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Processing Speed and Executive Attention as Causes of Intelligence

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Individual differences in processing speed and executive attention have both been proposed as explanations for individual differences in cognitive ability, particularly general and fluid intelligence (Engle et al., 1999; Kail & Salthouse, 1994). Both constructs have long intellectual histories in scientific psychology. This article attempts to describe the historical development of these constructs, particularly as they pertain to intelligence. It also aims to determine the degree to which speed and executive attention are theoretical competitors in explaining individual differences in intelligence. We suggest that attention is the more fundamental mechanism in explaining variation in human intelligence.

Keywords: mental speed, cognitive ability, executive functioning, working memory

"Intelligence" as most psychologists today understand the term is inherently a differential concept. The most widely accepted description of the structure of intellectual abilities of the Hebb–Cattell–Horn–Carroll (HCHC) model (Brown, 2016; Carroll, 1993; McGrew, 2009; see Figure 1) ascribes a hierarchical structure to intelligence. At the lowest level, specific skills and narrow cognitive abilities may be brought to bear on different cognitive tasks. At the second level, more generalizable broad ability factors help to explain why certain tasks are more strongly related to each other than they are to other tasks. These broad abilities are correlated, and this common, task-general variability is represented at the apex of the model's hierarchy as general intelligence, commonly denoted as *g* or the *g*-factor. The *g*-factor explains why all cognitive tasks tend to correlate with each other, a pattern known as the positive manifold (Carroll, 1993; McGrew, 2009).

Despite broad consensus on the structure of intellectual abilities, there is less agreement about the causal factors giving rise to individual differences in intelligence. One prominent explanation of intelligence differences is variation in the rate at which people can complete elementary cognitive operations, known as speed of information processing or processing speed. Another potential explanation is variation in executive attention or the ability to avoid distraction and to focus and maintain attention, sometimes referred to as "cognitive control" or "executive functioning."

Recently, tensions have risen between processing speed and executive attention as explanations of intelligence (Conway et al., 2002; Frischkorn et al., 2019; Rey-Mermet et al., 2019). Conway et al. (2002) were among the first to directly compare the prediction of fluid intelligence by processing speed, short-term memory, and working memory capacity, a construct which encompasses both short-term memory and executive attention (see Cowan, 2008; Engle et al., 1999; Mashburn et al., 2021). Each construct was defined by the common variation across multiple tasks in a structural equation model. Working memory capacity was measured by three complex span tasks. Short-term memory was measured with four versions of a simple word span task. Processing speed was measured with two perceptual comparison tasks and by a symbol copying task. Fluid intelligence was measured by the Cattell's Culture Fair Test and Raven's Progressive Matrices.

Conway et al. (2002) partialled out short-term memory related variance from a working memory latent factor using a bifactor approach.[1] If working memory is a complex of short-term memory and executive attention (cf. A. Baddeley, 1986; Engle et al., 1999), then this should have isolated executive attention in the residual working memory capacity factor. Further, if executive attention is a viable cause of fluid intelligence, then the predictive path from the residual working memory capacity (i.e., executive attention) factor to the fluid

