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Is General Intelligence Little More Than the Speed of Higher-Order Processing?

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Individual differences in the speed of information processing have been hypothesized to give rise to individual differences in general intelligence. Consistent with this hypothesis, reaction times (RTs) and latencies of event-related potential have been shown to be moderately associated with intelligence. These associations have been explained either in terms of individual differences in some brain-wide property such as myelination, the speed of neural oscillations, or white-matter tract integrity, or in terms of individual differences in specific processes such as the signal-to-noise ratio in evidence accumulation, executive control, or the cholinergic system. Here we show in a sample of 122 participants, who completed a battery of RT tasks at 2 laboratory sessions while an EEG was recorded, that more intelligent individuals have a higher speed of higher-order information processing that explains about 80% of the variance in general intelligence. Our results do not support the notion that individuals with higher levels of general intelligence show advantages in some brain-wide property. Instead, they suggest that more intelligent individuals benefit from a more efficient transmission of information from frontal attention and working memory processes to temporal-parietal processes of memory storage.

Keywords: ERP latencies, event-related potentials, intelligence, processing speed, reaction times

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General intelligence (*g*) is the common variance shared by different measures of cognitive ability. It is a powerful predictor for success in a variety of life outcomes, such as educational attainment, job performance (Schmidt & Hunter, 2004), development of expertise (Wai, 2014), general health (Der, Batty, & Deary, 2009), longevity (Deary, 2008), and well-being (Pesta, McDaniel, & Bertsch, 2010). General intelligence typically accounts for 40% to 50% of the variance shared by different measures of cognitive ability, and *g* factors from different cognitive test batteries are highly related (Johnson, Nijenhuis, & Bouchard, 2008). This functional invariance suggests that there may be a single common process underlying individual differences in general intelligence that affects all kinds of cognitive ability tests (Spearman, 1923).

One likely candidate for a single neuro-cognitive property affecting a variety of cognitive abilities is the speed of information processing (Jensen, 2006). On a behavioral level, information-processing speed can be measured as reaction times (RTs), which show moderate, but consistent negative associations with intelligence (Jensen, 2006; Sheppard & Vernon, 2008). Moreover, RTs have been shown to mediate the relationship between brain-wide white matter tract integrity and general intelligence, suggesting a functional anatomical basis for fast and efficient information processing (Kievit et al., 2016; Penke et al., 2012).

On a neurophysiological level, information-processing speed can be measured as the latency of event-related potentials (ERPs). ERPs allow decomposing the electrophysiological activity between stimulus onset and response into functionally distinct components. These ERP components are correlates of functionally distinct cognitive processes defined by their polarity, their latency, and their topography. A higher speed of information processing should be reflected in shorter ERP latencies (i.e., a shorter time interval between the onset of a stimulus and the maximum peak of the component). ERP components occurring early in the stream of information processing reflect early stages of information processing, whereas later components reflect higher-order processing. ERPs thus provide a means to identify which cognitive processes are faster in more intelligent individuals.

Previous research has shown only weak and often inconsistent associations between ERP latencies and general intelligence (Schulter & Neubauer, 2005), but several studies found a moderate negative association between ERP latencies and intelligence (Bazana & Stelmack, 2002; McGarry-Roberts, Stelmack, & Campbell, 1992; Troche, Houlihan, Stelmack, & Rammsayer, 2009; Troche, Indermühle, Leuthold, & Rammsayer, 2015). Moreover, RTs have been shown to mediate the association between ERP latencies and intelligence, suggesting a functional neuro-cognitive basis for faster information processing that may give rise to individual differences in intelligence (Schubert, Hagemann, Voss, Schankin, & Bergmann, 2015).

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ERP latencies may tend to show smaller and more inconsistent associations with general intelligence than RTs, because they may be more strongly influenced by situational factors unrelated to mental abilities. Because there is evidence that measures of general intelligence are minimally affected by situational (occasion-specific) factors and thus reflect a property of the person (Danner, Hagemann, Schankin, Hager, & Funke, 2011) plus measurement error, it may be presumed that occasion-specific effects in time-domain measures act as nuisance variables or "noise" when analyzing the association between these measures and general intelligence. Thus, only the temporally stable (trait-like) portion of variance in measures of information-processing speed can be considered as a property of the person that may explain individual differences in general intelligence. Not separating the temporally stable portion of variance from the occasion-specific portion of variance may have led to an underestimation of the relationship between chronometric variables and general intelligence in previous research. Previous research supported this view, suggesting a moderate temporal stability of RTs (Roznowski & Smith, 1993; Yap, Balota, Sibley, & Ratcliff, 2012) and substantial variance in the stability of ERP latencies ranging from $r = .19$ to $r = .89$ (Cassidy, Robertson, & O'Connell, 2012). Hence, the variances of ERP latencies may reflect differences in the speed of information processing both as a brain property and as brain states, resulting in an underestimation of the association between information-processing speed and general intelligence on a neurophysiological level. In the present study, we used a hierarchical extension of latent state-trait (LST) theory (Steyer, Ferring, & Schmitt, 1992) to measure ERP latency traits that are independent of situational factors.

A Chronometric Dissociation of the Relationship Between Information-Processing Speed and General Intelligence

The association between information-processing speed and general intelligence has been explained either in terms of individual differences in some brain-wide property such as myelination (Miller, 1994), the speed of neural oscillations (Jensen, 2006), or white matter tract integrity (Penke et al., 2012), or in terms of individual differences in specific processes such as the signal-to-noise ratio in evidence accumulation (van Ravenzwaaij, Brown, & Wagenmakers, 2011; Vickers & Smith, 1986), executive or attentional control (McVay & Kane, 2012), the cholinergic system (Stough, Thompson, Bates, & Nathan, 2001), or white matter organization in specific brain regions such as the forceps minor and the corticospinal tract (Kievit et al., 2016).

Instead of asking *which* neuro-cognitive processes underlie the association between general intelligence and information-processing speed, we could also ask *at which point in time* during information processing more intelligent individuals deviate from less intelligent individuals. If individual differences in some brain-wide property explained the relationship between information-processing speed and intelligence (general speed hypotheses), more intelligent individuals should show faster processing at all stages of information processing. If, however, specific cognitive or psychopharmacological processes explained this relationship (specific speed hypotheses), more intelligent individuals should show faster processing only at specific stages of information processing associated with these processes. To decide whether the whole stream of information processing prior to response execution or only specific stages of it are associated with intelligence, the stream of information processing has to be decomposed into functionally distinct components. This can be achieved by identifying ERP components reflecting both earlier stages of information processing immediately after stimulus onset and later stages of higher-order information processing. In the present study, we analyzed interindividual differences in the latencies of ERP components to determine whether intelligence is associated with faster information processing at all or only at very specific stages of information processing.

Method

Participants

Sample size was determined based on the hypothesis of close fit (H0: $\varepsilon \leq 0.05$, H1: $\varepsilon \geq 0.08$) for the structural equation model with the fewest degrees of freedom ($df = 133$), an alpha error of $\alpha = .05$, and a power of $1 - \beta = .80$ (MacCallum, Browne, & Sugawara, 1996). The resulting minimum sample size was $N = 109$. More participants were recruited to increase power and the stability of model estimates.

We recruited a sample of $N = 134$ participants (81 females, 53 males) between 18 and 60 years old ($M = 37.1$, $SD = 13.8$) from different educational and occupational backgrounds via local newspaper advertisement, announcements on social media platforms, and distribution of flyers in Heidelberg. Of these, $N = 122$ participants completed the second measurement occasion and $N = 114$ participants completed the third measurement occasion. We only included the $N = 122$ participants who showed up for at least the first two measurement occasions in the following analyses. This sample consisted of 72 women and 50 men with a mean age of $M = 36.7$ ($SD = 13.6$). A sample size of $N = 122$ participants corresponded to a power of $1 - \beta = .86$ for a structural equation model with 133 degrees of freedom (Preacher & Coffman, 2006).

All participants had normal or corrected to normal vision and no history of mental illness. At the first laboratory session, participants signed an informed consent. They received 100€ and feedback about their personal results as a reward for their participation. The study was approved by the ethics committee of the faculty of behavioral and cultural studies, Heidelberg University.

Materials

Single and choice RT task. We used a single and choice RT task with three conditions (one, two, and four alternatives) based on a previously used computer-adapted Hick task (Schubert et al., 2015). Each trial began with the presentation of four white squares in a row on a black screen and a white fixation cross in the middle of the squares that was shown for 1000–1500 ms. Next, the fixation cross disappeared and a larger cross appeared in one of the four squares. Participants had to press the corresponding response key as fast as possible. After their response, the screen remained unchanged for 1000 ms to allow the recording of post-decisional neuronal processes. The intertrial interval (ITI) consisted of a black screen and lasted between 1000 and 1500 ms. During the whole task, participants' middle and index fingers rested on four keys directly underneath the squares to increase stimulus-response compatibility. All keys irrelevant to the tasks had been removed from the modified keyboard.

Each of the three conditions consisted of 10 practice trials with immediate feedback followed by 200 test trials without feedback. The order of conditions was counterbalanced across participants. In the single RT (SRT) task, participants always knew exactly where the cross would appear. There were four blocks of 50 trials each with a counterbalanced order across participants, in which participants had to pay attention to only one of the four squares. In the two-choice RT (2CRT) task, participants knew in which two squares the cross could appear. There were four blocks of 50 trials each with a counterbalanced order across participants, in which participants had to pay attention only to the left/right/middle/outer two squares. In the four-choice RT (4CRT) task, participants were given no indication where the cross will appear.

Sternberg memory scanning task. Participants were shown memory sets consisting of digits between 0 and 9, and they had to indicate whether an immediately afterward presented probe stimulus was part of the previously presented memory set. We administered three different experimental conditions (set size one, three, and five) in an order counterbalanced across participants. Each of the three conditions consisted of 10 practice trials with immediate feedback followed by 100 test trials without feedback.

At the beginning of each trial, a white fixation cross was shown in the middle of a black screen for 1000–1500 ms. Digits were presented sequentially for 1000 ms with a blank screen shown for 400–600 ms between each digit. A black screen with a white question mark was shown for 1800–2200 ms after the last digit was presented, followed by a black screen showing the probe stimulus. Participants had to press one of two keys with their index fingers to indicate whether the digit was part of the memory set, which was the case in 50% of the trials. The position of keys was counterbalanced across participants. After their response, the screen remained unchanged for 1000 ms, followed by an ITI of 1000–1500 ms.

