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

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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.

Keywords
intelligence, mental speed, psychometrics, cognitive modeling

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 intelligence 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 reaction times (RTs) to external stimuli predicted individual differences in mental abilities. However, the low precision of his measures and lack of adequate statistical methods prevented him from finding any associations between mental speed and other variables. More recently, researchers have 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

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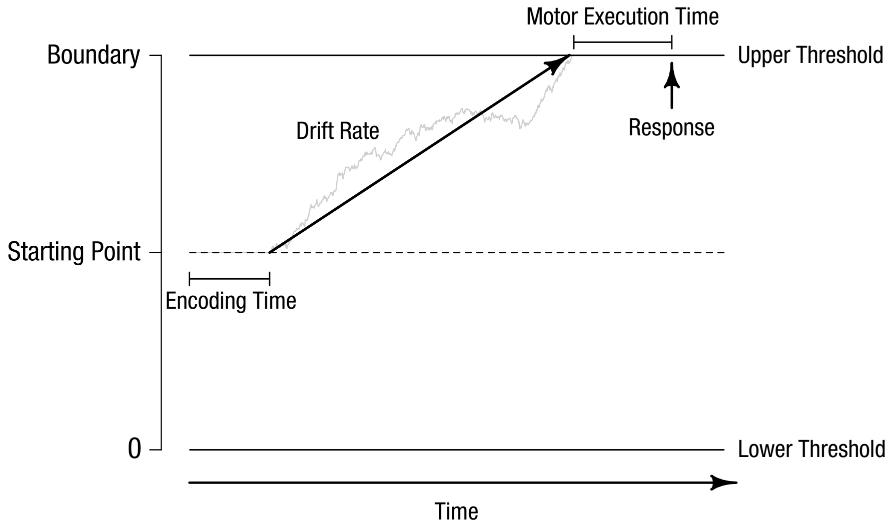

Fig. 1. Simplified illustration of the diffusion model. The model assumes that, after encoding, information is continuously accumulated toward one of the two decision thresholds. This accumulation process, illustrated by the jagged, light-gray line, consists of a systematic component—the drift rate, illustrated by the straight, diagonal 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 a key press).

motor execution, affects 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 speeds of different processing stages. This will allow assessment of 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 (a) mathematical models of cognition, which formally separate different processes contributing to RTs, and (b) chronometric analyses of the event-related potential (ERP) in the electroencephalogram (EEG). Therefore, 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 Fig. 1), which posits that during decision-making, evidence is accumulated in a random-walk process until one of two decision thresholds is reached, at which point the decision process is 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 is reflected in the boundary-separation parameter, and a bias in favor of one of the two choice alternatives is reflected in the starting-point parameter. Finally, the nondecision-time parameter is a residual parameter that reflects the speed of all nondecisional 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 or several subprocesses of decision-making.

Psychometric studies indicate that only the drift rate can be considered a trait, which is defined as a personality characteristic with high temporal stability and sufficient consistency across different tasks. Specifically, one study found that a common drift-rate factor accounted, on average, for 44% of the variation in drift-rate parameters estimated in a set of different tasks, while the other parameters were largely task dependent (Schubert, Frischkorn, Hagemann, & Voss, 2016). In particular, variation in boundary-separation and nondecision-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 because the drift rate can be decomposed into an ability and difficulty parameter, thus reflecting both individuals' speed and the 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 (*r*s) between drift rates and intelligence, ranging from .60 to .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, from both sensory input and 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 an EEG, which registers electrical currents generated by activity in cortical nerve cells. The ERP reflects cortical activity related to stimulus processing and allows the decomposition of 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 speed in the associated cognitive processes.

Research on ERP correlates of intelligence has shown that more intelligent individuals show selective advantages in some neurocognitive processes (e.g., stimulus evaluation, memory updating, or response selection), whereas 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). In Schubert et al.'s study, 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 components) explained about 80% of the variance in intelligence. 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 components). These results suggest that neurocognitive 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 the decomposition of the stream of information processing and identification of 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 because 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 explained only a negligible part of the association between 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 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 altered by changes in neurotransmitter concentration (see Fig. 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 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, the CALM Team, & Kievit, 2020; 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., 2020; 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 shed light on the neurocognitive processes underlying the well-established association between speed and age-related cognitive decline (Salthouse, 1996; Schubert, Hagemann, Löffler, & Frischkorn, 2020). Moreover, it allows the design of 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