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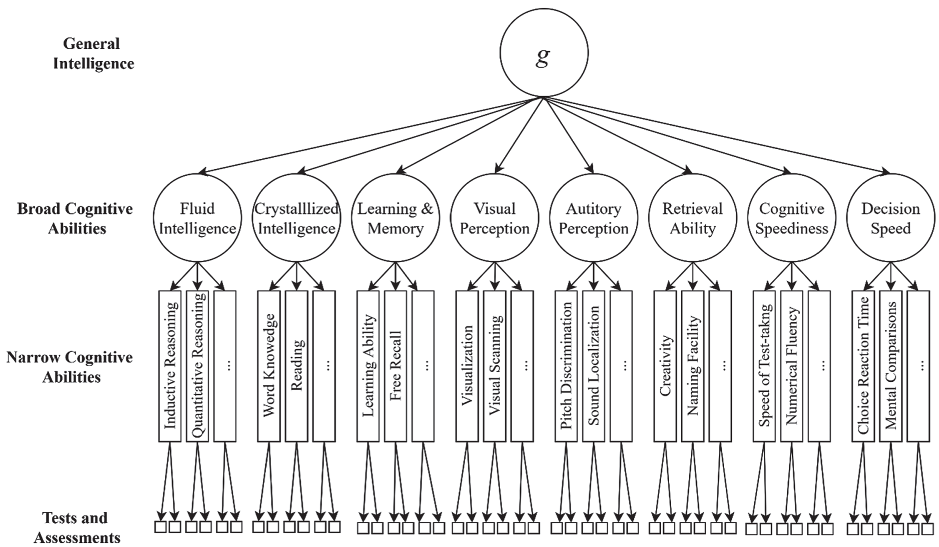
[1] Here, the bifactor approach was used to deal with multicollinearity between working memory and short-term memory capacity. One reviewer pointed out that a different way to deal with the multicollinearity issue would have been to reverse the predictive paths and to use fluid intelligence as a predictor of working memory capacity, short-term memory, and processing speed. We grant this, but doing so would alter the research question (i.e., "Which cognitive processes best predict intelligence?" becomes "Which cognitive processes are best predicted by intelligence?"). Additionally, bifactor models pose interpretive difficulties when applied to latent variables that are assumed to be unidimensional or to constructs with a hierarchical structure, including the *g*-factor (see Dolan & Borsboom, 2023). However, we argue that bifactor models pose fewer difficulties when modeling constructs with multidimensional structures and whose variance components are not related by higher order latent factors. For instance, working memory and executive functioning are both regarded as complexes of numerous constituent processes (e.g., A. D. Baddeley & Hitch, 1974; Engle et al., 1999; Miyake et al., 2000). In such cases, bifactor models can be used to partition variance into theoretically meaningful components.

Figure 1

A Depiction of a Hierarchical Factor Structure of Intelligence Based on the HCHC Model



Note. Ellipses (…) indicate that there are more narrow abilities than could be depicted. HCHC = Hebb–Cattell–Horn–Carroll.

intelligence factor should be strong and significant. Indeed, the residual working memory capacity variability was the only significant predictor of fluid intelligence ($\beta = .60$). Not only was processing speed not a reliable predictor but it was not significantly correlated with the working memory capacity residual (i.e., executive attention) latent variable ($r = -.06$). Executive attention, but not processing speed, was the important predictor of fluid intelligence in these data.

A recent, conceptually similar study to that of Conway et al. (2002) arrived at the opposite conclusion. Frischkorn et al. (2019) investigated the degree to which working memory capacity, executive functioning (inhibition, task-switching, and memory updating), and processing speed contribute to differences in general intelligence.[2] Frischkorn et al. (2019) used mean reaction times in an Attention Network Task to measure inhibition. Switching was measured by mean reaction times in a task where participants had to switch between parity and magnitude judgments (i.e., whether a given digit is greater or less than 5). Memory updating was measured using an *N*-back task. Frischkorn et al. (2019) used structural equation modeling, isolating variance specific to executive functioning with a bifactor approach. For example, in the Attention Network Task, they defined a general reaction time factor with common variation across mean reaction times from all task conditions. In addition, they specified other factors that captured the effects of particular manipulations. For instance, they defined an "inhibition" factor using the variance that was unique to incongruent trials in the flanker portion of the Attention Network Task. This procedure was repeated for both updating and switching, and these narrower, manipulation-specific factors were used to index executive functioning. Frischkorn et al. (2019) defined processing speed in two ways. First, the general reaction time factors from the bifactor models of each of the executive functioning tasks were used to indicate speed. Second, reaction times in two "elementary cognitive tasks," a Sternberg's memory-scanning task and a Posner letter-matching task (both of which will be described in later sections), were used as latent factor indicators. Working memory capacity was measured using a memory updating task, an operation span task, a symmetry span task, and a spatial short-term memory task. General intelligence was measured by the short Berlin Intelligence Structure Test, which has verbal, numerical, and figural components.