Posner letter-matching task. Participants were shown two letters and had to decide whether they were identical. In the physical identity (PI) condition, participants were instructed to identify letters as identical only if their physical characteristics were identical (i.e., "QQ" would be identical, whereas "Qq" or "QA" would be different). In the name identity (NI) condition, they were instructed to identify letters as identical if their names were identical (i.e., both "QQ" and "Qq" would be identical, whereas "QA" would still be different). Both conditions consisted of 10 practice trials with immediate feedback and 300 test trials without feedback. At the first measurement occasion, the PI condition was administered first to all participants, whereas at the second measurement occasion the NI condition was administered first to all participants.

Each trial began with a white fixation cross shown on a black screen for 1000–1500 ms, followed by a pair of white letters presented in the middle of the screen. Participants had to press one of two keys with their index fingers to indicate whether the letters were identical, which was the case in 50% of the trials. Again, the position of keys was counterbalanced across participants. After the response, the screen remained unchanged for 1000 ms, followed by an ITI that consisted of a black screen and lasted 1000–1500 ms.

Advances Progressive Matrices (APM). We used a computer adapted version of Raven's Advanced Progressive Matrices (Raven, Court, & Raven, 1994) to measure participants' general intelligence with a power test. The APM has been previously shown to be the best single indicator of *g* (Marshalek, Lohman, & Snow, 1983). Participants' performance was determined as the number of correctly solved items of the second set, as suggested by the test manual. Moreover, we performed an odd-even split of the test items in the second set and used the number of correctly solved items in the odd and even trials as two indicators of latent APM performance. We then transformed these raw test sores to *z* scores for further analyses.

The number of correctly solved items in the APM was $M = 23.43$ ($SD = 6.71$), which corresponds to a mean IQ of $M = 98.80$ ($SD = 15.68$). The number of correctly solved items in the even trials was $M_{even} = 12.23$ ($SD = 3.51$), and in the odd trials $M_{odd} = 11.20$ ($SD = 3.52$). Data from two participants was lost due to technical reasons.

Berlin Intelligence Structure Test (BIS). We administered the complete Berlin intelligence structure test (BIS; Jäger, Süß, & Beauducel, 1997) in groups of up to four participants. The BIS is based on the bimodal Berlin intelligence structure model (Jäger, 1982), which distinguishes between four operation-related (processing speed, memory, creativity, processing capacity) and three content-related (verbal, numerical, figural) components of general intelligence. The test consists of a total of 45 tasks with each task being a combination of one operation-related component with one content-related component of intelligence. According to the manual, participants' scores for all seven components were computed by aggregating the normalized *z*-scores of all tasks related to the respective operation and content components. We then transformed these scores to *z*-scores for further analyses. We did not compute IQ scores based on BIS results, because there is no adult normative sample with an appropriate age range available.

The mean score of the processing speed component was $M = 98.00$ ($SD = 7.10$), the mean score of the memory component was $M = 99.40$ ($SD = 6.51$), the mean score of the creativity component was $M = 98.02$ ($SD = 6.14$), the mean score of the processing capacity component was $M = 101.7$ ($SD = 7.99$), the mean score of the verbal component was $M = 102.40$ ($SD = 6.93$), the mean score of the numerical component was $M = 98.27$ ($SD = 6.79$), and the mean score of the figural component was $M = 97.69$ ($SD = 6.52$). Note that these are not IQ scores, but mean scores.

Procedure

The three measurement occasions were approximately four months apart. At the first and third measurement occasion, we administered the SRT and CRT task, the Sternberg memory scanning task, and the Posner letter-matching task in the same order for all participants while an EEG was recorded. Participants were seated in a sound-attenuated, dimly lit EEG cabin. At the beginning of the third measurement occasion, we additionally recorded 12 min of resting state EEG, which will not be reported here, because resting state data do not provide chronometric measures. Each session took approximately 3 hours. At the second measurement occasion participants completed the BIS, a personality questionnaire not reported here, the APM, and a questionnaire about demographic data. This session took approximately 3.5 hours.

EEG Recording

The EEG was recorded with 32 equidistant Ag–AgCl electrodes. We used the aFz electrode as the ground electrode. Electrodes were initially referenced to Cz and offline rereferenced to an average reference. To correct for ocular artifacts, we recorded the electrooculogram (EOG) bipolarly with two electrodes positioned above and below the left eye and two electrodes positioned at the outer canthi of the eyes. All electrode impedances were kept below 5 kΩ. The EEG signal was recorded continuously with a sampling rate of 1000 Hz (band-pass 0.1–100 Hz), and filtered offline with a low-pass filter of 16 Hz.

Data Analysis

Reaction time data. For intraindividual outlier detection in RTs, we discarded any RTs faster than 100 ms or slower than 3000 ms. In a second step, we discarded any trials with incorrect responses or with logarithmized RTs exceeding ±3 SDs of the mean of each condition. Subsequently, we calculated the mean RT for each condition and calculated inverted RTs as reaction speeds (RS). We then transformed these reaction speeds to *z*-scores for further analyses.

Electrophysiological data. We calculated ERPs separately for each ECT and each condition. ERPs were time-locked to the stimulus onset in the SRT, CRT and letter-matching task, whereas they were time-locked to the onset of the probe in the memory scanning task. Epochs were 1200 ms long including a baseline of 200 ms before stimulus onset. We corrected ocular artifacts using a regression procedure (Gratton, Coles, & Donchin, 1983). Epochs with amplitudes exceeding ± 70 μV, with amplitude changes exceeding 100 μV within 100 ms, or with activity lower than 0.5 μV were discarded as artifacts.

We determined the P100 peak latency at occipital electrodes contralateral to the position of the cross in the SRT and CRT task, and at the occipital electrode over midline for the Sternberg memory scanning task and the Posner letter-matching task because stimuli in these tasks were presented centered. We determined the N100 peak latency at the frontal electrode over midline, the P200 peak latency at fronto-central electrode over midline, and the N200 and P300 latency at the parietal electrode over midline. Peak latencies were determined separately for each condition of the three experimental tasks. Subsequently, we discarded any peak latencies exceeding ±3 SDs of the mean peak latency of each condition. Finally, peak latencies were averaged across conditions of each experimental task and *z*-standardized for further analyses.

Statistical analysis. Prior to multivariate analyses, we calculated the Mahalanobis distance to identify and subsequently exclude multivariate outliers. In the multivariate data space of reaction speeds and intelligence test scores, one participant was identified as a multivariate outlier ($D_M = 57.78$, $p < .001$) and excluded from further analyses, whereas no participant was identified as an outlier in the multivariate data space of ERP latencies and intelligence test scores.

Moreover, all manifest variables were inspected for univariate normal distribution, which is a prerequisite of multivariate normal distribution. Statistical tests of skewness and kurtosis indicated that the distribution of APM variables and of a few ERP latencies deviated from normal distribution ($p < .001$). Subsequent visual inspections revealed that these deviations were rather small and below threshold values of skewness = 2 and of kurtosis = 7. Because neither skewness nor kurtosis exceeded these threshold values, we followed recommendations to not use assumption-free estimates in structural equation models (West, Finch, & Curran, 1995).

We used structural equation modeling to assess the associations between reaction speeds, ERP latencies, and general intelligence. All models were fitted with the full information maximum likelihood algorithm implemented in AMOS (Arbuckle, 2006). Because some variables deviated slightly from normal distribution, we repeated all analyses with the bootstrap procedure implemented in AMOS (Arbuckle, 2006). As bootstrapped results did not deviate notably from nonbootstrapped results except for small deviations in the size of standard errors, we report only the nonbootstrapped results.

Within the framework of structural equation modeling, we built latent state-trait (LST) models with hierarchical traits and hierarchical method factors to achieve a virtually error-free measurement of trait reaction speeds and ERP latencies. LST theory is an expansion of classical test theory that takes into account that any measurement is always affected by situational factors (Steyer et al., 1992). In short, LST theory proposes that the variance of an observed variable Y_{ij} can be decomposed into the variance of the latent trait T, the variance of a latent state residual SR_i, the variance of a latent method residual M_j, and the variance of a latent unsystematic error residual ε_{ij}.

First, we fitted a structural equation model with a common trait T, a state residual SR_i for each of the two measurement occasions, and a hierarchical method factor M_j for each of the three experimental tasks to the reaction speed data (for details of the model specifications see Supplementary Table 1). Subsequently, we fitted two different structural equation models to the electrophysiological data to compare the model fit of a general processing speed-model to the model fit of a specific processing speed-model. In both models, each ERP latency (P100, N100, P200, N200, P300) was modeled hierarchically as the covariance of latencies of one ERP component across the three experimental tasks at one measurement occasion (e.g., the latent P100 variable at measurement occasion *i* was defined by the covariances between the P100 latencies in the single and choice RT, Sternberg, and Posner task at this measurement occasion). In addition, we included specific traits for each of the five ERP component latencies. Intercepts in all models were fixed to zero (for details of the model specifications see Supplementary Table 2).

The general processing speed-model consisted of a common trait T, a state residual SR_i for each of the two measurement occasions, a method factor M_j for each of the three experimental tasks, and five specific traits for the five ERP components. The specific processing speed-model consisted of two separate common traits, $T_{earlier\ latencies}$ and $T_{later\ latencies}$, a state residual SR_i for each of the two measurement occasions and each of the two traits, a method factor M_j for earlier and later ERP latencies of each of the three experimental tasks, and five specific traits for the five ERP components. 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, 1993), and compared model fit of the two models with the Akaike Information Criterion (AIC; Akaike, 1973). 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 (Browne & Cudeck, 1993; Hu & Bentler, 1999). If CFI values were < .90 and RMSEA values > .08, we considered the model to show mediocre model fit. If the two fit criteria diverged, we evaluated the model based on the more favorable criterion, because it has been previously shown that goodness-of-fit statistics underestimate absolute model fit when the sample size is relatively small (Kenny, Kaniskan, & McCoach, 2015; Schubert, Hagemann, Voss, & Bergmann, 2017). For model comparison purposes, we used an AIC difference > 10 as evidence that the model with the smaller AIC value provided a better fit (Burnham & Anderson, 2002). The statistical significance of model parameters was assessed with the two-sided critical ratio test.

