, the full statistical results of the ANOVAs calculated for the manipulation check can be found in Table 2. For descriptive plots that display the effects of experimental manipulations on behavioral RT in the three EF tasks see Figure 2.

Switching. There were substantial global switch costs as indicated by shorter response times in *control* than both the *shifting* and *shifting flanker* blocks, $\omega_p^2 = .54$. Within shifting blocks, response times were faster in trials with task repetition than task switches, $\omega_p^2 = .70$, indicating large local switch costs (see left part of Figure 2A). In detail, local switch costs were smaller in the *shifting flanker* than in the *shifting* block, $\omega_p^2 = .32$. With respect to the flanker manipulation in the *shifting flanker* block, response times were slowest in trials with incongruent flankers and response times did not differ between trials with neutral and congruent flankers, $\omega_p^2 = .31$ (see right part of Figure 3A). This results resembles the standard inhibition effect of flanker stimuli (c.f. Eriksen & Eriksen, 1974). Furthermore, the effect of flanker did not change between switch and repeat trials, $\omega_p^2 = .00$.

N-Back. Behavioral reaction times did not vary between the *2-back* and the *2-back flanker* block, $\omega_p^2 = .00$. However, response times were faster for match than for no-match trials in both blocks, $\omega_p^2 = .87$ (see left part of Figure 3B). This is a common difference between match

and no match retrievals from memory. Although reaction times varied across flanker conditions in the flanker block, $\omega_p^2 = .60$ (see right part of Figure 2B), this flanker effect was mostly due to differences between the neutral and no flanker condition with congruent or incongruent flankers. The critical inhibition effect – i.e. longer reaction times in incongruent than in congruent trials – was, however, only present in match trials. In sum, there was no consistent inhibition effect of flanker stimuli in the N-Back task on behavioral RTs.

   ANT. Overall, participants' response time varied across cue conditions (see Figure 2C), $\omega_p^2 = .87$. In detail, there was both a significant alerting effect (i.e. longer reaction times/latencies for no cues than for double cues), $\omega_p^2 = .71$, and orienting effect (i.e. shorter latencies for spatial than for central cues), $\omega_p^2 = .91$, consistent with the expected results from previous studies (Fan et al., 2009; Fan, McCandliss, Sommer, Raz, & Posner, 2002). More importantly, behavioral reaction times showed a strong inhibition effect, $\omega_p^2 = .93$, with slowest response times for trials with incongruent flankers compared to congruent or neutral flankers. While the inhibition effect changed significantly across cue conditions, this change was considerably smaller than the overall inhibition effect, $\omega_p^2 = .07$. In sum, the manipulation of inhibition was successful for behavioral reaction times.

SEM Analysis: Bi-factor models for the EF tasks

   Switching task. The bi-factor model capturing general and condition-specific variance of behavioral RTs in the Shifting task (see Figure 3A) fitted well to the data, $\chi^2(53) = 41.1$, $p <$ .884, CFI = 1.00, RMSEA = .00, 90% CI = [.00, .03]. The general processing speed factor explained between 43 to 76% of the variance of the manifest indicators, while all condition specific factors together explained between 36 to 51% of the variance in the manifest indicators.

In detail, the global shifting factor explained between 6 to 51%, the local shifting factor 9 to

10%, and the flanker factor between 21 to 23% of the variance in the manifest indicators.

Additional factors for inhibition or facilitation effects of flanker stimuli had non-significant

variances and were thus not included in the final model. Taken together, between 76 to 95% of

variance in manifest indicators was explained by both manipulation-specific factors and the

general factor.

N-Back task. The bi-factor model for the behavioral RTs in the *N*-Back task (see Figure

3B) fitted well to the data, $\chi^2(56) = 60.2$, $p < .326$, CFI = 1.00, RMSEA = .03, 90% CI = [.00,

.07]. The general processing speed factor again explained the largest proportion of variance in

manifest RTs in the *N*-Back task with 43 to 81%. All condition-specific factors together

explained 18 to 52% of variance. Specifically, the flanker factor explained between 27 to 29%,

the no match factor explained between 18 to 21% and the facilitation factor 3% of the variance in

manifest indicators. The factor for inhibition effects of flanker stimuli showed a non-significant

variance and was thus not included in the model. All these factors together explained between 81

to 95% of variance in manifest response times.

ANT. Consistent with results of the two other EF tasks, the bi-factor model for

behavioral RTs in the ANT (see Figure 3C) showed a good fit as well, $\chi^2(83) = 91.8$, $p < .238$,

CFI = 1.00, RMSEA = .03, 90% CI = [.00, .07]. Again, consistent with results from the other two

EF tasks, the general processing speed factor explained between 86 to 96% of variance in

manifest indicators. Contrary to results from the other two EF tasks, the condition-specific

factors explained a lower amount of variance in manifest variables with only 2 to 9%.

Specifically, the inhibition factor explained 7% and the no cue and spatial cue factor about 2% of

variance in manifest variables. Condition-specific factors for the other cue conditions and for

facilitation showed non-significant variances and were not included in the model. Taken

together, all factors explained between 93 and 96% of variance in manifest response times.