Frischkorn et al.'s (2019) findings contradicted the executive attention account. The manipulation-specific executive functioning factors showed little convergence with each other and little relation with working memory capacity, intelligence, or processing speed. Processing speed, meanwhile, was moderately related to both working memory capacity and fluid intelligence ($r = -.46$ to $-.55$). Thus, processing speed, but not executive functioning, was an important predictor of general intelligence in these data.

Conway et al. (2002) and Frischkorn et al. (2019) represent two extreme positions on the relationship between executive attention, processing speed, and intelligence, with each reaching strong, opposing conclusions about the importance of speed and executive attention for intelligence differences. However, the literature contains many other intermediary positions, including cascading effects of speed differences on other cognitive constructs (Coyle, 2017; Kail & Salthouse, 1994; Verhaeghen, 2014), positing speed of specific processes rather than general speed as the basis of intelligence differences (Jensen, 1998), and collapsing speed and executive attention into roughly the same construct (A. S. Kaufman

[2] Here, we understand "executive functioning" as an attempt to fractionate executive attention into more specific components and so use the terms interchangeably, but readers should be cautioned that this does not imply that there are no meaningful differences between the terms. "Executive functioning" most often refers to the processes of inhibition, shifting, and updating originally proposed by Miyake et al. (2000) and "executive attention" typically denoting a more broad-strokes conception of cognitive control (Engle, 2002; Martin et al., 2020).

et al., 2020; Stankov, 1988). Processing speed and executive attention have also frequently been allowed to coexist as partial explanations of cognitive ability differences (Barrouillet & Camos, 2021; Schretlen et al., 2000). There appears to be no clear consensus as to how processing speed and executive attention relate to one another, so there can be no consensus as to whether and how one, the other, or both contribute to individual differences in intelligence.

The aim of this article is twofold. Our first goal is to review some of the major developments in both streams of research. It is important to remember that neither processing speed nor executive attention are novel ideas. Speed and executive attention have long histories in psychology, and researchers would do well to keep those histories in mind. Our second aim is a conceptual and empirical comparison of the two constructs as predictors of intelligence and of each other. We suggest that the speed and efficiency of executive attention may account for the relationship between speed and intelligence, making executive attention a more fundamental mechanism than processing speed.

The Rise, Fall, and Rise of Speed

Mental Testing

The study of processing speed and mental ability is often traced to the founder of differential psychology, Francis Galton (Diamond, 1977; Johnson et al., 1985). Galton was an early proponent of the idea that an individual's performance in elementary domains might predict important life outcomes and more complex traits (Cattell, 1890; Tulsky & O'Brien, 2008). Galton collected extensive data about his subjects' physical traits and their performance on psychophysical and psychomotor tasks (Galton, 1885). Among these were measures of reaction time, although Galton (1883, 1885) placed no special importance on them.

Galton's research orientation was shared by James McKeen Cattell (Diamond, 1977), who, after completing his dissertation under Wundt, studied under Galton (Diamond, 1977). Following their collaboration, Cattell (1890) wrote a piece calling for the widespread administration of a battery of psychomotor and perceptual instruments, coining the term "mental tests." As with Galton's work (Galton, 1883, 1885; Johnson et al., 1985), reaction time measures were included in the proposed battery, but Cattell (1890) appears to have placed the tests in no hierarchy. He only noted that psychologists' conclusions must be based on sound tests and instrumentation. Galton concurred, adding that if the reductive approach was appropriate for the study of ability, then mental tests should be not only theoretically informative but also practically useful (Cattell, 1890).

Gilbert (1894) is among the first to provide support for a relationship between psychological tests and mental ability. He had a large sample of children aged 6–17 ($N > 1{,}100$) complete a battery of mental tests, including reaction time measures (i.e., simple reaction time to a perceived movement and a go/no-go task) as well as a slew of physical characteristics. Gilbert also obtained teacher ratings as to whether the students were intellectually bright, average, or dull. The older children tended to perform better on the tests than younger children. Within age groups, however, the simple reaction time task was the best at distinguishing between students of different intellectual ability, such that "bright" children responded more quickly than "average" children, who were faster than "dull" children, providing support for Galton and Cattell's approach.