Moreover, we fitted a hierarchical measurement model of general intelligence with a common *g*-factor and two lower-order factors defined by the covariances in BIS and APM scores, respectively. We did not model general intelligence with LST theory, because previous applications of LST theory to multiple measurements of intelligence have shown that the state residuals were zero (Danner et al., 2011). Again, we evaluated goodness-of-fit with the CFI and the RMSEA.

In a second step, we computed latent-state parameters of the behavioral and electrophysiological data based on the best-fitting LST model. For each manifest variable Y_{ij} measured with method *j* and at measurement occasion *i*, we computed coefficients of consistency, occasion-specificity, measurement-specificity, and reliability (Steyer, Schmitt, & Eid, 1999). For the LST model of reaction speeds, the coefficient of trait-specificity was computed as $\sigma^2(T)/\sigma^2(Y_{ij})$ and reflects the proportion of variance of the manifest variable Y_{ij} that can be accounted for by individual differences in the latent trait *T*. The coefficient of occasion-specificity was computed as $\sigma^2(SR_i)/\sigma^2(Y_{ij})$ and reflects the proportion of variance that is due to situational effects SR_i. Similarly, the coefficient of method-specificity was computed as $\sigma^2(M_j + C_k)/\sigma^2(Y_{ij})$ and reflects the proportion of variance that can be accounted for by a specific experimental task M_j and its conditions C_k. Taken together, these different sources of systematic variation contribute to the reliability of a manifest variable Y_{ij}, that is, to the proportion of variance explained by the specified model. Thus, the reliability coefficient can be computed as $[\sigma^2(T) + \sigma^2(SR_i) + \sigma^2(M_j + C_k)]/\sigma^2(Y_{ij})$.

For the LST model of ERP latencies, the coefficient of trait-specificity was computed as $\sigma^2(T_k + T_l)/\sigma^2(Y_{ij})$ and reflects the proportion of variance of the manifest variable Y_{ij} that can be accounted for by individual differences in the general trait T_k and by the specific trait T_l. The coefficient of occasion-specificity was computed as described above. The coefficient of method-specificity was computed as $\sigma^2(M_j)/\sigma^2(Y_{ij})$ and reflects the proportion of variance that can be accounted for by the shared variance of earlier and later latencies in a specific experimental task M_j. Finally, the coefficient of reliability was computed as $[\sigma^2(T_k + T_l) + \sigma^2(SR_i) + \sigma^2(M_j)]/\sigma^2(Y_{ij})$.

In a third step, we combined the behavioral and the best-fitting neurophysiological structural equation model with the measurement model of general intelligence to study the structural relations between (a) behavioral processing speed and general intelligence and (b) neurophysiological processing speed and general intelligence.

Results

Factor Structure and Temporal Stability of Reaction Speed

We used a hierarchical extension of latent state-trait (LST) theory (Steyer et al., 1992) to identify the common and temporally stable trait variance of three RT tasks at two measurement occasions approximately eight months apart. Mean reaction speeds for all conditions of the three experimental tasks are shown in Table 1 separately for the two measurement occasions. The full correlation matrix is included in Supplementary Table 3. We specified a structural equation model with a common trait *T*, a state residual SR_i for each of the two measurement occasions *i*, and a hierarchical method factor M_j for each of the three experimental tasks *j* as shown in the left part of Figure 1. The model provided a good fit to the data, $\chi^2(133) = 265.81$, $p < .001$, CFI = .95, RMSEA = .09. Because the variances of the first state residual and of several method residuals were nonsignificant or negative, they were fixed to zero. These modifications did not impair model fit, $\chi^2(137) = 283.26$, $p < .001$, CFI = .94, RMSEA = .09. See

Table 1
Mean RTs (SD in Parentheses) for All Conditions of the Three Experimental Tasks

Task	Session 1		Session 2	
	Accuracies	RTs	Accuracies	RTs
SRT/CRT tasks				
SRT	1.00 (.01)	315.51 (53.01)	1.00 (.00)	317.20 (80.45)
CRT2	.99 (.01)	382.79 (58.02)	1.00 (.01)	381.27 (61.01)
CRT4	.99 (.01)	477.22 (82.64)	.98 (.02)	467.31 (85.7)
Sternberg task				
Set size 1	.97 (.02)	590.96 (115.67)	.98 (.02)	584.02 (135.64)
Set size 3	.97 (.02)	728.46 (167.21)	.98 (.03)	706.61 (176.81)
Set size 5	.97 (.03)	890.03 (240.74)	.95 (.09)	850.98 (223.18)
Posner task				
Physical identity	.98 (.02)	617.79 (93.93)	.98 (.02)	605.19 (102.41)
Name identity	.98 (.02)	699.50 (113.02)	.97 (.02)	704.38 (126.36)

Note. SRT = single choice reaction time task; CRT2/4 = choice reaction time task with two/four alternatives. $N = 122$ (Session 1)/$N = 114$ (Session 2).

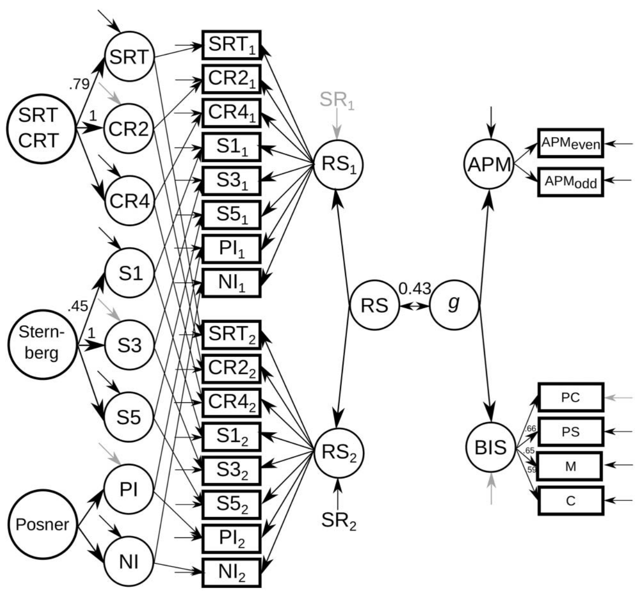

Figure 1. A structural equation model consisting of the latent-state-trait model of reaction speed and the hierarchical model of general intelligence. The LST model of reaction speed consists of a common trait *T*, a state residual SR_i for each of the two measurement occasions *i*, and a hierarchical method factor M_j for each of the three experimental tasks *j* and its conditions *k*. The hierarchical intelligence model consists of a common *g*-factor and two lower-order factors defined by the covariances in BIS and APM scores. The model provided an acceptable fit to the data, $\chi^2(253) = 480.32$, $p < .001$, CFI = .92, RMSEA = .09. All factor loadings are fixed to one; if not, standardized regression weights are shown next to paths. Nonsignificant latent variables, path coefficients, and residuals ($p \geq .05$) are grayed out. SRT = single RT task; CR2/4 = choice RT task with two/four alternatives; S1 = set size one; S3 = set size three; S5 = set size five; PI = physical identity; NI = name identity; PC = processing capacity; PS = processing speed; M = memory; C = creativity. Indices *i* at states RS_i and state residuals SR_i indicate the measurement occasion. $N = 121$.

Supplementary Table 1 for details of model specifications and a complete overview of estimated model parameters.

Based on this model, we calculated several LST parameters, namely the coefficients of reliability, consistency, occasion-specificity, and method-specify of the reaction speeds, which are shown in Table 2. The coefficient of reliability reflects the amount of variance accounted for by the hierarchical model, residual variances excluded, in each manifest variable. Reliabilities were high for all tasks and conditions, suggesting a great portion of systematic variance in each RS measurement and strong structural relations between variables. The coefficient of consistency reflects the amount of variance explained in each manifest variable by the shared variance of ERPs across tasks and laboratory sessions. Consistencies were greatest for the Posner letter-matching task, but substantial for all tasks ranging from .53 to .76. The coefficient of occasion-specificity reflects the amount of variance explained by situational influences and influences of person-situation interactions in each manifest variable. Occasion-specificities were negligible, which is consistent with previous work on the stability of RTs (Roznowski & Smith, 1993; Yap et al., 2012). The coefficient of method-specificity reflects the amount of variance explained in each manifest variable by task- and condition-specific factors. Method-specificities were moderate, ranging from .08 to .32, and highest for the SRT/CRT tasks and the Sternberg memory scanning task.

The Relationship Between Trait Reaction Speed and *g*

Previous research has shown that correlations between composite measures of mental speed and mental abilities tend to be higher than the correlations of single RT measures (Kranzler & Jensen, 1991; Miller & Vernon, 1996). Therefore, we assessed the correlation between the common reaction speed trait and general intelligence. For this purpose, we added a hierarchical model of general intelligence to the LST model and allowed the reaction speed trait to correlate with general intelligence (see Figure 1, Supplementary Table 1). This model provided an acceptable fit to the data, $\chi^2(253) = 480.32$, $p < .001$, CFI = .92, RMSEA = .09. The latent correlation between general intelligence and general behavioral information-processing speed was moderate, $r = .43$, $p < .001$.

This correlation is consistent with previous studies reporting correlations ranging from $r = -.22$ to $-.45$ between RTs in these tasks and mental abilities (Sheppard & Vernon, 2008). Given the high temporal stability and great reliability of RTs, it is not

Table 2
Latent-State-Trait Theory Parameters of Reaction Speed Variables

	Consistency		Occasion-specificity		Method-specificity		Reliability	
Task	Session 1	Session 2	Session 1	Session 2	Session 1	Session 2	Session 1	Session 2
SRT/CRT tasks								
SRT	.60	.54	0	.10	.30	.27	.90	.91
CRT2	.60	.54	0	.10	.30	.27	.90	.91
CRT4	.65	.59	0	.11	.24	.21	.89	.91
Sternberg task								
Set size 1	.71	.64	0	.11	.16	.15	.88	.89
Set size 3	.68	.61	0	.11	.21	.19	.89	.90
Set size 5	.58	.53	0	.09	.32	.29	.90	.91
Posner task								
Physical identity	.76	.68	0	.12	.10	.08	.87	.89
Name identity	.74	.66	0	.12	.13	.12	.88	.89

Note. SRT = single choice reaction time task; CRT2/4 = choice reaction time task with two/four alternatives.

surprising that the latent correlation did not exceed the size of these correlations notably.