SEM Analysis: Relationship of EFs with WMC, PS, and Intelligence

      Joint Models for the three EF tasks. A joint model of behavioral reaction times in the

three EF tasks (i.e. of all models depicted in Figure 3) indicated medium to large correlations

between the three general factors measured in the three EF tasks (r_s = .37 − .76). Additionally

estimating correlations between manipulation-specific factors of the three EF tasks did not

improve model fit, ΔAIC = -30.8, $\Delta\chi^2(27)$ = 23.2, p = .672. Moreover, joining the three general

processing speed factors into one factor did not impair model fit, ΔAIC = -1.8, $\Delta\chi^2(1)$ = 0.2, p =

.643, and represented a more parsimonious account of the covariance structure. Specifically, the

task-general factor explained all variance of the general factor from the shifting task, 56 % of

variance of the general ANT factor, and 27 % of variance of the general N-Back factor. As this

model showed a good fit to the data, $\chi^2(528)$ = 647.8, p < .001, CFI = .98, RMSEA = .05, 90%

CI = [.33, .06], it was retained for further analyses with the three covariates. Altogether, this joint

model of the three EF tasks indicated that general performance in the three EF tasks (i.e. general

factors from Figure 3 A to C) was consistently correlated and could be merged into one factor. In

addition, there were no consistent correlations between manipulation-specific factors (i.e.

manipulation specific factors from Figure 3 A to C) suggesting that individual differences with

respect to specific manipulations were divergent rather than unitary.

      Bi-variate models of EF tasks and covariates. Detailed results of the bi-variate models

between EF tasks and the three covariates can be found in the analysis scripts available at:

osf.io/6trne. Simplified path diagrams for the separate covariates are displayed in Figure 4. There

were no consistent correlations between the three covariates (i.e. WMC, PS, and intelligence)

and manipulation-specific factors in the EF tasks. Thus, these correlations were not estimated in the joint model with all three covariates and the three EF tasks. In contrast, the general factor that represented similar individual differences across the three EF tasks showed considerable correlations and were thus included in the model joining all three covariates and the three EF tasks. Detailed results will be reported in the next section.

Joint modeling of all covariates and EFs. A combined model with all three covariates and behavioral RTs in the three EF tasks showed a good fit to the data, $\chi^2(940) = 1168.6$, $p < .001$, CFI = .97, RMSEA = .05, 90% CI = [.04, .06]. The path diagram of this model is shown in the top part (A) of Figure 5. Specifically, the factor merging behavioral performance in the three EF tasks showed a large positive correlation with processing speed in the ECTs ($r = .77$), and slightly lower and negative correlations with both *Gf* ($r = -.55$) and WMC ($r = -.49$). In other words, short RTs in the EF tasks go along with short RTs in the ECTs and higher scores in the intelligence test as well as the WMC battery. In this, all these results follow the expected direction and replicate previous relationships between intelligence, working memory capacity, and processing speed.

In addition, results indicated a very high correlation between *Gf* and WMC ($r = .95$), and medium correlations of *Gf* and WMC with PS in the ECTs ($r = -.46$ to $-.55$). Due to the strong association between PS in ECTs and the general performance factor of EFs, we simplified the model by estimating one general processing speed factor consisting of EFs and ECTs and one factor tentatively named *higher cognition* summarizing *Gf* and WMC (see bottom part of Figure 5 for the path diagram). These simplifications did not impair model fit, ΔAIC = -4.0, $\Delta\chi^2(7) = 10.0$, $p = .191$, and the model itself fit the data well, $\chi^2(947) = 1178.6$, $p < .001$, CFI = .97,

RMSEA = .05, 90% CI = [.04, .06]. This model indicated a medium correlation between the factor for *higher cognition* and general processing speed (r = -.54).

Discussion

The present study aimed to disentangle the relationship between individual differences in processing speed, working memory capacity and executive functions with intelligence. Specifically, we were interested in two research questions: (1) in how far performance in EF tasks represented general or manipulation-specific aspects? And (2) which of these two different aspects of performance in EF tasks was related to intelligence, working memory capacity (WMC), and processing speed (PS)? Overall, performance in specific conditions within EF tasks seemed to largely capture general variance rather than variance specific to an experimental manipulation. Furthermore, manipulation-specific variance in EF tasks did not show any consistent relationships among the different EF tasks and with the three covariates, while general variance in behavioral RTs measured in EF was related to intelligence, working memory capacity, and processing speed.

Performance in EF tasks: What does it measure?

Before taking on the question in how far performance in EF tasks is related to WMC, PS and intelligence, we addressed the question what is measured by reaction times as performance measures in EF tasks. This is an important point as former studies investigating this relationship have used various indicators for individual differences in EFs. Some studies have used performance from specific conditions in an EF task that should require one specific executive function (e.g., RTs for incongruent conditions in a Stroop task; Wongupparaj et al., 2015) or average performance across conditions (e.g., mean proportion correct in updating tasks; Miyake et al., 2000), while differences between specific experimental conditions in EF tasks were used

in other studies (e.g. the difference between RTs in switch versus repeat trials in a shifting task; Friedman et al., 2006). Interestingly, these different measures have often been mixed within studies (Friedman & Miyake, 2017; Miyake et al., 2000; Wongupparaj et al., 2015) and in most cases difference measures have been used for inhibition and shifting tasks, while average performance across conditions has been used for updating tasks.

From a theoretical perspective, the use of either measure is not entirely unproblematic. Using performance from a single condition or average performance across conditions may confound different variance sources. In this case, such measures may contain variance specific to experimental manipulations that require specific executive functions and more general variance linked to processing speed or memory capacity (Frischkorn & Schubert, 2018). In contrast, difference measures assume that cognitive processes are additive and that experimental conditions vary in all but a single cognitive process (Donders, 1868, 1969). Yet, it is likely that cognitive processes are not additive and that inserting an additional cognitive process interacts with other cognitive processes required in the task (Alexander, Trengove, & van Leeuwen, 2015; Friston et al., 1996; Schubert et al., 2015).