The early promise of Galton and Cattell's brand of mental testing was tempered by contradictory findings in the late 19th and early 20th centuries (McFarland, 1928; Spearman, 1904). The most consequential failure of Cattell's mental tests was published by Clark Wissler, Cattell's own student. Wissler (1901) obtained correlations among mental tests collected from Columbia University undergraduates across their 4 years of enrollment, commensurate with Cattell's (1890) recommendations. Class standings and grades across several curricular areas were also collected. Wissler reported that, while the measures of educational attainment intercorrelated, the mental tests did *not* correlate with them nor did the mental tests correlate with each other. Although several methodological issues have been identified since (e.g., the selection of elite Columbia University students probably attenuated correlation estimates; see Buckhalt, 1991), the failure was sufficient to cast a cloud over the reductive approach to mental testing for years to come, prompting Cattell himself to pursue other interests.

Several other influences led to the study of intelligence by way of simple mental tests, especially reaction time, falling out of favor. First, alternative methods of measuring intelligence showed more promise, at least in attempts to predict performance in applied contexts such as education. Chief among these was the clinical approach developed and advocated by Binet et al. (1916) and later by Terman and Wechsler, who opted for more complex, less reductive tests (Tulsky & O'Brien, 2008). Furthermore, psychometric approaches to the study of intelligence came to dominate (Spearman, 1904; Thurstone, 1938). Whereas the Galtonian approach to the study of intelligence sought to understand the elementary psychological basis of mental ability, psychometric approaches were more interested in factor analyzing ability tests to enumerate the types of and relations between cognitive abilities (Spearman, 1904; Thurstone, 1938). In parallel, the study of reaction time became increasingly obscure as behaviorism, which had little need to measure it, came to dominate mainstream experimental psychology (Lachman et al., 1979). The reaction time–intelligence relationship would remain obscure until the onset of the information processing paradigm in the 1950s and 1960s (Lachman et al., 1979).

Information Processing Psychology

The seminal studies on choice reaction time by Hick (1952) and Hyman (1953) provided the impetus for psychology's renewed interest in reaction time. Hick (1952) noted that there is a nonlinear increase in choice reaction time as the number of response options increases. Hick explained this pattern using developments from information theory, the most important of these being the mathematical quantification of the information value of a signal, measured in bits (Lachman et al., 1979; Proctor & Schneider, 2018). A signal is informative to the degree that it reduces uncertainty, and a 50% reduction in uncertainty corresponds to one bit of information conveyed.

Hick's experimental setup consisted of a set of 10 lights arranged in a circle, with each light and corresponding response button placed equidistant from a home key. Each bulb was mapped to a response button, and participants pressed the button that corresponded to a particular light when it appeared. Response options ranged from 1 to 10 or 0 to 3.32 bits. Hick replicated the nonlinear relationship between reaction time and the number of response options but more importantly found a strong *linear* relationship between reaction time and the information (bit) value of a particular stimulus display (Hick, 1952).

At nearly the same time, Hyman (1953) published a complementary set of studies, providing greater generality to the findings initially reported by Hick (1952). Hyman's participants also responded to bulbs as they lit up, with the number of response options ranging from 1 to 8. While Hick's studies required a manual button press, Hyman's participants made a verbal response. The stimulus display also differed from the circular display used by Hick, consisting of eight lights arranged in two concentric squares. Hyman also manipulated the contingencies among responses, such that some lights were more or less likely to follow other lights, which reduces overall uncertainty and a signal's information value. Despite these differences, Hyman's results corroborated Hick's results, revealing a strong linear relationship between reaction times and stimulus bit values (intraindividual Spearman's ρ values exceeded 0.93).

This finding, now referred to as Hick's law or the Hick–Hyman law, provided an avenue for studying reaction time and intelligence, as evidenced by Roth (1964) in one of the first attempts to relate information theoretic measures to psychometric tests of intelligence. Roth argued that the slope of the line relating bit values to reaction times should be taken as an indicator of an individual's speed of information processing (cf. Sternberg, 1969). He surmised that this slope parameter might be related to intelligence even if simple reaction time was not (cf. Wissler, 1901). In simple reaction time tasks, the information value of the task is 0 bits because there is no uncertainty; in such tasks, there is no information to process. If the speed of information processing is one determinant of individual differences in intelligence, it is unsurprising that simple reaction times had not correlated with intelligence test scores in prior work.