The latent trait factor of response times was defined by two first-order factors, which is common in LST models (Steyer et al., 1999), but not ideal from a structural equation modeling perspective as two variables always share some covariance. Instead, it is more desirable to define higher order factors by at least three first-order factors. Therefore, we also tested a more straightforward bifactor model to ensure that our results are not dependent on our modeling approach (see Figure 2). Model fit of the bifactor was worse than model fit of the LST model, $\chi^2(275) = 755.52$, $p < .001$, CFI = .82, RMSEA = .14, although we did not constrain any variable loadings except where necessary. The latent correlation between general intelligence and general behavioral information-processing speed was still large, $r = .49$, $p < .001$, and comparable to the correlation found in the original model, $r = .43$, $p < .001$.

Factor Structure and Temporal Stability of ERP Latencies

To analyze whether more intelligent individuals show advantages in the speed of information processing at all stages of information processing, or specifically only at earlier or later stages, we compared two structural equation models of neurophysiological processing speed. Similar to the model for reaction speed, these models were LST models (Steyer et al., 1992) that allowed identifying the common and temporally stable trait variance of five ERP components across three experimental tasks and two measurement occasions. Grand-average waveforms of event-related potentials averaged across measurement occasions are presented in Figure 3 separately for more and less intelligent individuals and for each of the three tasks.

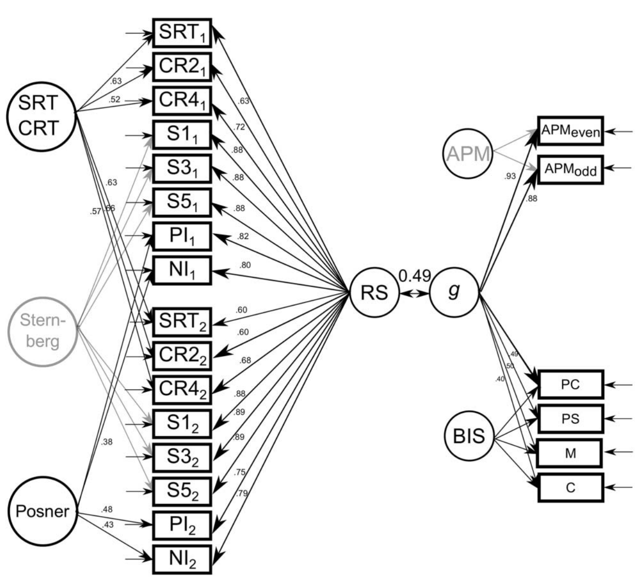

Figure 2. A structural equation model consisting of bifactor models of reaction speed and general intelligence. The bifactor model of reaction speed consists of a common factor *RS* and three orthogonal task-specific factors. The bifactor model of general intelligence consists of a common factor *g* and two orthogonal test-specific factors. The model provided a mediocre fit to the data, $\chi^2(275) = 755.52$, $p < .001$, CFI = .82, RMSEA = .14. Standardized regression weights are shown next to paths unless paths were fixed to one. Nonsignificant latent variables, path coefficients, and residuals ($p \geq .05$) are grayed out. SRT = single RT task; CR2/4 = choice RT task with two/four alternatives; S1 = set size one; S3 = set size three; S5 = set size five; PI = physical identity; NI = name identity; PC = processing capacity; PS = processing speed; M = memory; C = creativity. $N = 121$.

The general processing speed model consisted of a hierarchical common trait T, a state residual SR_i for each of the two measurement occasions i, and a method factor M_j for each of the three experimental tasks j. The specific processing speed model assumed two separate hierarchical common traits for earlier and later ERP latencies. ERP latencies, averaged across conditions, are shown in Table 3 for each of the three experimental tasks and each of the two measurement occasions. The full correlation matrix is included in Supplementary Table 4.

The specific processing speed model provided a notably better account for the data, $\chi^2(469) = 689.08$, $p < .001$, CFI = .85, RMSEA = .06, AIC = 749.08, than the general processing speed model, $\chi^2(472) = 880.95$, $p < .001$, CFI = .73, RMSEA = .09, AIC = 926.95. Therefore, we used the specific processing speed model for all further analyses and fixed all nonsignificant variances in this model to zero as shown in the left part of Figure 4, which did not impair model fit significantly, $\chi^2(481) = 719.22$, $p < .001$, CFI = .84, RMSEA = .06. See Supplementary Table 2 for details of model specifications and a complete overview of estimated model parameters for the specific processing speed model.

As shown in Table 4, the reliability of ERP latencies was as low as expected with very low reliabilities for the earlier latencies and somewhat higher reliabilities for the later latencies. Consistencies (.11 to .14) and method-specificities (.11 to .17) contributed about equally to the variance of the earlier ERP latencies, whereas consistencies were notably greater (.42 to .63) than method specificities (.08 to .09) for the later latencies. We observed relevant occasion-specificities for earlier latencies at the second measurement occasion, whereas the influence of occasion-specificities on later latencies was negligible.

The Relationship Between Trait ERP Latencies and *g*

To compare the plausibility of general speed hypotheses with the plausibility of specific speed hypotheses, we determined whether intelligence is associated with faster information processing at all or only at very specific stages of information processing. For this purpose, we analyzed how the common traits for earlier and later latencies correlated with general intelligence. Our results concerning the psychometric properties of ERP latencies indicate that the low reliabilities and consistencies of ERP measurements may have led to an underestimation of the relationship between ERP latencies and general intelligence in previous studies (Schulter & Neubauer, 2005). Hence, the latent correlations between ERP latency traits and general intelligence should be greater than the typically observed moderate manifest correlations.

For this purpose, we again added the hierarchical model of general intelligence to the structural model of ERP latencies and allowed the general ERP latency traits to correlate with general intelligence. This model (see Figure 4, Supplementary Table 2) provided a good fit to the data, $\chi^2(679) = 1048.84$, $p < .001$,

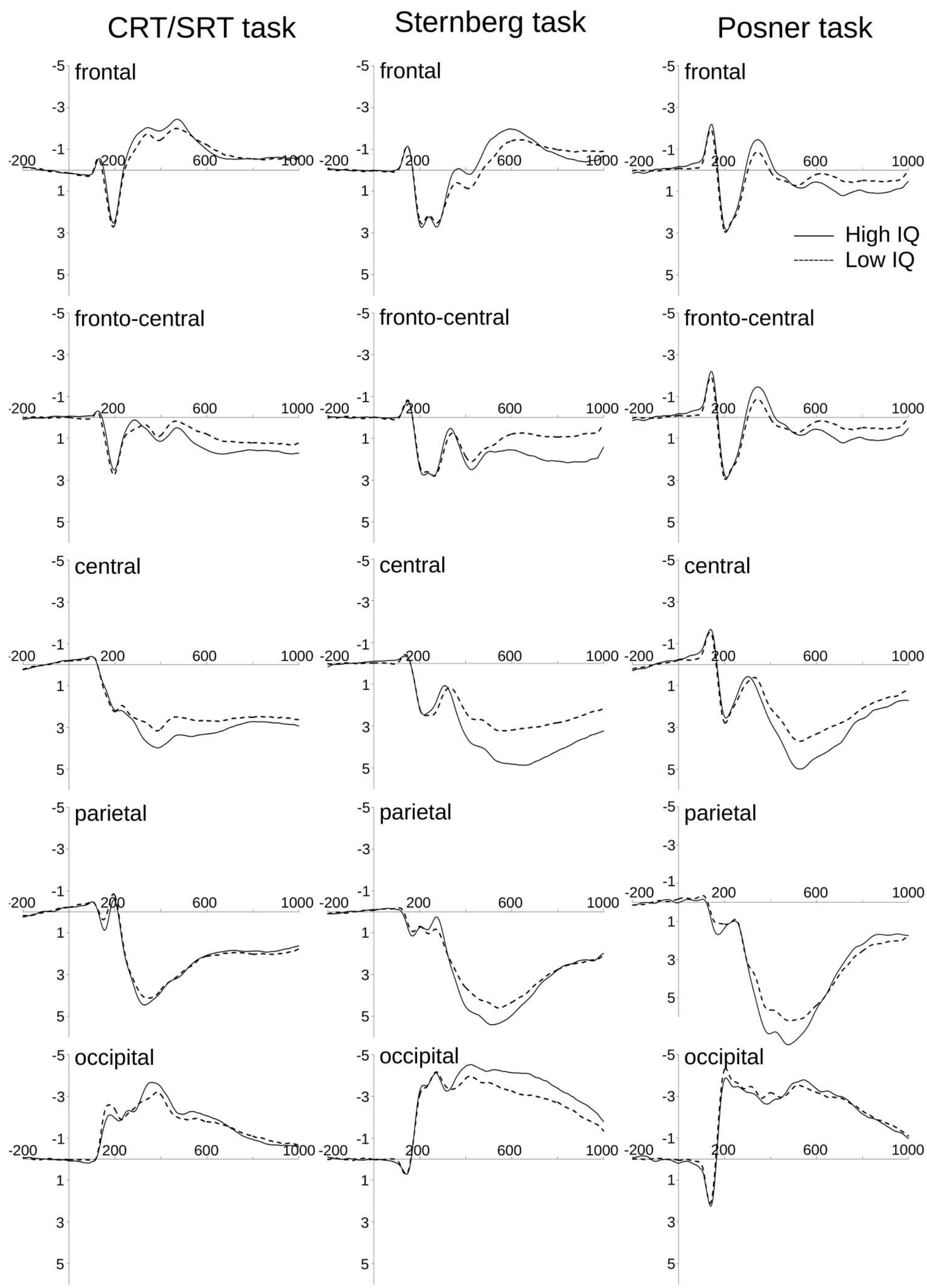

Figure 3. Grand averages of event-related potentials as measured at frontal, fronto-central, central, parietal, and occipital electrodes over midline, separately for more and less intelligent individuals and experimental tasks. ERPs were elicited by the stimulus onset and averaged across measurement occasions and conditions for each experimental task. High and low IQ groups were created based on a median split of the BIS total score. $N = 122$.