Our results from the bi-factor models of the three EF tasks indicate that behavioral RTs from one condition within any EF task represented mostly general performance. Specifically, the general factors summarizing the variance consistent across all manipulations did capture the largest proportion of variance in manifest indicators across all EF tasks (on average 71%), while each manipulation-specific factor captured considerably smaller variance proportions (on average 16%). Hence, behavioral measures from a single condition or average performance across all conditions will mostly represent individual differences in general rather than manipulation-specific cognitive processes.

Furthermore, there was no consistent relationship between manipulation-specific factors of the three EF tasks (i.e. differences in reaction time between conditions), while the general factors across the three EF tasks (i.e. the average of reaction times across conditions) could be merged into one factor. With respect to the discussion on the unity versus diversity of executive functions (Friedman & Miyake, 2017; Karr et al., 2018), these results suggest that the unity of executive functions might largely be due to similar processes being involved across different EF tasks and their respective conditions. In contrast, diversity of EF might be reflected in the manipulation specific variance within EF tasks, as this manipulation specific variance did not show any consistent correlations between the different EF tasks. This is in line with the results of the present study that suggest unity of EF with only little diversity as reflected in small task- and manipulation specific variances.

As manipulation-specific factors can be interpreted as latent difference scores, the small amount of variance of manipulation-specific factors might also explain why difference scores in experimental paradigms often show low reliabilities (Hedge, Powell, & Sumner, 2018). In detail, when calculating the difference between two correlated experimental conditions, the small amount of systematic variance in this difference (i.e. the variance of manipulation-specific factors) gets outweighed by unsystematic error variance that gets amplified when calculating the difference between highly correlated variables. One very recently proposed solution to this may be to account for trial-to-trial noise by adopting a hierarchical modeling approach (Rouder & Haaf, 2019). However, there is also first evidence that this approach does not solve the measurement issues of difference measures (Rouder, Kumar, & Haaf, 2019), and thus does not provide an increment above the here used method of latent difference scores that are virtually error free (Kievit et al., 2018; Steyer et al., 1997).

In conclusion, researchers have to consider that the selection of a specific measure such as difference scores or performance in a single experimental condition may change both the interpretation of the measure and the relationship with covariates. Specifically, results from studies that have not used difference scores as indicators of EFs could also be interpreted as indication that general processing speed (when using RTs in shifting or inhibition tasks) or memory/processing capacity (when using accuracies in updating tasks) are related to intelligence instead of individual differences specific to executive functions. However, additivity of different cognitive processes is not necessarily given and thus both manifest and latent difference measures are not unproblematic either (Cronbach & Furby, 1970; Friston et al., 1996). In this, the general factors of EF tasks from this study may also have included cognitive processes related to experimental manipulations of the EF tasks. Nonetheless the general factors from the EF tasks showed a large overlap with basic processing speed. So assuming that general factors captured EF would suggest that ECTs require executive functions to some extent despite not explicitly introducing manipulations related to EF. Altogether, the solution to an adequate measurement of individual difference in EFs still seems to be elusive (Hedge et al., 2018; Rey-Mermet, Gade, & Oberauer, 2018; Rouder et al., 2019). Ultimately, establishing theoretically grounded measures for executive functions is a critical step towards accurately assessing the relationship between EFs and individual differences in other cognitive processes such as intelligence, WMC, and PS.

Executive Functions: Still no bridge across the gap.

While theoretically and empirically executive functions[5] are supposed to underlie

working memory capacity and thus should be related to intelligence as well (Kane, Conway,

Hambrick, & Engle, 2007; Kane & Engle, 2003; Unsworth, 2010; Unsworth et al., 2014), the

results of the present study indicated that variance specific to experimental manipulations in the

task used in this study is not related to working memory capacity, processing speed, and

intelligence. Moreover, manipulation-specific factors did not show any consistent correlational

pattern with each other, indicating that executive functions required by the different experimental

manipulations are divergent rather than unitary. While this may arguably be specific to the task

used within this study, our results are in line with recent results suggesting that individual

differences in executive functions, specifically inhibition, may not be as unitary as suggested

(Rey-Mermet et al., 2018; Stahl et al., 2014). In detail, Rey-Mermet et al. (2018) did not find any

correlations among difference scores in a set of eight different inhibition tasks. In sum,

correlations between difference measures from a set of heterogeneous executive functioning

tasks both with each other and with external criteria seem to be small and largely inconsistent

(Hedge et al., 2018; Rey-Mermet, Gade, Souza, von Bastian, & Oberauer, 2019; Stahl et al.,

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[5] Please note that we still use the term executive functions in the sense of attention regulation mechanisms

described by Miyake et al. (2000). Therefore, executive functions conceptualized in a broader fashion as all

cognitive processes involving voluntary or top-down control (Diamond, 2013) may well integrate working memory

capacity and processing speed as correlated predictors of intelligence. However, we also think that executive

functions in this broad sense do not provide a proper theoretical account for this integration but rather serve as an

umbrella term for a heterogeneous set of higher cognitive processes that share a very abstract property (i.e. the

voluntary control).

2014), calling into question (1) whether individual differences in executive functions are unitary

at all and (2) whether they underlie the relationship between WMC, PS and intelligence.

Instead, only variance consistent across experimental manipulations showed relationships

with the three covariates. Specifically, behavioral RTs in EF tasks showed medium-sized

negative relationships with working memory capacity and intelligence (r = -.49 to -.55), and a

large positive relationship with PS from ECTs (r = .77). It is especially interesting that general

performance in EF tasks measured by RTs could be merged into one factor with processing

speed measured in RTs. This suggests that RTs in EF tasks measure processing speed to a large

degree. While it could also be argued that this factor represents some broad attention regulation

mechanism that is required in both simple ECTs and more complex EF tasks, this account would

have to specify which attention regulation mechanism this may be and how it is different from

attentional mechanisms supposedly related to the manipulations in executive functions.