Roth administered a Hick-like task in which lights were arranged in a semicircular array with each light paired with a button response. Participants held their hand in the center of the array, equidistant from the response buttons, and initiated an appropriate button press whenever a light came on. Roth also administered the Amthauer Intelligence Structure Test, which has verbal, numerical, and figural components. Consistent with his expectations, raw reaction times and intelligence test scores were not correlated. However, intelligence test scores and individual slope values were moderately negatively correlated, $r(56) = -.39$, $p < .01$, suggesting that more intelligent individuals processed information faster than less intelligent individuals (Roth, 1964).

These developments were seized upon by researchers who had grown frustrated with the dominant, atheoretical factor analytic approach to studying intelligence. Eysenck (1967), for instance, complained that "the psychometric approach has become almost completely divorced from both psychological theory and experiment, and that factor analysis … cannot bear the whole burden which has been placed upon it" (p. 83). Moreover, Roth's (1964) results provided a convenient avenue for dismissing prior failures to find relationships between measures of "speed" and mental ability. In many previous studies (e.g., Wissler, 1901), researchers measured the speed of simple reaction times, where only a single response is possible. As Eysenck (1967) stated, "If intelligence is conceived of as speed of information processing, then simple reaction time … should not correlate with intelligence, but the slope of the regression line, showing increase of reaction time with amount of information processed, should correlate (negatively) with intelligence" (p. 86). This is just what Roth (1964) showed, and researchers have subsequently noted that simple reaction times may even suppress the true correlation between choice reaction times and criterion ability measures (Jensen & Reed, 1990). Thus, information theory provided researchers with a way of reconceptualizing their interest in speed as well as an explanation for prior failures in finding a relationship between speed and intelligence (McFarland, 1928; Spearman, 1904; Wissler, 1901).

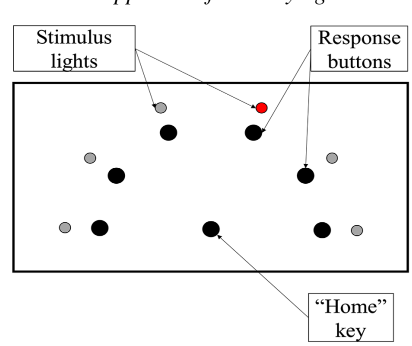
Roth's (1964) study typified the "cognitive-correlates" approach to the study of intelligence (Larson & Saccuzzo, 1989; Roberts & Stankov, 1999). The cognitive-correlates approach attempts to identify the basic information processing demands underlying performance on intelligence tests and the elementary components of cognition necessary to meet those demands. It does so by means of administering simple measures that are often interpreted as relatively pure measures of individual cognitive processes. Extraneous sources of individual variation in these "elementary cognitive tasks" are controlled for via the use of stimuli that are entirely novel or that are so ubiquitously familiar as to be overlearned by all participants (e.g., alphanumeric symbols). Additionally, the tasks employed are intended to be trivially easy, such that all participants could do the tasks accurately, given sufficient time. This is intended to prevent individual differences in knowledge and/or strategy use from contaminating the reaction time–intelligence relationship (Jensen, 1980; Roberts & Stankov, 1999).

Jensen (1980) described several studies that adopted this approach. He detailed his own work using a variation of a Hick's (1952) apparatus (illustrated in Figure 2; Jensen, 1987). Jensen's apparatus requires participants begin a trial by pressing a "home key" in the center and to hold it until a stimulus appears. This permits reaction time to be separated into *decision time* (the time taken to remove their hand from the home key after a stimulus appears) and *movement time* (the time taken to move their hand from the home key to a response button) components (see also Fitts & Peterson, 1964). The former is thought to be related to the rate of mental operations and the latter measures psychomotor speed (Jensen & Munro, 1979; Roberts, 1997). Decision time, but not movement time, is related to intelligence in normal young adults (Jensen, 1980; Roberts, 1997).

