Neurocognitive Psychometrics of Intelligence: How Measurement Advancements Unveiled the Role of Mental Speed in Intelligence Differences

Schubert, Anna-Lena ; Frischkorn, Gidon T

Abstract: More intelligent individuals typically show faster reaction times. However, individual differences in reaction times do not represent individual differences in a single cognitive process but in multiple cognitive processes. Thus, it is unclear whether the association between mental speed and intelligence reflects advantages in a specific cognitive process or in general processing speed. In this article, we present a neurocognitive-psychometrics account of mental speed that decomposes the relationship between mental speed and intelligence. We summarize research employing mathematical models of cognition and chronometric analyses of neural processing to identify distinct stages of information processing strongly related to intelligence differences. Evidence from both approaches suggests that the speed of higher-order processing is greater in smarter individuals, which may reflect advantages in the structural and functional organization of brain networks. Adopting a similar neurocognitive-psychometrics approach for other cognitive processes associated with intelligence (e.g., working memory or executive control) may refine our understanding of the basic cognitive processes of intelligence.

DOI: https://doi.org/10.1177/0963721419896365

Originally published at:
Schubert, Anna-Lena; Frischkorn, Gidon T (2020). Neurocognitive Psychometrics of Intelligence: How Measurement Advancements Unveiled the Role of Mental Speed in Intelligence Differences. Current Directions in Psychological Science, 29(2):140-146.
DOI: https://doi.org/10.1177/0963721419896365

Neurocognitive psychometrics of intelligence: How measurement advancements in mental speed unveiled the role of processing speed in intelligence differences

Anna-Lena Schubert[a*] & Gidon T. Frischkorn[b*]

[a]Heidelberg University, Institute of Psychology

[b]University of Zurich, Department of Psychology

[*]Both authors contributed equally to the manuscript.

Word Count: 2499

Author Note

Correspondence concerning this article should be addressed to Anna-Lena Schubert, Institute of Psychology, Heidelberg University, Hauptstrasse 47-51, D-69117 Heidelberg, Germany, Phone: +49 (0) 6221-547746, Fax: +49 (0) 6221-547325, E-mail: anna-lena.schubert@psychologie.uni-heidelberg.de

Abstract

More intelligent individuals typically show faster reaction times. However, individual differences in reaction times do not represent individual differences in a single, but in multiple cognitive processes. Thus, it is unclear whether the association between mental speed and intelligence reflects advantages in a specific cognitive process or in general processing speed. This article presents a neurocognitive psychometrics account of mental speed that decomposes the relationship between mental speed and intelligence. We summarize research employing mathematical models of cognition and chronometric analyses of neural processing to identify distinct stages of information-processing strongly related to intelligence differences. Evidence from both approaches suggests that smarter individuals show a greater speed of higher-order processing, which may reflect advantages in the structural and functional organization of brain networks. Adopting a similar neurocognitive psychometrics approach for other cognitive processes associated with intelligence (e.g. working memory or executive control) may refine our understanding of the basic cognitive processes of intelligence.

Keywords: Intelligence, Mental Speed, Psychometrics, Cognitive Modeling

Neurocognitive psychometrics of intelligence: How measurement advancements in mental speed unveiled the role of processing speed in intelligence differences

Intelligence is a captivating psychological construct positively related to a number of important life outcomes such as educational attainment, job performance, development of expertise, general health, longevity, and well-being. Because it is such a powerful predictor, identifying which elementary processes give rise to individual differences in intelligence is of great relevance. One often discussed candidate property of information-processing that may underlie intelligence differences is mental speed (Jensen, 2006), usually defined as the time taken to process and respond to information.

At the turn of the 20th century, Francis Galton conducted the first study on individual differences in mental speed. He assumed that response times (RTs) to external stimuli predicted individual differences in mental abilities. However, low precision of his measures and lack of adequate statistical methods prevented him from finding any associations between mental speed and other variables. More recent research has overcome these problems by using standardized response devices and computerized measurements. By now, it is well-established that more intelligent individuals show moderately shorter RTs than less intelligent individuals (Doebler & Scheffler, 2016; Jensen, 2006; Kail & Salthouse, 1994; Salthouse, 1996; Vernon, 1987). This indicates that the ability to quickly process information in a broad range of different tasks is related to intelligence.