Irrespective of this hypothesis, the present results replicated the negative relationship ($r = -.54$)

of behavioral processing speed with both intelligence and working memory capacity and the

strong relationship between the latter processes (Ackerman et al., 2005; Kyllonen & Christal,

1990; Schmiedek et al., 2007; Schmitz & Wilhelm, 2016; Schubert et al., 2015).

It is important to note that even though researchers have often argued for a causal

relationship between basic cognitive processes such as processing speed or working memory and

intelligence, there may also be a confounding variable that affects all these different cognitive

processes. For instance, a recent study using a psychopharmacological manipulation of

processing speed with nicotine indicated that the speed of neural information processing might

not causally underlie individual differences in intelligence (Schubert, Hagemann, Frischkorn, &

Herpertz, 2018). In detail, nicotine administration did increase neural as well as behavioral

processing speed, while not showing any effect on performance in a matrix reasoning task. Hence, processing speed may not causally underlie individual differences in intelligence despite being correlated with intelligence.

Conclusion

Altogether, the present results further emphasize the important role of processing speed and working memory for individual differences in intelligence. In contrast, executive functions seemingly do not underlie either individual differences in processing speed or working memory capacity and thus do not explain why working memory capacity and processing speed are related to intelligence. Nevertheless, it is reasonable to assume that individual differences in both processing speed and working memory capacity arise due to similar limitations in the cognitive system (Meiran & Shahar, 2018; Wilhelm & Oberauer, 2006). A promising approach to further investigate this idea might lie in joining theoretically grounded measures for behavioral indicators of processing speed and working memory capacity (e.g. cognitive models; Frischkorn & Schubert, 2018), with biological indicators of neural processing related to these two processes (c.f. Schubert, Nunez, Hagemann, & Vandekerckhove, 2018).

More comprehensive insights on the basic cognitive processes underlying individual differences in intelligence may be gained by specifying how structural and functional architectural features of the brain related to intelligence (Hilger, Ekman, Fiebach, & Basten, 2017; Menon & Uddin, 2010) can be more closely associated with cognitive process parameters related to working memory capacity and processing speed. This may provide an integration of cognitive and biological process parameters of working memory capacity and processing speed as related predictors of intelligence. Such an integration would undergird established theories discussing the biological basis of intelligence such as the P-FIT theory (Basten, Hilger, &

Fiebach, 2015; Jung & Haier, 2007) or the neural efficiency hypothesis (Neubauer & Fink, 2009)

with insights on the underlying cognitive process. As exemplified by the watershed model of

human intelligence (Kievit, Davis, Griffiths, Correia, & Henson, 2016), this may ultimately

result in a unified neuro-cognitive theory of intelligence.

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Tables

Table 1

Descriptive Statistics for the Executive Functioning tasks

Task	Block	Task Shifting	Flanker	M_{RT} (SD_{RT})		M_{Pc} (SD_{Pc})	
Shifting	Control LM			583.23	(94.12)	0.93	(0.01)
	Control OE			679.28	(130.57)	0.80	(0.02)
	Shifting (SH)	Switch		1'383.33	(306.83)	0.95	(0.09)
		Repeat		1'181.51	(245.18)	0.97	(0.08)
	SH Flanker	Switch	congruent	1'176.39	(249.79)	0.98	(0.03)
			neutral	1'181.13	(246.60)	0.98	(0.03)
			incongruent	1'215.83	(251.07)	0.98	(0.03)
		Repeat	congruent	1'072.24	(234.69)	0.99	(0.02)
			neutral	1'080.16	(242.77)	0.99	(0.02)
			incongruent	1'132.30	(248.04)	0.99	(0.03)
	Block	**Match**	**Flanker**				
N-Back	2-Back	False		1'108.53	(186.25)	0.91	(0.10)
		True		911.32	(190.45)	0.95	(0.06)
	2-Back Flanker	False	no	1'059.88	(189.14)	0.95	(0.08)
			congruent	1'144.80	(202.73)	0.94	(0.09)
			neutral	1'106.65	(190.48)	0.93	(0.10)
			incongruent	1'133.33	(202.27)	0.94	(0.08)
		True	no	843.02	(169.66)	0.97	(0.04)
			congruent	912.05	(163.71)	0.97	(0.05)
			neutral	859.21	(163.17)	0.96	(0.05)
			incongruent	934.95	(165.75)	0.97	(0.05)
	Cue	**Flanker**					
ANT	no	congruent		703.76	(93.69)	1.00	(0.00)
		neutral		684.50	(85.34)	1.00	(0.00)
		incongruent		825.63	(103.92)	0.98	(0.05)
	central	congruent		669.78	(97.38)	1.00	(0.00)
		neutral		660.10	(90.57)	1.00	(0.00)
		incongruent		809.02	(102.68)	0.98	(0.04)
	double	congruent		653.44	(92.16)	1.00	(0.00)
		neutral		652.69	(90.99)	1.00	(0.00)
		incongruent		790.15	(105.19)	0.98	(0.04)
	spatial	congruent		593.61	(93.37)	1.00	(0.00)
		neutral		593.61	(88.29)	1.00	(0.00)
		incongruent		706.48	(113.98)	0.99	(0.03)

Note. RT = Reaction Time in ms; Pc = Proportion correct responses; LM = Less More; OE = Odd-Even

Table 2

Statistical results from the manipulation check.