CFI = .83, RMSEA = .07. The common trait for earlier latencies was positively correlated with general intelligence, $r = .33$, $p < .001$, indicating that more intelligent individuals tended to show later P100 and N100 peak amplitudes. Moreover, the common trait for later latencies was negatively correlated with general intelligence, $r = -.89$, $p < .001$, indicating that more intelligent individuals showed earlier P200, N200, and P300 peak amplitudes. In particular, P300 latencies showed the highest standardized loadings on the common trait for later latencies. This suggests that P300 latencies showed the greatest association of all ERP latencies with general intelligence. Taken together, ERP latency traits explained 90.10% of the variance in general intelligence.

To analyze whether the correlation between ERP latency traits and general intelligence may be driven by the great heterogeneity

Table 3
Mean ERP Latencies (SD in Parentheses) Averaged Across Conditions of Each of the Three Experimental Tasks

Task	P100	N100	P200	N200	P300
Session 1					
SRT/CRT	92.28 (23.52)	131.11 (14.88)	211.54 (32.82)	206.15 (27.71)	330.67 (44.26)
Sternberg	98.10 (27.83)	129.70 (27.02)	234.08 (34.48)	251.11 (42.05)	374.35 (74.76)
Posner	91.35 (37.39)	129.05 (25.71)	222.26 (33.74)	247.87 (36.80)	414.97 (86.45)
Session 2					
SRT/CRT	104.21 (18.81)	128.11 (15.95)	208.44 (33.77)	210.38 (29.62)	324.40 (42.04)
Sternberg	94.82 (19.37)	132.53 (17.28)	230.35 (28.19)	248.48 (43.74)	382.39 (81.13)
Posner	124.78 (23.76)	140.76 (11.06)	218.16 (25.27)	240.02 (44.65)	377.74 (75.09)

Note. SRT/CRT = single and choice reaction time task. $N = 122$ (Session 1)/$N = 114$ (Session 2).

in age in our sample, we refitted the model with age-corrected residuals of the common ERP latency traits and general intelligence, $\chi^2(740) = 1103.15$, $p < .001$, CFI = .82, RMSEA = .07. The correlations between ERP latency traits and g did not change when corrected for age, $r_{earlierlatencies} = .34$, $p < .001$, $q\Delta = .01$, $r_{laterlatencies} = -.89$, $p < .001$, $q\Delta = .00$.

We also tested a simpler bifactor model for the electrophysiological data (see Figure 5). Model fit was again slightly worse than model fit of the LST model, $\chi^2(654) = 1121.64$, $p < .001$, CFI = .78, RMSEA = .08, probably because the model did not include factors accounting for component-specific variances. The correlation between the latent factor for earlier latencies and general intelligence was positive, $r = .30$, $p < .001$, and the correlation between the latent factor for later latencies and general intelligence was negative, $r = -.78$, $p < .001$. Correlations were probably somewhat smaller because the common factor for later latencies contained more component-specific variance than in the original model. All in all, this result shows that our results were independent of specific modeling choices.[1]

Discussion

The current study investigated whether more intelligent individuals have advantages in the speed of information processing at all stages of information processing, or only at specific earlier or later stages as reflected in the latency of specific ERP components. General intelligence was weakly associated with longer latencies of earlier ERP components (i.e., P100 and N100), and strongly associated with shorter latencies of later ERP components (i.e., P200, N200, and P300). This result suggests that smarter individuals do not have a general, but a very specific advantage in the speed of higher-order information processing.

Our results contradict popular theories proposing that individual differences in some brain-wide property explain the relationship between processing speed and general intelligence (Jensen, 2006; Miller, 1994; Penke et al., 2012). Instead, they suggest that more intelligent individuals process information faster specifically because of faster higher-order processing. The greatest association between ERP latencies and general intelligence was found for the P300, which is consistent with previous studies reporting an association between mental abilities and the visual or auditory P300 (Bazana & Stelmack, 2002; McGarry-Roberts et al., 1992; Troche et al., 2009). According to the context-updating interpretation of the P300 (Donchin, 1981), this association may reflect a faster inhibition of extraneous processes that facilitates the transmission of information from frontal attention and working memory processes to temporal-parietal processes of memory storage (Polich, 2007). This interpretation is consistent with previous research showing that individual differences in inhibition and updating are related to general intelligence (Wongupparaj, Kumari, & Morris, 2015).

Moreover, this key finding is consistent with predictions from the parieto-frontal integration theory of intelligence (P-FIT, Jung & Haier, 2007), which proposes that an effective interaction between association cortices within frontal and parietal brain regions underlies individual differences in mental abilities. This central assumption of P-FIT theory has seen great support based on a variety of structural and functional neuroimaging approaches (see Basten, Hilger, & Fiebach, 2015; Colom & Thompson, 2011, for a review), including voxel-based morphometry (Colom, Jung, & Haier, 2007; Colom et al., 2009; Colom et al., 2013), cortical surface area and cortical thickness analyses (Colom et al., 2013), voxel-based lesion mapping (Gläscher et al., 2010), and functional MRI (Burgess, Gray, Conway, & Braver, 2011). In particular, P-FIT theory proposes that the efficiency of white matter structures linking frontal and parietal brain regions (i.e., the arcuate fasciculus and the superior longitudinal fasciculus) determines the efficiency of information transmission in the parieto-frontal network underlying higher-order cognitive functioning (Jung & Haier, 2007). Our results support this assumption, because individual differences in the latency of ERP components associated with the transmission of information from frontal to temporal-parietal processes were strongly related to individual differences in general intelligence.

It is, however, important to note that there may be other properties of this parieto-frontal network related to intelligence that play a crucial role in explaining individual differences in general intelligence that are not directly related to the speed of neural transmissions. Using a network approach, Pineda-Pardo, Martínez, Román, and Colom (2016) demonstrated that local and global network efficiency in frontal, parietal, and temporal regions were

[1] We tested the same model but included only measures of fluid intelligence (APM, processing capacity subtest of the BIS) as cognitive abilities variables to assess the relationship between fluid intelligence and general intelligence on a neurophysiological level. The latent correlations between earlier ERP latencies and fluid intelligence, $r = .32$, $p < .001$, and between later ERP latencies and fluid intelligence, $r = -.83$, $p < .001$, were comparable with the correlations we found when other facets of intelligence were included in the model.

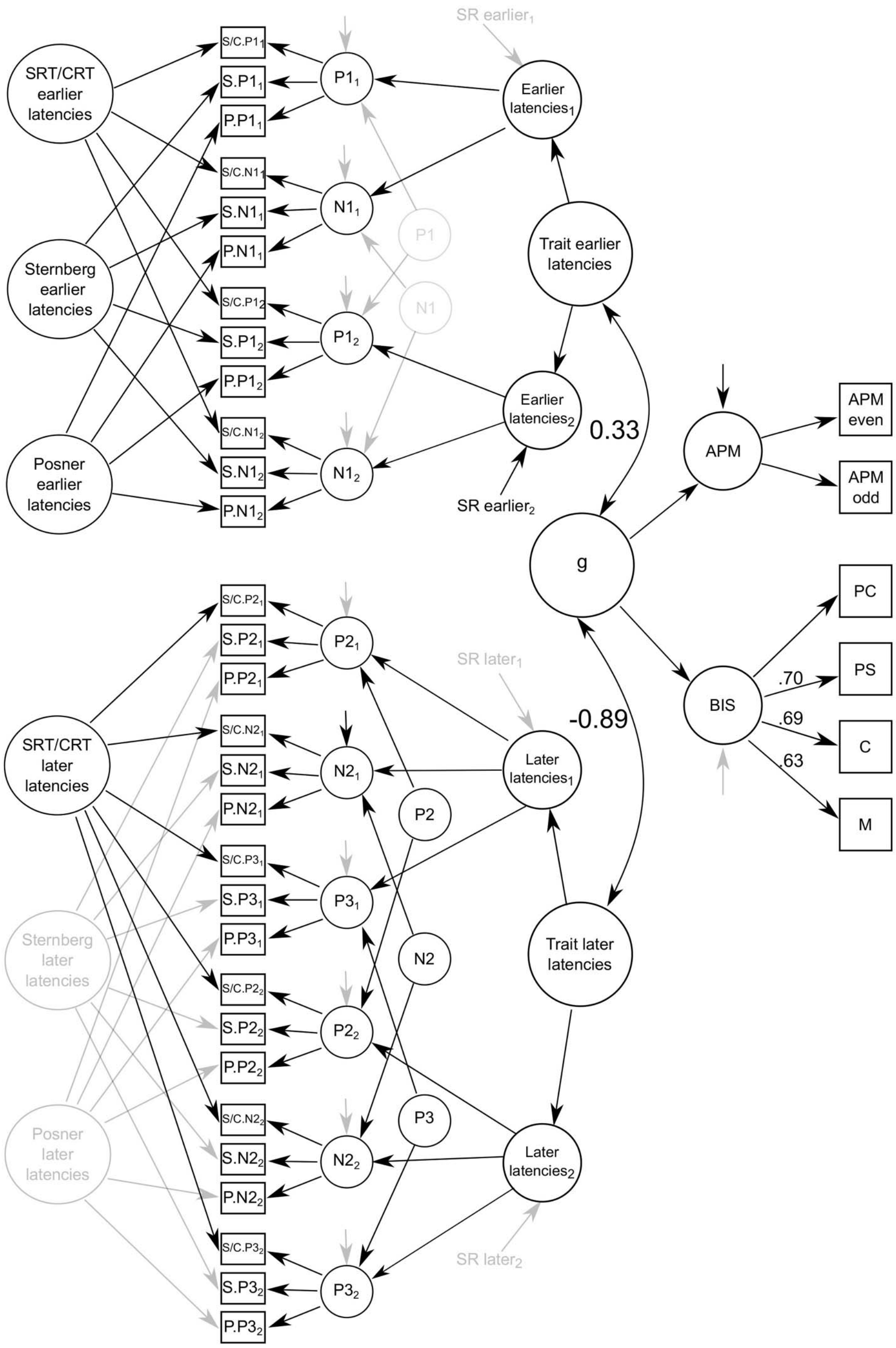

Figure 4. A structural equation model consisting of the specific processing speed-model of ERP latencies and the hierarchical model of general intelligence. The specific processing speed-model consisted of two separate hierarchical common traits, $T_{ealier\ latencies}$ and $T_{later\ latencies}$, a state residual SR_i for each of the two measurement occasions and each of the two traits, specific traits for the five ERP components (only significant specific traits are shown in the figure) and a method factor M_j for earlier and later ERP latencies of each of the three experimental tasks. The model provided a good fit to the data, $\chi^2(679) = 1048.84$, $p < .001$, CFI = .83, RMSEA = .07. All factor loadings are fixed to one; if not, standardized regression weights are shown next to paths. Error residuals are not shown. Nonsignificant latent variables, path coefficients, and residuals ($p \geq .05$) are grayed out. SRT/CRT = single/choice RT task; S = Sternberg letter-matching task; P = Posner letter-matching task; PC = processing capacity; PS = processing speed; M = memory; C = creativity. Indices i at states ERP$_i$ and state residuals SR$_i$ indicate the measurement occasion. $N = 122$.