Decomposing the Relationship between Mental Speed and Mental Abilities

Individual differences in RTs do not represent a single cognitive process. Instead, time taken by several processes, such as the encoding of information, decision making, and motor execution, affect RTs. What therefore remained an open question was whether more intelligent individuals showed a greater mental speed because of advantages in all or some of these processes, and whether these advantages were related to individual differences in global or focal neural organization.

To address this problem, it is necessary to decompose the stream of information-processing to distinguish between the speed of different processing stages. This way it can be assessed whether the general speed of processing across all processing stages or the speed of specific processes is related to intelligence. Such a decomposition of mental speed can be achieved in a neurocognitive psychometrics approach that combines (1) mathematical models of cognition, which formally separate different processes contributing to RTs, and (2) chronometric analyses of the event-related potential (ERP) in the electroencephalogram (EEG). As such, a neurocognitive psychometrics account of mental speed integrates mathematical models and neurophysiological indicators of cognitive processes in psychometric models to reliably and validly identify specific cognitive processes giving rise to the association between mental speed and mental abilities.

Mathematical Models of Cognition

Mathematical models of cognition translate verbal theories of cognitive processes into mathematical formalizations that specify the workings and interplay of mechanisms contributing to observed behavior. One particular mathematical model often used to describe binary decision making is the diffusion model (see Figure 1), which assumes that during decision making evidence is accumulated in a random walk process until one of two decision thresholds is reached, the decision process terminated, and a motor response initiated (Ratcliff, 1978).

The model decomposes RT distributions into four parameters: The velocity of evidence accumulation is reflected in the drift rate parameter, decision cautiousness in the boundary separation parameter, and a bias in favor of one of the two choice alternatives in the starting point parameter. Finally, the non-decision time parameter represents a residual parameter that

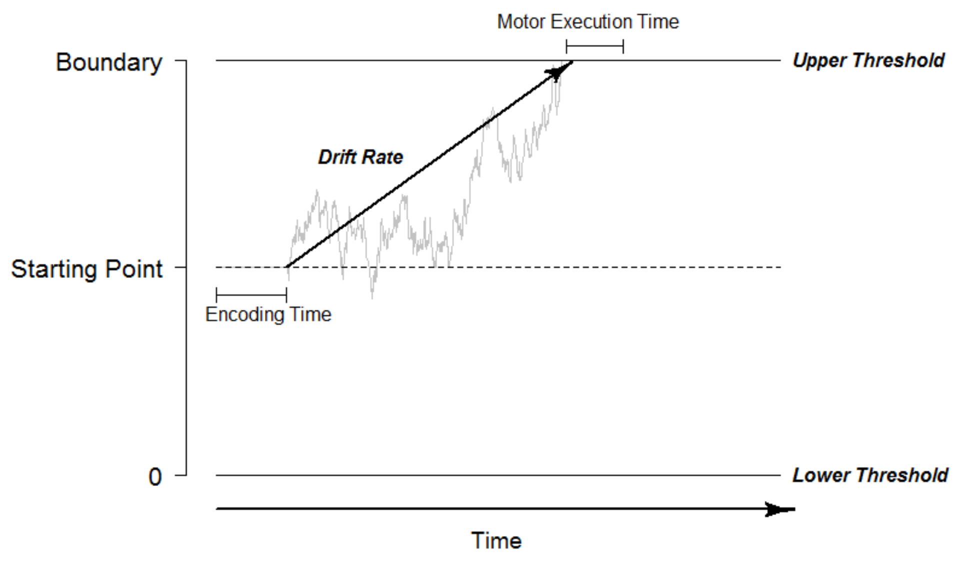

Figure 1. Simplified illustration of the diffusion model: The model assumes that, after encoding, information is continuously accumulated towards one of the two decision thresholds. This accumulation process, illustrated by the grey line, consists of a systematic component – the drift rate, illustrated by the black arrow - and random noise. As soon as one of the two thresholds is reached, the decision is made and can then be executed, e.g. via key press.

reflects the speed of all non-decisional processes such as (but not limited to) encoding and motor response. Hence, the diffusion model can be used to investigate whether more intelligent individuals show advantages in one specific or in several sub-processes of decision making.