Task	Factor	EF effect	F	df_Z	df_N	p	ε_{GG}	ω^2
Shifting	Block	*Global ShiftCost*	118.10	1	98	> .001		.539
	Block		53.71	1	98	> .001		.345
	Switch	*Local ShiftCost*	230.72	1	98	> .001		.697
	Block x Switch		47.28	1	98	> .001		.316
	Switch	*Local ShiftCost*	166.49	1	98	> .001		.623
	Flanker	*Inhibition*	45.51	2	196	> .001	.99	.309
	Switch x Flanker		0.84	2	196	.434	.93	.000
NBack	Block		0.70	1	100	.404		.000
	Match		696.37	1	100	> .001		.872
	Block x Match		1.09	1	100	.298		.001
	Match		624.70	1	100	> .001		.859
	Flanker	*Inhibition*	150.71	3	300	> .001	.85	.596
	Match x Flanker		20.27	3	300	> .001	.97	.160
ANT	Cue	*Alerting / Orienting*	653.05	3	294	> .001	.79	.868
	Flanker	*Inhibition*	1299.24	2	196	> .001	.77	.929
	Cue x Flanker		8.34	6	588	> .001	.88	.069

Note. The column EF effect highlights the effects related to specific executive functions.
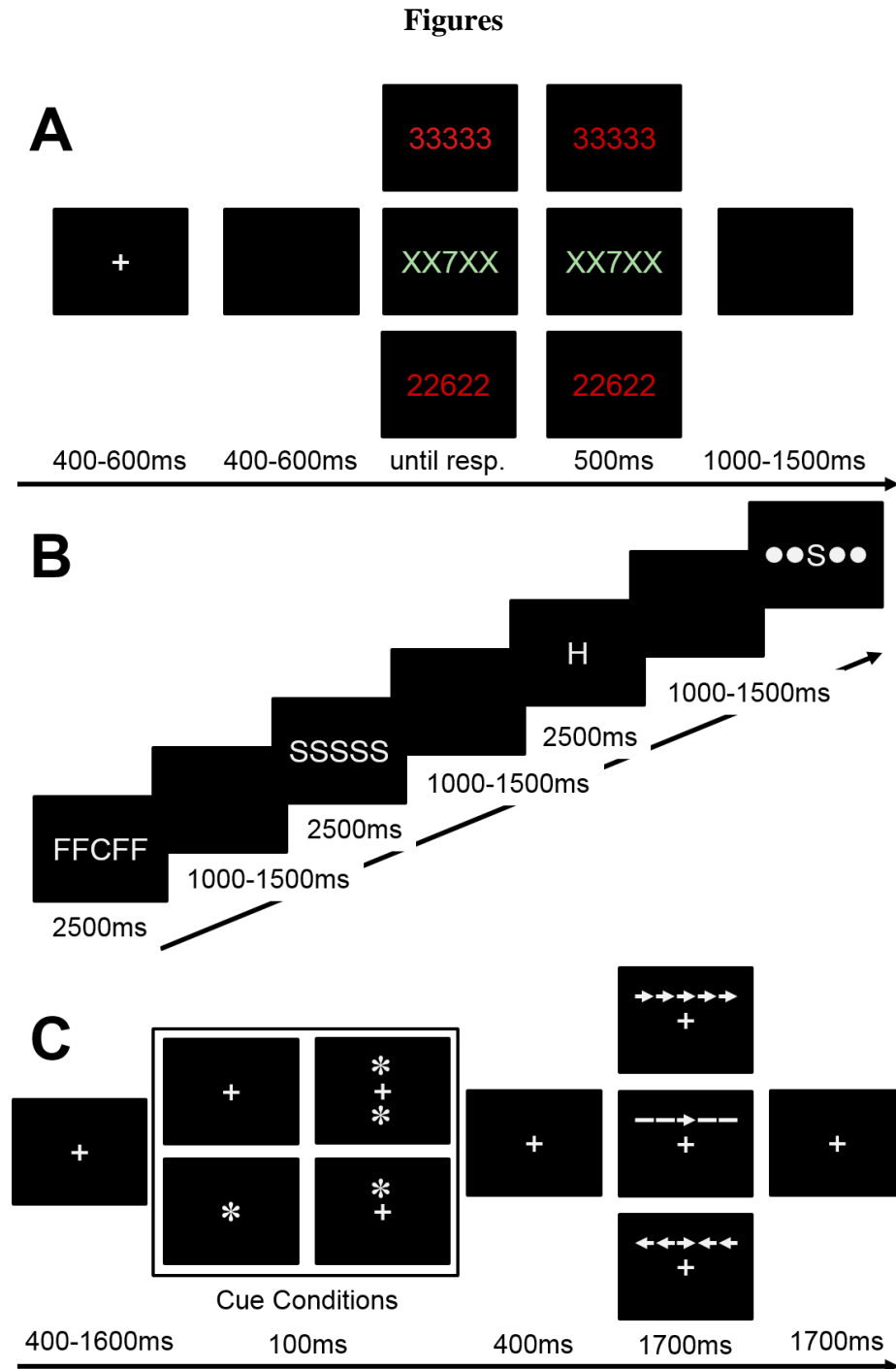
Figures