Jensen (1980) described work involving measures of short-term memory-scanning speed. In a typical memory-scanning task, participants are presented with a memory set containing a variable number of targets followed by a probed memory item. Participants

Figure 2

Diagram of Jensen's Apparatus for Studying Hick's Law



Note. See the online article for the color version of this figure.

indicate whether the probe was present in the memory set. Typical findings include a uniform linear increase in reaction time with each additional item added to the memory set, indicating a serial exhaustive search of items in short-term memory (but see Townsend, 1972; Van Zandt & Townsend, 1993, for evidence that parallel and/or self-terminating search processes can also produce this pattern). The slope of this increasing function is taken as the rate of short-term memory scanning, and the intercept of the function reflects all other aspects of the task, including stimulus encoding and response execution (Sternberg, 1969). Both intercept and slope values correlate with intelligence tests (Jensen, 1980).

Finally, Jensen (1980) noted a tendency for those with higher SAT (formerly known as the Scholastic Aptitude Test) verbal scores to access long-term memory faster than those with lower scores. This was examined using Posner's letter-matching task (Posner & Mitchell, 1967), in which participants are presented with a pair of letters. In the "physical identity" condition, participants must indicate whether letters are visually identical (e.g., *AA* and *bb* would warrant a "yes" response, where *Aa*, *bB*, or *AB* would warrant a "no" response). In the "name identity" condition, participants must indicate whether letters share the same name, regardless of appearance (e.g., *Aa*, *AA*, *bb*, and *bB* would all warrant a "yes" response, where *AB* or *ab* would warrant a "no" response). Typically, participants take longer to respond "Yes" to items that are physically different but semantically identical (*Aa*) than to items that are physically identical (*bb*). This reflects the additional time taken to retrieve the semantic information for *A* and *a* from long-term memory, which is required to know that they are the same letter. This is not required for the *bb* pair, which can be identified based on appearance alone. Participants high in verbal ability perform this task more quickly than participants low in verbal ability. This suggests that speed of long-term memory access is a component of verbal ability (see also Hunt et al., 1975).

The Hick task, Sternberg memory-scanning task, and Posner letter-matching task are exemplars of the processing speed approach, each having been studied extensively (e.g., Frischkorn et al., 2019; Jensen, 1980; Neubauer et al., 1997; Schubert et al., 2015). However, despite early enthusiasm about processing speed as it pertained to information theory, the information processing parameters derived from reaction time tasks do not always behave predictably. Thus, in the years since Roth's work on the Hick task and intelligence, researchers have often opted to use reaction times themselves rather than information theoretic measures derived from them. Recall that, in the early work on the Hick paradigm, the most theoretically interesting correlate of intelligence was the slope of the line relating stimulus bits to reaction times (Eysenck, 1967; Roth, 1964). As pointed out by Neubauer et al. (1997), in many studies, the slope parameter fails to demonstrate stronger relations with intelligence tests than mean reaction times (see also Bors et al., 1993). In their study in which Raven's Advanced Progressive Matrices was used to measure intelligence, Neubauer et al. (1997) found the Hick slope parameter and simple reaction times to correlate equally with intelligence (compare $r = -.24$ to $r = -.21$). This is problematic for the processing speed approach because the meaning of raw reaction time is much more ambiguous than that of derived information processing parameters. It is also inconsistent with the seminal Roth (1964) finding that Hick slopes, but not simple reaction times, predict intelligence test scores. Likewise, slopes from the Sternberg memory-scanning task had a low correlation with intelligence ($r = -.17$). The Posner letter-matching task showed larger, more substantive correlations with intelligence ($r = -.40$ to $-.50$, depending on how the outcome variable was calculated). In their expansive review and meta-analysis on the relationship between processing speed and intelligence, Sheppard and Vernon (2008) did not even quantify the association between information processing parameters and intelligence, only that between reaction times and intelligence.