Psychometric studies indicate that only the drift rate can be considered a trait, which is defined as a person characteristic with high temporal stability and sufficient consistency across different tasks. While a common drift rate factor accounted on average for 44 percent of the variation in drift rate parameters estimated in a set of different tasks, the other parameters were largely task-dependent (Schubert, Frischkorn, Hagemann, & Voss, 2016). In particular, variation in boundary separation and non-decision time parameters was on average less well accounted for by their respective common traits, with several parameter estimates showing extremely low consistencies.

In addition, the drift rate is the most interesting parameter for intelligence research, because it reflects the speed of information-uptake free of confounding sources of variance such as speed-accuracy trade-offs or encoding and motor speed. It can even be directly linked to psychometric theories, as the drift rate can be decomposed into an ability and difficulty parameter, thus reflecting both individuals' speed and efficiency of evidence accumulation with regard to a specific item (van der Maas, Molenaar, Maris, Kievit, & Borsboom, 2011). Hence, it is not surprising that several studies found associations between drift rates and intelligence ranging from r=0.60 to r=0.90 that were substantially larger than typical correlations between RTs and intelligence (Ratcliff, Thapar, & McKoon, 2010; Schmiedek, Oberauer, Wilhelm, Süss, & Wittmann, 2007). Furthermore, the drift rate is the only model parameter consistently associated with cognitive abilities across a wide range of different tasks and samples (for a summary, see Frischkorn & Schubert, 2018).

Taken together, these results indicate that more intelligent individuals benefit from a greater velocity of evidence accumulation, both from sensory input as well as from memory, but do not show a greater encoding or motor response speed.

Chronometric Analyses of the ERP

Similar to mathematical models of cognition, the ERP can be used to measure individual differences in specific cognitive processes. It is based on electrophysiological brain activity recorded with the EEG, which registers electrical currents generated by cortical nerve cell activity in the brain. The ERP reflects cortical activity related to stimulus processing and allows to decompose the electrophysiological activity between stimulus onset and response into functionally distinct components associated with certain cognitive processes. Shorter latencies in specific ERP components reflect a higher processing speed of the associated cognitive processes.

Research on ERP correlates of intelligence has shown that more intelligent individuals show selective advantages in some neuro-cognitive processes (e.g. stimulus evaluation, memory updating, or response selection), while others (e.g., response organization and execution) are not related to intelligence (Bazana & Stelmack, 2002; Kapanci, Merks, Rammsayer, & Troche, 2019; Saville et al., 2016; Troche, Houlihan, Stelmack, & Rammsayer, 2009; Troche, Indermühle, Leuthold, & Rammsayer, 2015).

Because latencies of ERP components are largely task-dependent, they cannot simply be measured in any experimental task, but need to be aggregated across different tasks to reflect consistent person properties (Schubert, Hagemann, & Frischkorn, 2017). Across three different experimental tasks, individual differences in latencies of ERP components associated with higher-order processing (i.e., stimulus evaluation, memory updating, and response selection processes captured in the P2, N2, and P3 component) explained about 80 percent of variance in intelligence (Schubert et al., 2017). In contrast, smarter individuals did not show any advantages in the speed of ERP components reflecting sensory processing (i.e., in latencies of the P1 and N1 component). These results suggest that neuro-cognitive processes reflected in ERP components associated with higher-order attentional processing may give rise to individual differences in intelligence.

Similar to the use of mathematical models, chronometric analyses of the ERP thus allowed to decompose the stream of information-processing and to identify specific higher-order cognitive processes related to intelligence.

Why do Benefits in the Speed of Higher-Order Processing give Rise to Greater Intelligence?