Table 4
Latent-State-Trait Theory Parameters of ERP Latencies

Task	Consistency		Occasion-specificity		Method-specificity		Reliability	
	Session 1	Session 2	Session 1	Session 2	Session 1	Session 2	Session 1	Session 2
SRT/CRT tasks								
P100	.14	.11	0	.17	.14	.12	.28	.40
N100	.14	.11	0	.17	.14	.12	.28	.40
P200	.51	.51	0	0	.08	.08	.59	.59
N200	.42	.48	.12	0	.08	.09	.62	.56
P300	.57	.57	0	0	.09	.09	.66	.66
Sternberg task								
P100	.13	.11	0	.16	.17	.14	.30	.42
N100	.13	.11	0	.16	.17	.14	.30	.42
P200	.55	.55	0	0	0	0	.55	.55
N200	.46	.46	.13	0	0	0	.58	.46
P300	.63	.63	0	0	0	0	.63	.63
Posner task								
P100	.14	.11	0	.17	.13	.11	.27	.39
N100	.14	.11	0	.17	.13	.11	.27	.39
P200	.55	.55	0	0	0	0	.55	.55
N200	.46	.46	.13	0	0	0	.58	.46
P300	.63	.63	0	0	0	0	.63	.63

Note. SRT/CRT = single and choice reaction time task.

associated with general intelligence, but independent of the behavioral speed of information-processing. Moreover, a recent graph-analysis approach to resting state fMRI data found that smarter individuals showed a more distributed brain source allocation at rest, challenging the role of parieto-frontal areas as the primary brain regions related to general intelligence (Santarnecchi, Rossi, & Rossi, 2015).

We found that a latent composite measure of neurophysiological information-processing speed explained 90% of the variance in general intelligence in the present study. This association exceeds the weak negative correlations between ERP latencies and mental abilities reported in previous studies notably (Schulter & Neubauer, 2005) and demonstrates the benefits of latent variable modeling. Contrary to our expectations, neurophysiological processing speed was not more strongly influenced by situational factors than behavioral processing speed. Instead, ERP latencies had lower consistencies than reaction speeds, indicating that the covariance between different ERP components and tasks is relatively low and that measuring neurophysiological processing speed reliably requires multiple measurements. Hence, it is not surprising that the P300 is the only one of the measured ERP components for which associations with general intelligence have been repeatedly reported (Bazana & Stelmack, 2002; McGarry-Roberts et al., 1992; Troche et al., 2009), as P300 latencies had the highest reliabilities and showed the greatest association with general intelligence of all ERP latencies in the present study.

It is intriguing that latent measures of neurophysiological information-processing speed showed greater associations with general intelligence than latent measures of behavioral processing speed. These findings contrast with reports in the related literature in which behavioral processing speed was more strongly and more consistently associated with mental abilities than neurophysiological processing speed. Our results make it clear that measures of neurophysiological processing speed contain a great amount of task- and component-specific variance, and that once this unique variance has been accounted for, neurophysiological processing speed explains a great amount of variance in general intelligence. In fact, our results suggest that ERP latencies may provide a more precise measurement of information-processing speed, whereas reaction speeds may be contaminated by other response-related processes such as motor preparation and execution.

The strong association between the speed of higher-order processing and general intelligence is seemingly at odds with several studies reporting similarly strong associations between short-term/working memory capacity and general intelligence (e.g., Colom, Chuderski, & Santarnecchi, 2016; Conway, Cowan, Bunting, Therriault, & Minkoff, 2002; Engle, Tuholski, Laughlin, & Conway, 1999; Kyllonen & Christal, 1990). If both the speed of information-processing and short-term/working memory capacity explain more than 50% of the variance in general intelligence, the two processes cannot contribute to individual differences in intelligence independently. Hence, we propose that the two processes interact in the way that a higher speed of information-processing facilitates the processing and manipulation of information in working memory by a faster inhibition of irrelevant information. As such, the speed of higher-order information processing directly affects the efficiency of selective attention and working memory updating, which in turn affects both working memory capacity and general intelligence.

Several studies have demonstrated large correlations between the speed of information-processing and short term-/working memory-capacity (e.g., Ackerman, Beier, & Boyle, 2002; Kyllonen & Christal, 1990; Schmiedek, Oberauer, Wilhelm, Süß, & Wittman, 2007; Schmitz & Wilhelm, 2016). Conway et al. (2002) found that the speed of information-processing was specifically associated with shared variance between performance in simple and complex memory span tasks, but not with a latent factor reflecting only performance in span tasks. This result suggests that the speed of information-processing is not related to working memory performance attributable to the processing component of

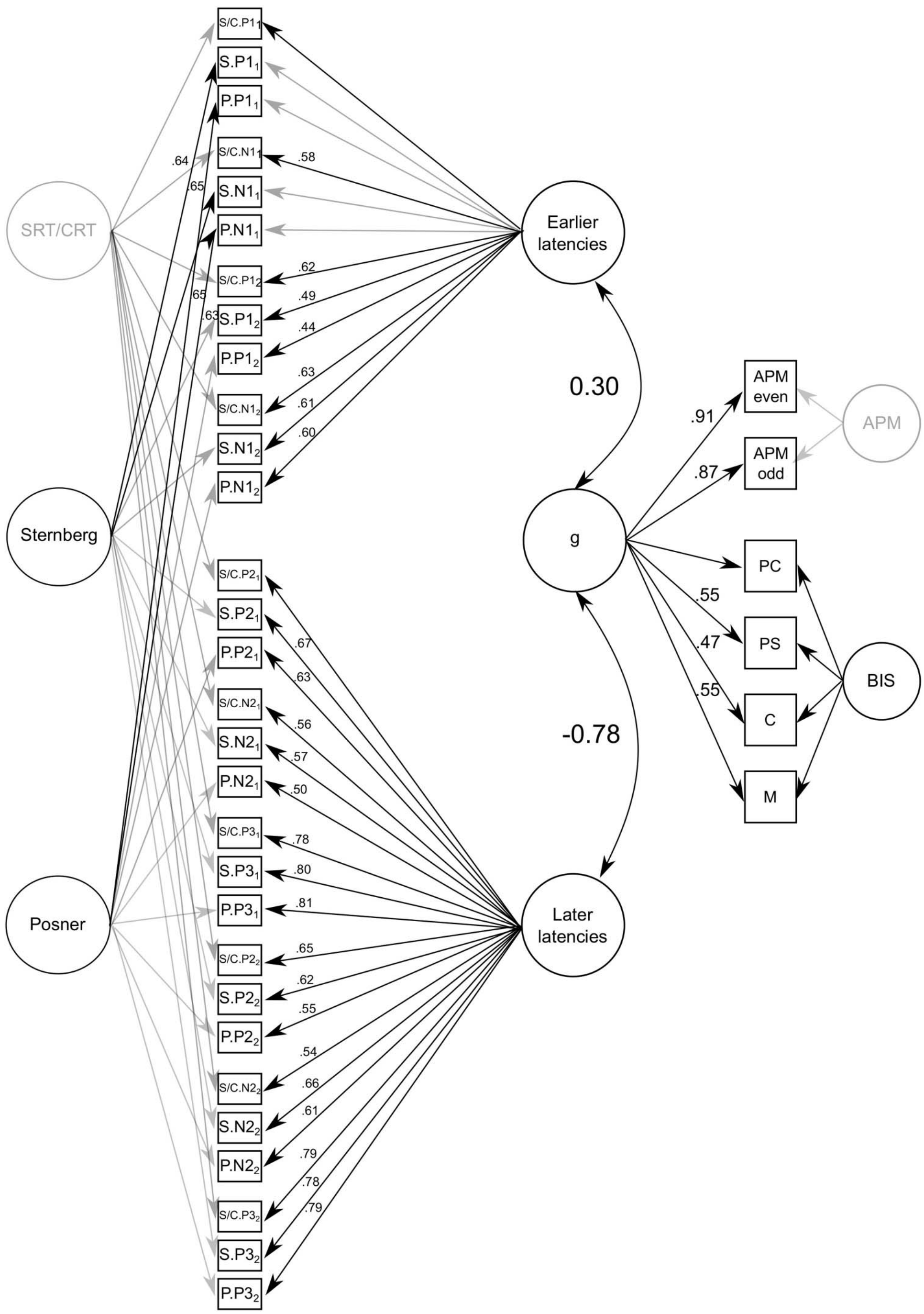

Figure 5. A structural equation model consisting of bifactor models of ERP latencies and general intelligence. The bifactor model of ERP latencies consists of a two orthogonal common factors for earlier and later latencies and three orthogonal task-specific factors. The bifactor model of general intelligence consists of a common factor *g* and two orthogonal test-specific factors. The model provided an acceptable fit to the data, $\chi^2(654) = 1121.64$, $p < .001$, CFI = .78, RMSEA = .08. Standardized regression weights are shown next to paths unless paths were fixed to one. Nonsignificant latent variables, path coefficients, and residuals ($p \geq .05$) are grayed out. SRT/CRT = single/choice RT task; S = Sternberg letter-matching task; P = Posner letter-matching task; PC = processing capacity; PS = processing speed; M = memory; C = creativity. $N = 122$.

complex span tasks but rather to some other property shared by simple and complex span tasks.