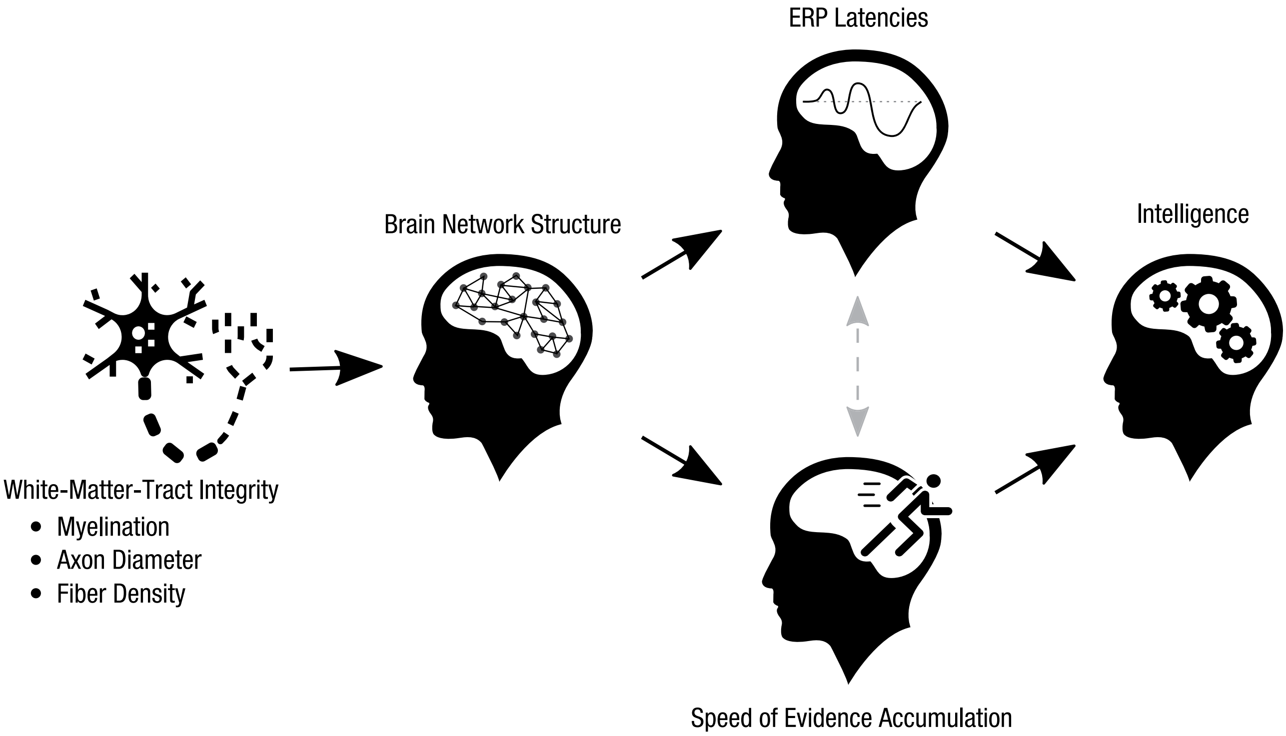

Fig. 2. Simplified illustration of the proposed relationships between basic brain properties, such as white-matter-tract integrity and brain network structure, and neurocognitive measures of mental speed and intelligence. Properties of neural fibers reflected in white-matter-tract integrity positively affect the brain network structure. In turn, individual differences in these network structures give rise to individual differences in event-related-potential (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 the brain network structure and intelligence. Apart from white-matter-tract integrity, many other brain properties not shown here may also affect both mental speed and 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, integrating 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 in understanding 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).

Recommended Reading

Frischkorn, G. T., & Schubert, A.-L. (2018). (See References). A comprehensive overview of the benefits of cognitive modeling in intelligence research with practical recommendations for empirical research.

Jensen, A. R. (2006). (See References). 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). (See References). Integrates diffusion modeling and chronometric analyses of the event-related potential 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. doi:10.1016/j.jmp.2016.01.001. An accessible overview of 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 References). A technical and detailed, but still accessible, comparison of different cognitive models of attentional-control processes.

Transparency

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