Taken together, mathematical models of cognition and chronometric analyses of the ERP represent two complimentary neurocognitive psychometric approaches that aim to identify specific cognitive processes giving rise to individual differences in intelligence. Across both approaches, there is converging evidence that more intelligent individuals benefit from a greater speed of higher-order information-processing. Electrophysiological results in particular suggest that greater intelligence should be associated with higher attentional control in working memory, a notion that is propagated by many current theories of intelligence (e.g., Engle, 2018; Kovacs & Conway, 2016). Further evidence that individual differences in the speed of higher-order processing contribute to intelligence differences by affecting processing in working memory comes from research showing that the association between working memory capacity and intelligence becomes near-isomorphic when intelligence tests are administered under extreme time-constraints (Chuderski, 2013).

Although there is a substantial body of research relating measures of attentional control to mental abilities (Engle, 2018), recent psychometric work challenges the notion that individual differences in attentional control can be reliably and validly measured (Frischkorn, Schubert, & Hagemann, 2019; Hedge, Powell, & Sumner, 2018; Rey-Mermet, Gade, & Oberauer, 2018). On the one hand, the ongoing psychometric debate suggests that experimentally validated slope measures of attentional control may be task-specific and elicit very little variation between individuals. On the other hand, intercept measures of attentional control (e.g., performance in a single condition or average task performance) have been shown to mostly reflect individual differences in general processing speed (Frischkorn et al., 2019). Together, these problems considerably complicate the reliable and valid measurement of attentional control.

Here, too, neurocognitive psychometrics might remedy the situation and provide alternative approaches to the measurement of attentional control. First, mathematical models of attentional control processes might provide more reliable estimates of process parameters, as these models dissociate individual differences in attention-related parameters from individual differences in general processing speed without resorting to the calculation of slopes (Frischkorn & Schubert, 2018). Second, neural correlates of attentional control can be recorded to dissociate attention-related neurocognitive processes from other neurocognitive processes across a wide set of different cognitive control tasks. In fact, first results suggest that more intelligent individuals benefit from more efficient interregional goal-directed information-processing as indicated by an adaptive modulation of synchronized brain rhythms associated with attention (Schubert, Hagemann, Löffler, Rummel, & Arnau, 2019). This again supports the idea that individual differences in attentional control processes contribute to individual differences in intelligence.

If we consider that both the neural speed of higher-order processing (reflected in ERP latencies occurring later in the stream of information-processing) and the speed of information-uptake (reflected in the drift rate parameter of the diffusion model) are substantially related to intelligence, it may be proposed that a greater neural speed gives rise to greater intelligence by enhancing the speed of information-uptake. A direct test of this hypothesis, however, revealed that individual differences in drift rates only explained a negligible part of the association between the neural speed and intelligence (Schubert, Nunez, Hagemann, & Vandekerckhove, 2018). Moreover, experimental enhancements of mental speed by nicotine administration have not translated into intelligence gains (Schubert, Hagemann, Frischkorn, & Herpertz, 2018). In sum, these results do not support the idea of a simple causal cascade model, in which a greater neural speed facilitates evidence accumulation, which in turn gives rise to greater cognitive abilities. Instead, they suggest that the relationship between the speed of higher-order processing and intelligence may reflect individual differences in properties of brain networks that are not easily malleable by changes in neurotransmitter concentration (see Figure 2 for a conceptual illustration).

This idea is further supported by research on white matter tract integrity. Measures of white matter tract integrity reflect a range of tissue characteristics (e.g., myelination, axon diameter, fiber density, and fiber organization) that determine the accuracy and speed of information transmission across the nerve fiber. As with a cable, better insulation (i.e., a denser myelin-layer) and a larger diameter mean that information can be transmitted faster. Moreover, a higher cable and a higher axon density allow more information to be transmitted in a specific amount of time. These properties positively affect processing speed and functional connectivity within and between brain regions (Ferrer et al., 2013; Kievit et al., 2016; Penke et al., 2012; Wendelken et al., 2017). Moreover, greater white matter tract