Figure 1. Trial Procedure of the three EF tasks for (A) Task Shifting with red (dark) as cue for less/more decision and green (light) for odd/even decision (Switching Task), (B) Updating (N-Back task), and (C) Inhibition (Attention Network Test, ANT). Presentation times are given below the different screens in the trial procedure. In the Shifting task and the N-Back task, the flanker stimuli as shown above were only presented in the flanker blocks. The other blocks in these two tasks did not include flanker stimuli and only showed the central target stimulus.
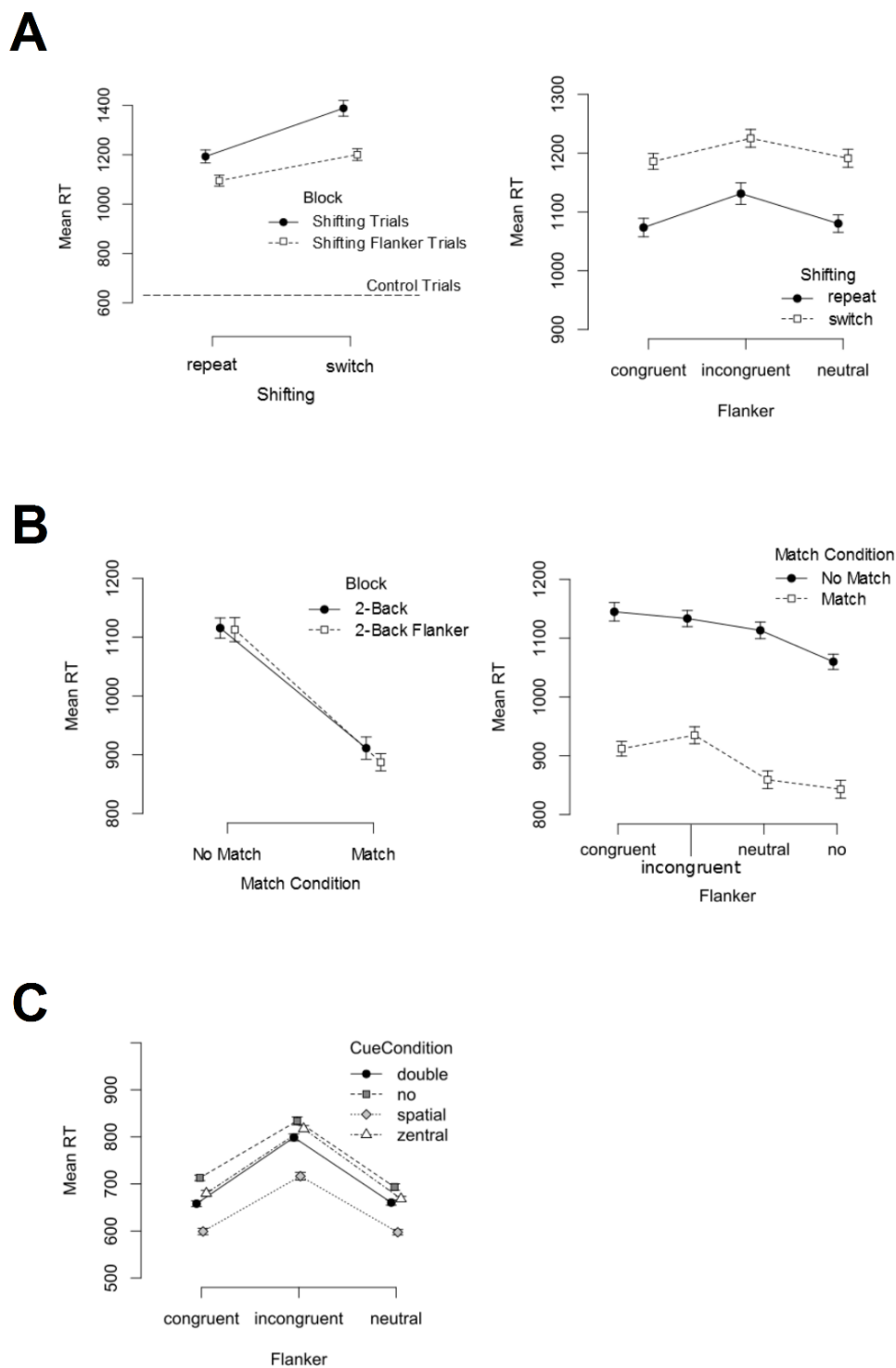
Figure 2. Descriptive Plots displaying the effects of experimental manipulations on behavioral RTs in the three EF tasks. The top panel (A) displays the effects in the Shifting task, the mid panel (B) the effects in the N-Back task, and the bottom panel (C) the effects in the ANT.
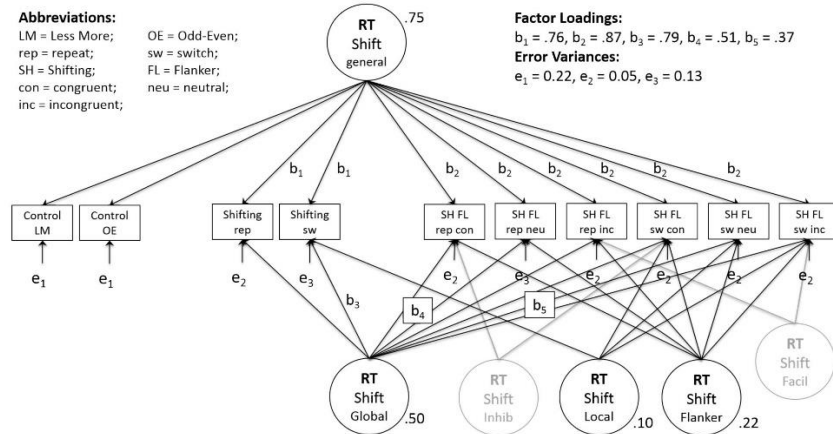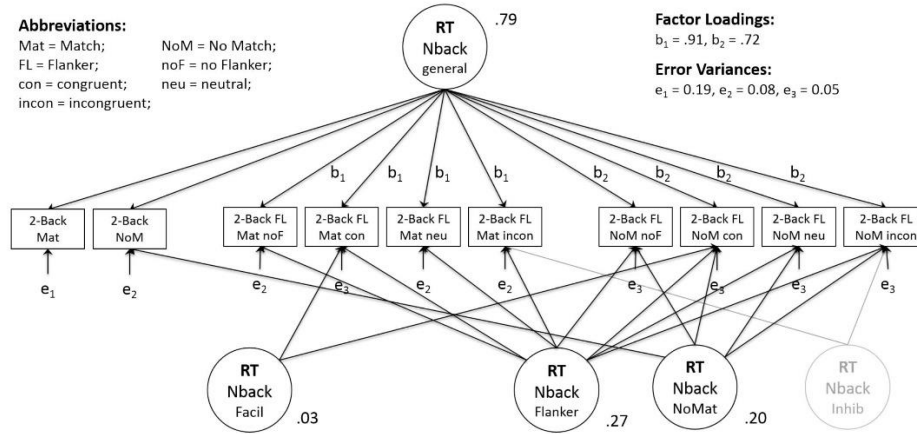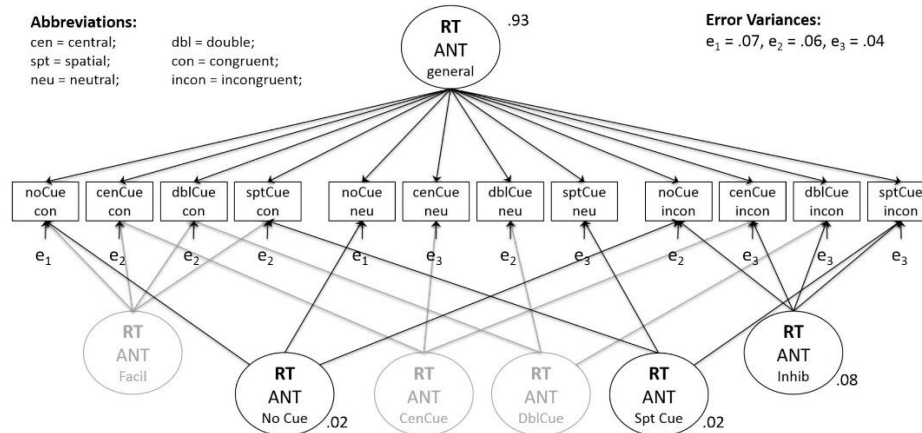