Information theory has not been abandoned; however, the substantive meaning of this pattern of inconsistent correlations is difficult to interpret, especially as many cognitive-correlates studies employ single measures of constructs and small samples. Many cognitive-correlates studies also use basic linear correlation and regression-based methodologies where more sophisticated statistical methodologies might provide greater clarity. For instance, Rammsayer et al. (2017) observed correlations of $-.22$, $-.25$, and $-.30$ between reaction times in 0-, 1-, and 2-bit conditions of a Hick task and general intelligence as measured by the short Berlin Intelligence Structure Test. All correlations between reaction time and intelligence were significant and of similar magnitude, and reaction times in the three conditions were strongly correlated with each other. Based on these statistics alone, it is hard to say anything more specific than "reaction time negatively predicts intelligence." However, Rammsayer et al. (2017) also used structural equation modeling to derive latent variables representing Hick slope and intercept values and used these latent variables to predict general intelligence. Replicating Roth's (1964) findings, the Hick slope latent variable predicted intelligence ($\beta = -.34$, $p < .01$), whereas the intercept variable representing simple reaction time did not ($\beta = -.16$, $p > .06$). The structural equation model thus revealed an especially strong relationship between Hick slopes and intelligence *at the construct level*, a relationship that was not readily apparent from the bivariate correlations (see also Pahud et al., 2018).[3]

The three tasks mentioned thus far (the Hick, Sternberg, and Posner tasks) are choice reaction time tasks, but another nonreaction time measure of speed, inspection time, warrants mention (see Danthiir et al., 2005, for a more extensive discussion of various speed tasks). Inspection time tasks were designed to measure the speed of information intake (Nettelbeck, 1987; Vickers et al., 1972). Though many variations exist in both the visual and auditory modalities (e.g., Bates, 2005; McCrory & Cooper, 2005), the classic version of the inspection time task involves presenting participants with an image of two lines of differing length which are joined at the top (see the left pane of Figure 3). After presentation of the stimulus, a backward mask is presented to disrupt further information processing (see the right pane of Figure 3), forcing participants to respond based on the information encoded about the stimulus while it was presented. Participants indicate which of the two lines appears longer. The difference in length between the two lines is chosen to be trivially easy under normal viewing conditions; in the depicted example, the line on the right is clearly the longer of the two. However, the presentation duration differs across trials, and the

[3] An additional benefit of latent variable modeling is that the slope latent variable will tend to be more reliable than the slopes calculated via other methods. This low reliability may help explain some of the heterogeneity in the literature on the utility of information theoretic parameters as predictors of intelligence differences. We thank an anonymous reviewer for pointing this out.

Figure 3

Depictions of the Classic Two-Line Inspection Time Task (Left) and a Typical Backward Mask (Right)

dependent variable is the minimum presentation duration at which participants' identification is virtually error free.[4]

Its apparent simplicity has led some to treat the inspection time task as a pure measure of processing speed (e.g., Jensen, 1998). Some have even suggested that inspection time is "precognitive" in that inspection time should be immune to strategy differences, arguing that when properly measured, inspection time should be fundamental (Nettelbeck, 1987; but see Deary, 2001; Nettelbeck, 2001, for alternative views). Consistent with the processing speed hypothesis, inspection time estimates correlate strongly with intelligence, $r \approx -.50$ (Grudnik & Kranzler, 2001; Kranzler & Jensen, 1989; Nettelbeck, 1987).

Since these elementary cognitive tasks have been interpreted as relatively simple and process-pure indicators of their respective cognitive functions, and each is associated with individual differences in psychometric intelligence, advocates of the cognitive-correlates approach would conclude that the speed with which such elementary information processing steps can be completed constitute at least a partial explanation for individual differences in intelligence.

Thus far, we have described several simple speed tasks which have commonly been used to study psychometric intelligence. However, we have yet to establish that the concept of general "processing speed" is derivable from performance on such tasks. It could be that performance on each of these tasks accounts for orthogonal variation in intelligence. This would indicate that intelligence is related to faster processing in multiple unrelated cognitive domains, but there is no general "processing speed" latent construct. One reason to doubt this is the Brinley plot (Brinley, 1965), which has most notably been used to document cognitive slowing in old age (see Figure 4). In a Brinley analysis, the performance of one group (e.g., older adults) on some speeded task battery is regressed onto the performance of another group (e.g., younger adults). Several findings are typical within cognitive aging research. First, the slope of the line will tend to be positive and usually larger than 1. This indicates a general slowing in older adults' responding. Another typical finding is a negative intercept, demonstrated by Verhaeghen (2014) to stem from a failure to account for noncognitive psychomotor speed (i.e., simple reaction times). Correcting for this situates the intercept at the origin of a Cartesian plane.