Moreover, both cross-sectional and longitudinal developmental studies have shown that developmental changes in working memory capacity are mediated by developmental changes in the speed of information-processing, and that developmental changes in fluid intelligence are in turn mediated by changes in working memory capacity and the speed of information-processing (Fry & Hale, 1996; Kail, 2007). These results do not only emphasize the close relationship between the two constructs, but suggest clear trajectories in developmental changes that underline the role that the speed of information-processing plays for the efficiency of working memory processes.

We suppose that a greater speed of higher-order information processing (as measured by the latencies of ERP components occurring later in the stream of information-processing) increases working memory capacity and general intelligence by increasing the efficiency of selective attention and memory updating. This interpretation is consistent with the context updating theory of the P300, which proposes that this component reflects the inhibition of ongoing neural activity to facilitate memory-related storage operations in temporal and parietal areas (Polich, 2007). Moreover, it is also consistent with the notion that the relationship between working memory capacity and fluid intelligence is partly mediated by individual differences in attentional control (Unsworth, Fukuda, Awh, & Vogel, 2014), and with previous findings showing that any effect of inhibition on fluid intelligence is fully mediated by primary memory (Shipstead, Lindsey, Marshall, & Engle, 2014). In addition, the speed of neural higher-order processing may also affect the efficiency of secondary memory or increase capacity by facilitating the development and disintegration of temporary bindings (Oberauer, Süß, Wilhelm, & Sander, 2007; Unsworth & Spillers, 2010).

Moreover, this interpretation of our results is consistent with process overlap theory (POT; Kovacs & Conway, 2016), which proposes that a limited number of independent domain-specific and domain-general cognitive processes contribute to individual differences in general intelligence. In particular, process overlap theory assumes that domain-general executive processes may serve as a bottleneck constraining performance in a wide number of cognitive tasks, giving rise to the positive manifold typically observed in cognitive abilities test batteries. Consistent with this assumption of POT, we found that latencies of later event-related potentials associated with the efficiency of executive processes were strongly related to general intelligence.

One feature of the present study that limits the conclusions which can be drawn about the association between the speed of information processing and general intelligence is that we used only very simple RT tasks. These so-called elementary cognitive tasks are cognitively undemanding to minimize the unwanted influence of individual differences in strategy use and previous experience with specific elements of these tasks on RTs (Carroll, 1993). Whether cognitively more demanding RT tasks such as working memory tasks or information-processing speed paradigms not requiring a motor response such as the inspection time task would yield comparable results is an open question.

Another feature limiting the conclusions we can draw about the mechanism by which the speed of higher-order information processing affects general intelligence is the correlational nature of the present study. Future studies should use experimental approaches to study the effect of increased demands on specific executive functions on the speed of information-processing, working memory capacity, and general intelligence. Moreover, pharmacological approaches tailored to the neuromodulation of the speed of higher-order processing might yield further insights into the specific mechanisms underlying the correlational relationship. Based on the current study, we cannot rule out that other variables—probably on a molecular level—underlie the relationship between the speed of higher-order information processing and general intelligence.

Taken together, our results illustrate that the speed of information processing is a crucial component of general intelligence. Given that general intelligence was only associated with a higher speed in the peak latency of ERP components occurring later in the stream of information processing, and given that the latencies of these later components explained 80% of the variance in general intelligence, we conclude that general intelligence is little more than the speed of higher-order processing.

References

Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2002). Individual differences in working memory within a nomological network of cognitive and perceptual speed abilities. *Journal of Experimental Psychology: General, 131,* 567–589. http://dx.doi.org/10.1037/0096-3445.131.4.567

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In B. N. Petrov & F. Caski (Eds.), *Proceedings of the Second International Symposium on Information Theory* (pp. 267–281). Budapest, Hungary: Akademiai Kiado.

Arbuckle, J. L. (2006). *Amos 7.0 user's guide*. Chicago, IL: SPSS.

Basten, U., Hilger, K., & Fiebach, C. J. (2015). Where smart brains are different: A quantitative meta-analysis of functional and structural brain imaging studies on intelligence. *Intelligence, 51,* 10–27. http://dx.doi.org/10.1016/j.intell.2015.04.009

Bazana, P. G., & Stelmack, R. M. (2002). Intelligence and information processing during an auditory discrimination task with backward masking: An event-related potential analysis. *Journal of Personality and Social Psychology, 83,* 998–1008. http://dx.doi.org/10.1037/0022-3514.83.4.998

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107,* 238–246. http://dx.doi.org/10.1037/0033-2909.107.2.238

Browne, M., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Sage focus editions: Vol. 154. Testing structural equation models* (pp. 136–162). Newbury Park, CA: Sage.

Burgess, G. C., Gray, J. R., Conway, A. R., & Braver, T. S. (2011). Neural mechanisms of interference control underlie the relationship between fluid intelligence and working memory span. *Journal of Experimental Psychology: General, 140,* 674–692. http://dx.doi.org/10.1037/a0024695

Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multimodel inference: A practical information-theoretic approach* (2nd ed.). New York, NY: Springer.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. Cambridge, UK: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511571312

Cassidy, S. M., Robertson, I. H., & O'Connell, R. G. (2012). Retest reliability of event-related potentials: Evidence from a variety of paradigms. *Psychophysiology, 49,* 659–664. http://dx.doi.org/10.1111/j.1469-8986.2011.01349.x

Colom, R., Burgaleta, M., Román, F. J., Karama, S., Álvarez-Linera, J., Abad, F. J., . . . Haier, R. J. (2013). Neuroanatomic overlap between intelligence and cognitive factors: Morphometry methods provide support for the key role of the frontal lobes. *NeuroImage, 72,* 143–152. http://dx.doi.org/10.1016/j.neuroimage.2013.01.032

Colom, R., Chuderski, A., & Santarnecchi, E. (2016). Bridge over troubled water: Commenting on Kovacs & Conway's process overlap theory. *Psychological Inquiry, 27,* 181–189. http://dx.doi.org/10.1080/1047840X.2016.1181513

Colom, R., Haier, R. J., Head, K., Álvarez-Linera, J., Quiroga, M. A., Shih, P. C., & Jung, R. E. (2009). Gray matter correlates of fluid, crystallized, and spatial intelligence: Testing the P-FIT model. *Intelligence, 37,* 124–135. http://dx.doi.org/10.1016/j.intell.2008.07.007

Colom, R., Jung, R. E., & Haier, R. J. (2007). General intelligence and memory span: Evidence for a common neuroanatomic framework. *Cognitive Neuropsychology, 24,* 867–878. http://dx.doi.org/10.1080/02643290701781557

Colom, R., & Thompson, P. M. (2011). Understanding Human Intelligence by Imaging the Brain. In T. Chamorro-Premuzic, S. von Stumm, & A. Furnham (Eds.), *Handbook of individual differences*. London, UK: Wiley-Blackwell. http://dx.doi.org/10.1002/9781444343120.ch12

Conway, A. R. A., Cowan, N., Bunting, M. F., Therriault, D. J., & Minkoff, S. R. B. (2002). A latent variable analysis of working memory capacity, short term memory capacity, processing speed, and general fluid intelligence. *Intelligence, 30,* 163–183. http://dx.doi.org/10.1016/S0160-2896(01)00096-4

Danner, D., Hagemann, D., Schankin, A., Hager, M., & Funke, J. (2011). Beyond IQ: A latent state-trait analysis of general intelligence, dynamic decision making, and implicit learning. *Intelligence, 39,* 323–334. http://dx.doi.org/10.1016/j.intell.2011.06.004

Deary, I. (2008). Why do intelligent people live longer? *Nature, 456,* 175–176. http://dx.doi.org/10.1038/456175a

Der, G., Batty, G. D., & Deary, I. J. (2009). The association between IQ in adolescence and a range of health outcomes at 40 in the 1979 US National Longitudinal Study of Youth. *Intelligence, 37,* 573–580. http://dx.doi.org/10.1016/j.intell.2008.12.002

Donchin, E. (1981). Presidential address, 1980. Surprise! . . . Surprise? *Psychophysiology, 18,* 493–513. http://dx.doi.org/10.1111/j.1469-8986.1981.tb01815.x

Engle, R. W., Tuholski, S. W., Laughlin, J. E., & Conway, A. R. A. (1999). Working memory, short-term memory, and general fluid intelligence: A latent-variable approach. *Journal of Experimental Psychology: General, 128,* 309–331. http://dx.doi.org/10.1037/0096-3445.128.3.309

Fry, A., & Hale, S. (1996). Processing speed, working memory, and fluid intelligence: Evidence for a developmental cascade. *Psychological Science, 7,* 237–241. http://dx.doi.org/10.1111/j.1467-9280.1996.tb00366.x

Gläscher, J., Rudrauf, D., Colom, R., Paul, L. K., Tranel, D., Damasio, H., & Adolphs, R. (2010). Distributed neural system for general intelligence revealed by lesion mapping. *Proceedings of the National Academy of Sciences of the United States of America, 107,* 4705–4709. http://dx.doi.org/10.1073/pnas.0910397107

Gratton, G., Coles, M. G., & Donchin, E. (1983). A new method for off-line removal of ocular artifact. *Electroencephalography & Clinical Neurophysiology, 55,* 468–484. http://dx.doi.org/10.1016/0013-4694(83)90135-9

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6,* 1–55. http://dx.doi.org/10.1080/10705519909540118

Jäger, A. O. (1982). Mehrmodale Klassifikation von Intelligenzleistungen. Experimentell kontrollierte Weiterentwicklung eines deskriptiven Intelligenzstrukturmodells [Multimodal classification intelligence lest performances. Experimentally controlled further development of a descriptive intelligence structure model]. *Diagnostica, 28,* 195–226.

Jäger, A. O., Süß, H.-M., & Beauducel, A. (1997). *Berliner Intelligenzstruktur-Test. Form 4*. Göttingen, Germany: Hogrefe.

Jensen, A. R. (2006). *Clocking the mind: Mental chronometry and individual differences*. Amsterdam, the Netherlands: Elsevier.