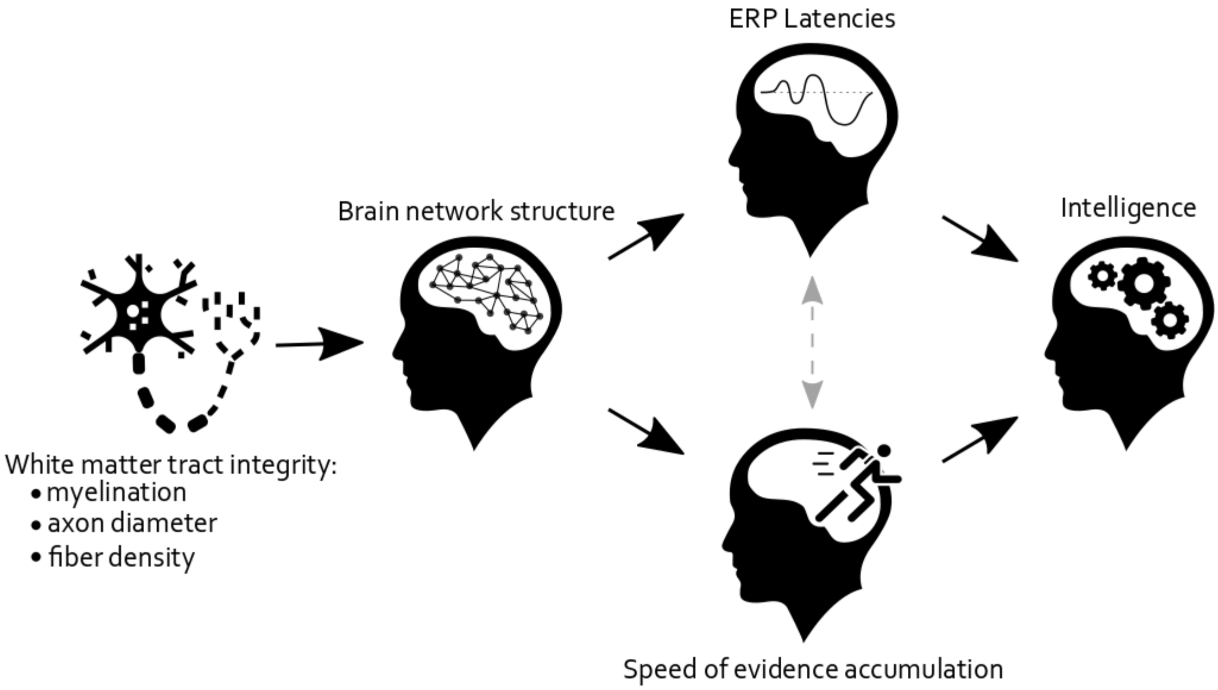

Figure 2. Simplified illustration of the proposed relationships between basic brain properties, such as white matter tract integrity and brain network structure, with neurocognitive measures of mental speed and intelligence. Properties of neural fibers reflected in white matter tract integrity positively affect the brain network structure. In turn, individual differences in these network structures give rise to individual differences in ERP latencies and the speed of evidence accumulation, which may therefore be correlated. Together, individual differences in these neurocognitive measures of mental speed mediate the relationship between brain network structures and intelligence. Apart from white matter tract integrity, many other brain properties not shown here may also affect both mental speed and intelligence.

integrity has been repeatedly associated with greater mental abilities in different age groups (Booth et al., 2013; Ferrer et al., 2013; Fuhrmann, Simpson-Kent, Bathelt, Team, & Kievit, 2019; Kievit et al., 2016; Wendelken et al., 2017)

Most intriguingly, the effects of greater white matter tract integrity on intelligence seem to be fully mediated by individual differences in processing speed and working memory capacity, suggesting that greater white matter tract integrity enhances the speed and capacity of information-processing, which in concert positively affect reasoning ability (Ferrer et al., 2013; Fuhrmann et al., 2019; Kievit et al., 2016; Wendelken, Ferrer, Whitaker, & Bunge, 2016). Longitudinal research on children and adolescents even supports a developmental cascade model, in which individual differences in white matter tract integrity drive changes in processing speed, which in turn drive changes in working memory capacity, which ultimately determine the development of reasoning ability (Fry & Hale, 1996; Wendelken et al., 2016).