Figure 3. Path-diagrams of the Bi-factor models for behavioral RT in the three executive function tasks. The top part (A) shows the model for the shifting task (Shift), the middle part (B) shows the model for the N-Back task, and the lower part (C) the model for the Attention Network Test (ANT). All loadings that are not explicitly stated were fixed to one and unstandardized parameters are reported. Manipulation specific factors that showed variances not significantly different from zero are displayed greyed out and were not included in the final model.
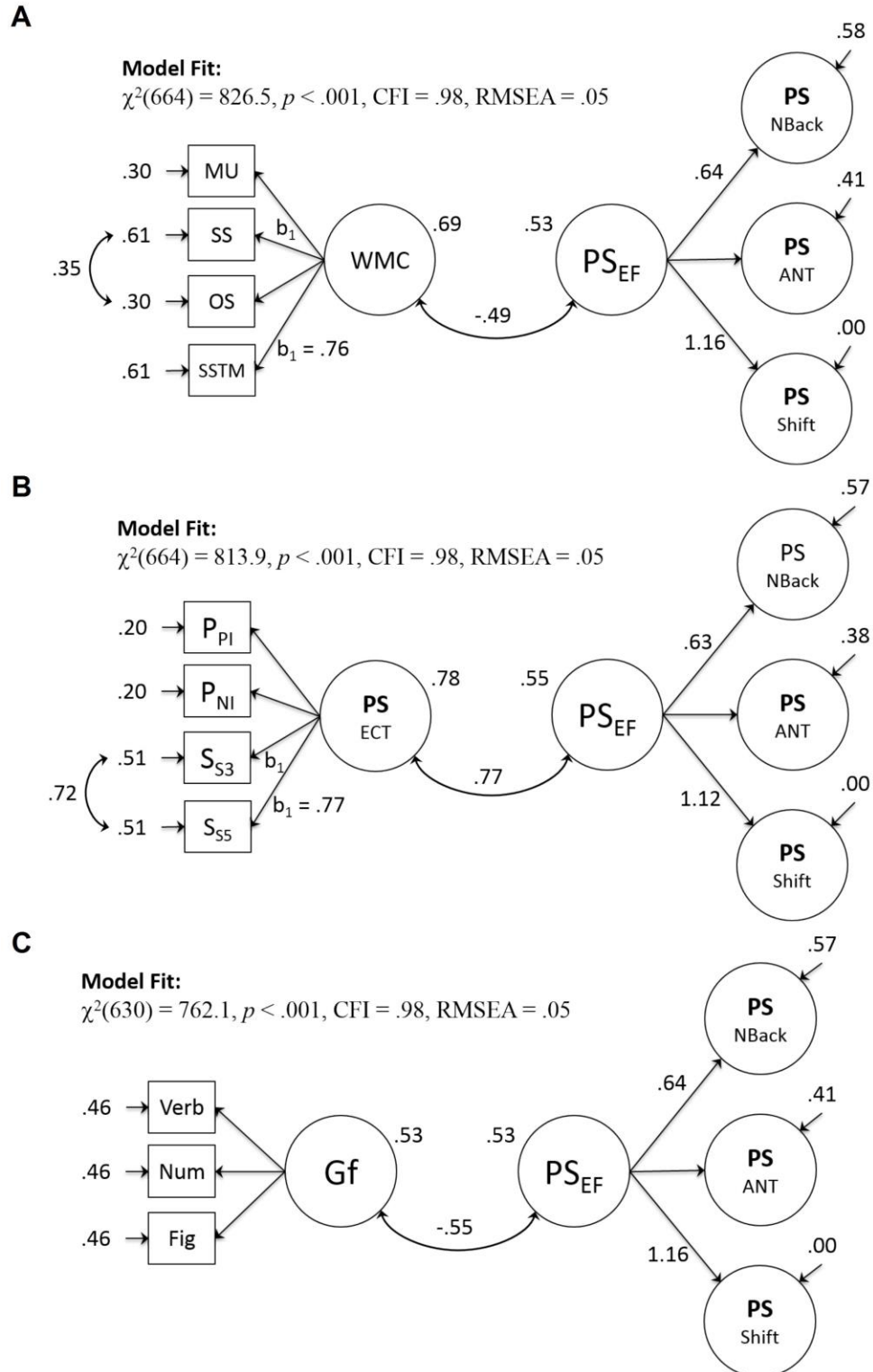
Figure 4. Path-diagrams for SEM of the bivariate relationships of behavioral RT in the three executive function tasks with working memory capacity (A), processing speed (B), and intelligence(C). Manipulation specific factors in the EF tasks (see Figure 3) are not depicted as none of them showed any significant relationship with any of the covariates.
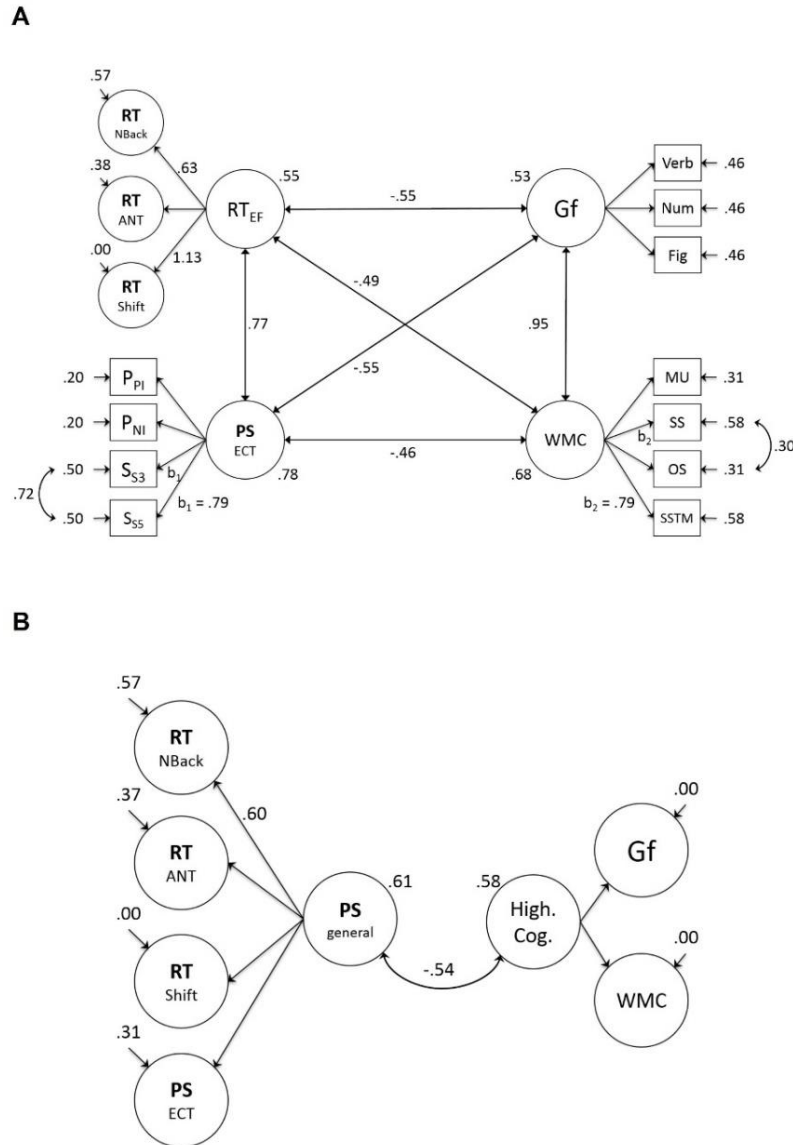
Figure 5. Path-diagrams for SEM of behavioral reaction times (RTs) in three EF tasks with the three covariates processing speed (PS), intelligence (Gf), and working memory capacity (WMC). Gf indicators are: verbal (Verb), numerical (Num), and figural (Fig) score from the BIS. Indicators for WMC are: proportion correct in a memory updating (MU), a sentence span (SS), an operation span (OS), and a spatial short-term memory (SSTM) task. Processing Speed indicators are: name identity (NI), and physical identity (PI) RTs from the Posner task (P), and set size 3 (S3) and set size 5 (S5) RTs from the Sternberg task (S). The top part (A) shows a correlational model, whereas the bottom part (B) shows a simplified model joining PS and EF performance into one general processing speed factor and Gf and WMC into a factor for higher cognitive abilities. Manipulation-specific factors of EF tasks are not depicted as all relationships of these factors with other factors were fixed to zero. All loadings that are not explicitly stated were fixed to one. Parameters are unstandardized except for correlations and differ all significantly from zero.