Johnson, W., Nijenhuis, J. T., & Bouchard, T. J., Jr. (2008). Still just 1 g: Consistent results from five test batteries. *Intelligence, 36,* 81–95. http://dx.doi.org/10.1016/j.intell.2007.06.001

Jung, R. E., & Haier, R. J. (2007). The parieto-frontal integration theory (P-FIT) of intelligence: Converging neuroimaging evidence. *Behavioral and Brain Sciences, 30,* 135–154. http://dx.doi.org/10.1017/S0140525X07001185

Kail, R. V. (2007). Longitudinal evidence that increases in processing speed and working memory enhance children's reasoning. *Psychological Science, 18,* 312–313. http://dx.doi.org/10.1111/j.1467-9280.2007.01895.x

Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research, 44,* 486–507. http://dx.doi.org/10.1177/0049124114543236

Kievit, R. A., Davis, S. W., Griffiths, J., Correia, M. M., Cam-Can., & Henson, R. N. (2016). A watershed model of individual differences in fluid intelligence. *Neuropsychologia, 91,* 186–198. http://dx.doi.org/10.1016/j.neuropsychologia.2016.08.008

Kovacs, K., & Conway, A. R. A. (2016). Process overlap theory: A unified account of the general factor of intelligence. *Psychological Inquiry, 27,* 151–177. http://dx.doi.org/10.1080/1047840X.2016.1153946

Kranzler, J. H., & Jensen, A. R. (1991). The nature of psychometric g: Unitary process or a number of independent processes? *Intelligence, 15,* 397–422. http://dx.doi.org/10.1016/0160-2896(91)90003-V

Kyllonen, P., & Christal, R. (1990). Reasoning ability is (little more than) working memory capacity?! *Intelligence, 14,* 389–433. http://dx.doi.org/10.1016/S0160-2896(05)80012-1

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1,* 130–149. http://dx.doi.org/10.1037/1082-989X.1.2.130

Marshalek, B., Lohman, D. F., & Snow, R. E. (1983). The complexity continuum in the radex and hierarchical models of intelligence. *Intelligence, 7,* 107–127. http://dx.doi.org/10.1016/0160-2896(83)90023-5

McGarry-Roberts, P. A., Stelmack, R. M., & Campbell, K. B. (1992). Intelligence, reaction time, and event-related potentials. *Intelligence, 16,* 289–313. http://dx.doi.org/10.1016/0160-2896(92)90011-F

McVay, J. C., & Kane, M. J. (2012). Drifting from slow to "D'oh!": Working memory capacity and mind wandering predict extreme reaction times and executive control errors. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 38,* 525–549. http://dx.doi.org/10.1037/a0025896

Miller, E. M. (1994). Intelligence and brain myelination: A hypothesis. *Personality and Individual Differences, 17,* 803–832. http://dx.doi.org/10.1016/0191-8869(94)90049-3

Miller, L. T., & Vernon, P. A. (1996). Intelligence, reaction time, and working memory in 4- to 6-year-old children. *Intelligence, 22,* 155–190. http://dx.doi.org/10.1016/S0160-2896(96)90014-8

Oberauer, K., Süß, H.-M., Wilhelm, O., & Sander, N. (2007). Individual differences in working memory capacity and reasoning ability. In A. R. A. Conway, C. Jarrold, M. J. Kane, A. Miyake, & J. N. Towse (Eds.), *Variation in working memory* (pp. 49–75). Oxford, UK: Oxford University Press.

Penke, L., Maniega, S. M., Bastin, M. E., Valdés Hernández, M. C., Murray, C., Royle, N. A., . . . Deary, I. J. (2012). Brain white matter tract integrity as a neural foundation for general intelligence. *Molecular Psychiatry, 17,* 1026–1030. http://dx.doi.org/10.1038/mp.2012.66

Pesta, B. J., McDaniel, M. A., & Bertsch, S. (2010). Toward an index of well-being for the fifty U.S. states. *Intelligence, 38,* 160–168. http://dx.doi.org/10.1016/j.intell.2009.09.006

Pineda-Pardo, J. A., Martínez, K., Román, F. J., & Colom, R. (2016). Structural efficiency within a parieto-frontal network and cognitive differences. *Intelligence, 54,* 105–116. http://dx.doi.org/10.1016/j.intell.2015.12.002

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical neurophysiology: Official journal of the International Federation of Clinical Neurophysiology, 118,* 2128–2148.

Preacher, K. J., & Coffman, D. L. (2006, May). Computing power and minimum sample size for RMSEA [Computer software]. Available from http://quantpsy.org/

Raven, J. C., Court, J. H., & Raven, J. (1994). *Manual for Raven's progressive matrices and mill hill vocabulary scales. Advanced progressive matrices*. Oxford, UK: Oxford University Press.

Roznowski, M., & Smith, M. L. (1993). A note on some psychometric properties of Sternberg task performance: Modifications to content. *Intelligence, 17,* 389–398. http://dx.doi.org/10.1016/0160-2896(93)90006-Q

Santarnecchi, E., Rossi, S., & Rossi, A. (2015). The smarter, the stronger: Intelligence level correlates with brain resilience to systematic insults. *Cortex, 64,* 293–309. http://dx.doi.org/10.1016/j.cortex.2014.11.005

Schmidt, F. L., & Hunter, J. (2004). General mental ability in the world of work: Occupational attainment and job performance. *Journal of Personality and Social Psychology, 86,* 162–173. http://dx.doi.org/10.1037/0022-3514.86.1.162

Schmiedek, F., Oberauer, K., Wilhelm, O., Süss, H.-M., & Wittmann, W. W. (2007). Individual differences in components of reaction time distributions and their relations to working memory and intelligence. *Journal of Experimental Psychology: General, 136,* 414–429. http://dx.doi.org/10.1037/0096-3445.136.3.414

Schmitz, F., & Wilhelm, O. (2016). Modeling mental speed: Decomposing response time distributions in elementary cognitive tasks and correlations with working memory capacity and fluid intelligence. *Journal of Intelligence, 4,* 13. http://dx.doi.org/10.3390/jintelligence4040013

Schubert, A.-L., Hagemann, D., Voss, A., & Bergmann, K. (2017). Evaluating the model fit of diffusion models with the root mean square error of approximation. *Journal of Mathematical Psychology, 77,* 29–45. http://dx.doi.org/10.1016/j.jmp.2016.08.004

Schubert, A.-L., Hagemann, D., Voss, A., Schankin, A., & Bergmann, K. (2015). Decomposing the relationship between mental speed and mental abilities. *Intelligence, 51,* 28–46. http://dx.doi.org/10.1016/j.intell.2015.05.002

Schulter, G., & Neubauer, A. (2005). Zentralnervensystem und Persönlichkeit [Central nervous system and personality]. In J. Henning & P. Netter (Eds.), *Biopsychologische Grundlagen der Persönlichkeit* (pp. 35–190). Munich, Germany: Elsevier. http://dx.doi.org/10.1007/978-3-8274-3089-2_2

Sheppard, L. D., & Vernon, P. A. (2008). Intelligence and speed of information-processing: A review of 50 years of research. *Personality and Individual Differences, 44,* 535–551. http://dx.doi.org/10.1016/j.paid.2007.09.015

Shipstead, Z., Lindsey, D. R. B., Marshall, R. L., & Engle, R. W. (2014). The mechanisms of working memory capacity: Primary memory, secondary memory, and attention control. *Journal of Memory and Language, 72,* 116–141. http://dx.doi.org/10.1016/j.jml.2014.01.004

Spearman, C. (1923). *The nature of 'intelligence' and the principles of cognition*. Oxford, UK: Macmillan.

Steyer, R., Ferring, D., & Schmitt, M. J. (1992). States and traits in psychological assessment. *European Journal of Psychological Assessment, 8,* 79–98.

Steyer, R., Schmitt, M., & Eid, M. (1999). Latent state–trait theory and research in personality and individual differences. *European Journal of Personality, 13,* 389–408. http://dx.doi.org/10.1002/(SICI)1099-0984(199909/10)13:5<389::AID-PER361>3.0.CO;2-A

Stough, C., Thompson, J., Bates, T., & Nathan, P. (2001). Examining neurochemical determinants of inspection time: Development of a biological model. *Intelligence, 29,* 511–522. http://dx.doi.org/10.1016/S0160-2896(01)00077-0

Troche, S. J., Houlihan, M. E., Stelmack, R. M., & Rammsayer, T. H. (2009). Mental ability, P300, and mismatch negativity: Analysis of frequency and duration discrimination. *Intelligence, 37,* 365–373. http://dx.doi.org/10.1016/j.intell.2009.03.002

Troche, S. J., Indermühle, R., Leuthold, H., & Rammsayer, T. H. (2015). Intelligence and the psychological refractory period: A lateralized readiness potential study. *Intelligence, 53,* 138–144. http://dx.doi.org/10.1016/j.intell.2015.10.003

Unsworth, N., Fukuda, K., Awh, E., & Vogel, E. K. (2014). Working memory and fluid intelligence: Capacity, attention control, and secondary memory retrieval. *Cognitive Psychology, 71,* 1–26. http://dx.doi.org/10.1016/j.cogpsych.2014.01.003

Unsworth, N., & Spillers, G. J. (2010). Working memory capacity: Attention control, secondary memory, or both? A direct test of the dual-component model. *Journal of Memory and Language, 62,* 392–406. http://dx.doi.org/10.1016/j.jml.2010.02.001

van Ravenzwaaij, D., Brown, S., & Wagenmakers, E. J. (2011). An integrated perspective on the relation between response speed and intelligence. *Cognition, 119,* 381–393. http://dx.doi.org/10.1016/j.cognition.2011.02.002

Vickers, D., & Smith, P. L. (1986). The rationale for the inspection time index. *Personality and Individual Differences, 7,* 609–623. http://dx.doi.org/10.1016/0191-8869(86)90030-9

Wai, J. (2014). Experts are born, then made: Combining prospective and retrospective longitudinal data shows that cognitive ability matters. *Intelligence, 45,* 74–80. http://dx.doi.org/10.1016/j.intell.2013.08.009

West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with non-normal variables: Problems and remedies. In R. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 56–75). Thousand Oaks, CA: Sage.

Wongupparaj, P., Kumari, V., & Morris, R. G. (2015). The relation between a multicomponent working memory and intelligence: The roles of central executive and short-term storage functions. *Intelligence, 53,* 166–180. http://dx.doi.org/10.1016/j.intell.2015.10.007

Yap, M. J., Balota, D. A., Sibley, D. E., & Ratcliff, R. (2012). Individual differences in visual word recognition: Insights from the English Lexicon Project. *Journal of Experimental Psychology: Human Perception and Performance, 38,* 53–79. http://dx.doi.org/10.1037/a0024177

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