The Potential of Neurocognitive Psychometrics: Benefits and Future Directions

We believe that using a neurocognitive psychometrics approach that combines mathematical models of cognition and neural correlates of cognitive processes in individual differences research will ultimately help to identify elementary processes underlying intelligence differences. It has already allowed to shed light on the neurocognitive processes underlying the well-established association between speed and age-related cognitive decline (Salthouse, 1996; Schubert, Hagemann, Löffler, & Frischkorn, 2019). Moreover, it allows designing training and intervention studies aimed at the enhancement of specific neurocognitive processes contributing to intelligence differences.

This approach can be extended to other domains of information-processing associated with intelligence (e.g., working memory or attentional control). In fact, promising cognitive models for these domains have been put forth recently (Oberauer & Lewandowsky, 2019; White, Servant, & Logan, 2018). In addition, multinomial processing tree models have been used to distinguish between processes and abilities involved in fast and slow responses in reasoning tests (Partchev & De Boeck, 2012).

Ultimately, an integration of mathematical models and neurophysiological indicators of cognitive processes directly relates constructs to their measurement and allows for theoretical discussions on the structure of cognitive abilities beyond psychometric models of observed behavior. In this, a neurocognitive psychometrics of intelligence – as described here for mental speed – will also help to understand whether interrelations between different cognitive ability measures arise because they are all influenced by a set of very broad and general cognitive processes (Jensen, 1998) or because they emerge from a network of mutually interrelated but independent cognitive processes (Kovacs & Conway, 2016; Van Der Maas et al., 2006).

Acknowledgments

We thank Dirk Hagemann for the innovative ideas and helpful suggestions he has brought to our joint research program. Moreover, we thank Christoph Löffler and Johanna Hein for their helpful comments on an earlier version of this manuscript.

References

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*(4), 998–1008. https://doi.org/10.1037/0022-3514.83.4.998

Booth, T., Bastin, M. E., Penke, L., Maniega, S. M., Murray, C., Royle, N. A., … Deary, I. J. (2013). Brain White Matter Tract Integrity and Cognitive Abilities in Community-Dwelling Older People: The Lothian Birth Cohort, 1936. *Neuropsychology*, *27*(5), 595–607. https://doi.org/10.1037/a0033354

Chuderski, A. (2013). When are fluid intelligence and working memory isomorphic and when are they not? *Intelligence*, *41*(4), 244–262. https://doi.org/10.1016/j.intell.2013.04.003

Doebler, P., & Scheffler, B. (2016). The relationship of choice reaction time variability and intelligence: A meta-analysis. *Learning and Individual Differences*, *52*, 157–166. https://doi.org/10.1016/j.lindif.2015.02.009

Engle, R. W. (2018). Working Memory and Executive Attention: A Revisit. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, *13*(2), 190–193. https://doi.org/10.1177/1745691617720478

Ferrer, E., Whitaker, K. J., Steele, J. S., Green, C. T., Wendelken, C., & Bunge, S. A. (2013). White matter maturation supports the development of reasoning ability through its influence on processing speed. *Developmental Science*, *16*(6), 941–951. https://doi.org/10.1111/desc.12088

Frischkorn, G. T., & Schubert, A.-L. (2018). Cognitive Models in Intelligence Research: Advantages and Recommendations for Their Application. *Journal of Intelligence*, *6*(3), 34. https://doi.org/10.3390/jintelligence6030034

Frischkorn, G. T., Schubert, A.-L., & Hagemann, D. (2019). Processing speed, working memory, and executive functions: Independent or inter-related predictors of general intelligence. *Intelligence*, *75*, 95–110. https://doi.org/10.1016/j.intell.2019.05.003

Fry, A. F., & Hale, S. (1996). Processing Speed, Working Memory, and Fluid Intelligence: Evidence for a Developmental Cascade. *Psychological Science*, *7*(4), 237–241. Retrieved from JSTOR.

Fuhrmann, D., Simpson-Kent, I. L., Bathelt, J., Team, the C., & Kievit, R. A. (2019). A hierarchical watershed model of fluid intelligence in childhood and adolescence. *BioRxiv*, 435719. https://doi.org/10.1101/435719

Hedge, C., Powell, G., & Sumner, P. (2018). The reliability paradox: Why robust cognitive tasks do not produce reliable individual differences. *Behavior Research Methods*, *50*(3), 1166–1186. https://doi.org/10/gddfm4

Jensen, A. R. (1998). *The g Factor—The Science of Mental Ability*. Westport, CT, USA: Praeger Publishers.

Jensen, A. R. (2006). *Clocking the Mind: Mental Chronometry and Individual Differences* (1st ed.). Amsterdam ; Boston ; London: Elsevier Science.

Kail, R., & Salthouse, T. A. (1994). Processing speed as a mental capacity. *Acta Psychologica*, *86*(2), 199–225. https://doi.org/10.1016/0001-6918(94)90003-5

Kapanci, T., Merks, S., Rammsayer, T. H., & Troche, S. J. (2019). On the Relationship between P3 Latency and Mental Ability as a Function of Increasing Demands in a Selective Attention Task. *Brain Sciences*, *9*(2), 28. https://doi.org/10.3390/brainsci9020028

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. https://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*(3), 151–177. https://doi.org/10.1080/1047840X.2016.1153946

Oberauer, K., & Lewandowsky, S. (2019). Simple Measurement Models for Complex Working-Memory Tasks. *Psychological Review*.

Partchev, I., & De Boeck, P. (2012). Can fast and slow intelligence be differentiated? *Intelligence*, *40*(1), 23–32. https://doi.org/10.1016/j.intell.2011.11.002

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*(10), 1026–1030. https://doi.org/10.1038/mp.2012.66

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108. https://doi.org/10.1037/0033-295X.85.2.59

Ratcliff, R., Thapar, A., & McKoon, G. (2010). Individual differences, aging, and IQ in two-choice tasks. *Cognitive Psychology*, *60*(3), 127–157. https://doi.org/10.1016/j.cogpsych.2009.09.001

Rey-Mermet, A., Gade, M., & Oberauer, K. (2018). Should we stop thinking about inhibition? Searching for individual and age differences in inhibition ability. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *44*(4), 501–526. https://doi.org/10.1037/xlm0000450

Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review*, *103*(3), 403–428.

Saville, C. W. N., Beckles, K. D. O., MacLeod, C. A., Feige, B., Biscaldi, M., Beauducel, A., & Klein, C. (2016). A neural analogue of the worst performance rule: Insights from single-trial event-related potentials. *Intelligence*, *55*, 95–103. https://doi.org/10.1016/j.intell.2015.12.005

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*(3), 414–429. https://doi.org/10.1037/0096-3445.136.3.414

Schubert, A.-L., Frischkorn, G. T., Hagemann, D., & Voss, A. (2016). Trait Characteristics of Diffusion Model Parameters. *Journal of Intelligence*, *4*(3), 7. https://doi.org/10.3390/jintelligence4030007

Schubert, A.-L., Hagemann, D., & Frischkorn, G. T. (2017). Is general intelligence little more than the speed of higher-order processing? *Journal of Experimental Psychology. General*, *146*(10), 1498–1512. https://doi.org/10.1037/xge0000325

Schubert, A.-L., Hagemann, D., Frischkorn, G. T., & Herpertz, S. C. (2018). Faster, but not smarter: An experimental analysis of the relationship between mental speed and mental abilities. *Intelligence*, *71*, 66–75. https://doi.org/10.1016/j.intell.2018.10.005

Schubert, A.-L., Hagemann, D., Löffler, C., & Frischkorn, G. T. (2019). *Disentangling the Effects of the Age-Related Decline in Processing Speed on Fluid Intelligence* [Preprint]. https://doi.org/10.31234/osf.io/5rdfg

Schubert, A.-L., Hagemann, D., Löffler, C., Rummel, J., & Arnau, S. (2019). *A chronometric model of the relationship between frontal midline theta functional connectivity and human intelligence*. https://doi.org/10.31234/osf.io/5yru4

Schubert, A.-L., Nunez, M. D., Hagemann, D., & Vandekerckhove, J. (2018). Individual Differences in Cortical Processing Speed Predict Cognitive Abilities: A Model-Based Cognitive Neuroscience Account. *Computational Brain & Behavior*. https://doi.org/10.1007/s42113-018-0021-5

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*(4), 365–373. https://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. https://doi.org/10.1016/j.intell.2015.10.003

Van Der Maas, H. L. J., Dolan, C. V., Grasman, R. P. P. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. J. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, *113*(4), 842–861. https://doi.org/10/c3jm44

van der Maas, H. L. J., Molenaar, D., Maris, G., Kievit, R. A., & Borsboom, D. (2011). Cognitive psychology meets psychometric theory: On the relation between process models for decision making and latent variable models for individual differences. *Psychological Review*, *118*(2), 339–356. https://doi.org/10/drf5nw

Vernon, P. A. (1987). *Speed of information-processing and intelligence*. Westport, CT, US: Ablex Publishing.

Wendelken, C., Ferrer, E., Ghetti, S., Bailey, S. K., Cutting, L., & Bunge, S. A. (2017). Frontoparietal Structural Connectivity in Childhood Predicts Development of Functional Connectivity and Reasoning Ability: A Large-Scale Longitudinal Investigation. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *37*(35), 8549–8558. https://doi.org/10.1523/JNEUROSCI.3726-16.2017

Wendelken, C., Ferrer, E., Whitaker, K. J., & Bunge, S. A. (2016). Fronto-Parietal Network Reconfiguration Supports the Development of Reasoning Ability. *Cerebral Cortex*, *26*(5), 2178–2190. https://doi.org/10.1093/cercor/bhv050

White, C. N., Servant, M., & Logan, G. D. (2018). Testing the validity of conflict drift-diffusion models for use in estimating cognitive processes: A parameter-recovery study. *Psychonomic Bulletin & Review*, *25*(1), 286–301. https://doi.org/10.3758/s13423-017-1271-2

Recommended Readings

- Frischkorn, G. T. & Schubert, A.-L. (2018). See reference list. → A comprehensive overview of the benefits of cognitive modeling in intelligence research with practical recommendations for empirical research.
- Jensen, A. R. (2006). See reference list. → A clearly written and relatively comprehensive review for readers who wish to expand their knowledge on mental speed research.
- Schubert, A.-L., Nunez, M. D., Hagemann, D., & Vandekerckhove, J. (2018). → This paper integrates diffusion modeling and chronometric analyses of the ERP in a hierarchical Bayesian framework, demonstrating the benefits and potential of the neurocognitive psychometrics approach.
- Turner, B. M., Forstmann, B. U., Love, B. C., Palmeri, T. J., & Van Maanen, L. (2017). Approaches to analysis in model-based cognitive neuroscience. *Journal of Mathematical Psychology*, *76*, 65–79. https://doi.org/10.1016/j.jmp.2016.01.001 → An accessible overview over several approaches for linking brain and behavioral data, published in a special issue on the integration of cognitive models and neural correlates.
- White, C. N., Servant, M., & Logan, G. D. (2018). See reference list. → A technical and detailed, but still accessible comparison of different cognitive models of attentional control processes.

Figure Captions

Figure 1. Simplified illustration of the diffusion model: The model assumes that, after encoding, information is continuously accumulated towards one of the two decision thresholds. This accumulation process, illustrated by the grey line, consists of a systematic component – the drift rate, illustrated by the black arrow - and random noise. As soon as one of the two thresholds is reached, the decision is made and can then be executed, e.g. via key press.

Figure 2. Simplified illustration of the proposed relationships between basic brain properties, such as white matter tract integrity and brain network structure, with neurocognitive measures of mental speed and intelligence. Properties of neural fibers reflected in white matter tract integrity positively affect the brain network structure. In turn, individual differences in these network structures give rise to individual differences in ERP latencies and the speed of evidence accumulation, which may therefore be correlated. Together, individual differences in these neurocognitive measures of mental speed mediate the relationship between brain network structures and intelligence. Apart from white matter tract integrity, many other brain properties not shown here may also affect both mental speed and intelligence.

Notes

[1]Address correspondence to Anna-Lena Schubert, Institute of Psychology, Heidelberg University, Hauptstrasse 47-51, D-69117 Heidelberg, Germany, Phone: +49 (0) 6221-547746, Fax: +49 (0) 6221-547325, E-mail: anna-lena.schubert@psychologie.uni-heidelberg.de