The most striking feature of most Brinley plots is their "cleanness." Figure 4 illustrates a fabricated but representative example of a Brinley plot. In this example, the reaction times of young adults account for 90% of the variability in older adults' reaction times with a slowing of approximately 53%. This lends credence to the idea that processing speed is a general capability affecting many tasks, since there is a cross-task slowing with advancing age, which is well-described by a single function. While Brinley plots were first used to study age differences in speed, Hale and Jansen (1994) found that, even among a sample of young adults, speed differences across tasks are well described by a single linear function.

Outgrowing Reaction Time: Mathematical Modeling and Speed

For much of its history, processing speed has been studied by way of reaction times and information processing parameters derived from them. This is problematic, as reaction time gives incomplete information about an individual's ability to complete cognitive tasks. This is because the relationship between reaction time and accuracy, which are often in tension with one another, is ignored. Depending on their strategy, participants may either emphasize speed of responding, in which case they may consequently accept higher error rates, or they may prioritize accuracy with a resultant loss in speed. This pattern is called a speed–accuracy trade-off, and though by no means a law of behavior (i.e., it is possible to be both fast and accurate), it is prevalent enough, even in nonhuman species, to be a source of consternation because of the ambiguity it creates for interpreting either speed or accuracy alone. When speed and accuracy are at odds, it is unclear what constitutes "good" performance (Draheim et al., 2019; Heitz, 2014; Wickelgren, 1977).

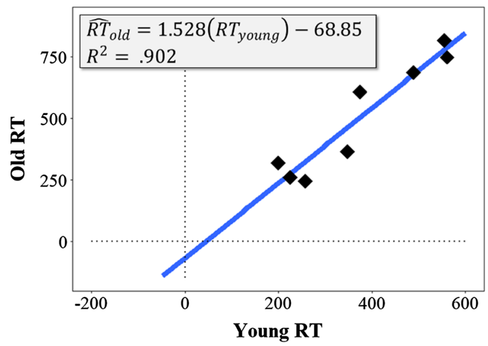
Another issue with the interpretation of reaction times is *process purity*. Reaction time, like all psychological measures, is multiply determined, making it difficult to interpret without some theory-driven methodology (Miller & Ulrich, 2013). Most researchers will be familiar with the subtractive methodology for isolating the time course of cognitive processes (Donders, 1969). This involves contrasting the mean reaction times derived from nested experimental manipulations to estimate the duration of discrete information processing stages within a task, a classic example being the calculation of interference effects in tasks like the Stroop task. While simple and intuitive, the subtractive methodology makes two crucial assumptions. The first is that cognition unfolds according to a serial set of processing stages. The second is that these processing stages can be selectively manipulated, that is, changing one aspect of a task to add an information processing stage leaves other stages unaffected.

A third assumption is required to use the subtractive method in differential research: Participant variables (e.g., age, gender, intelligence) must only affect the targeted information processing stage(s). For example, if one is interested in comparing the conflict resolution efficiency of older and younger adults, the subtractive methodology is valid only if age specifically impairs conflict resolution. If older adults suffer impairments to other information processing stages, the subtractive methodology will not detect them. This may lead to the misguided conclusion that older adults suffer from worse conflict resolution than younger adults, which may be but one facet of a more general decline (see Figure 5).

[4] To score inspection time, some researchers sample discrete target durations from a limited set of values and interpolate the duration that would be associated with a given accuracy rate. Others opt for adaptive procedures, which increase or decrease the presentation duration based on participant accuracy with the goal of converging on some accuracy threshold (e.g., 97.5%; Nettelbeck, 1987).

Figure 4

A Brinley Plot of Hypothetical Data on Eight Speeded Tasks



Note. The slope indicates age-related slowing such that the older sample is 52.8% slower than the younger sample. RT = reaction time. See the online article for the color version of this figure.

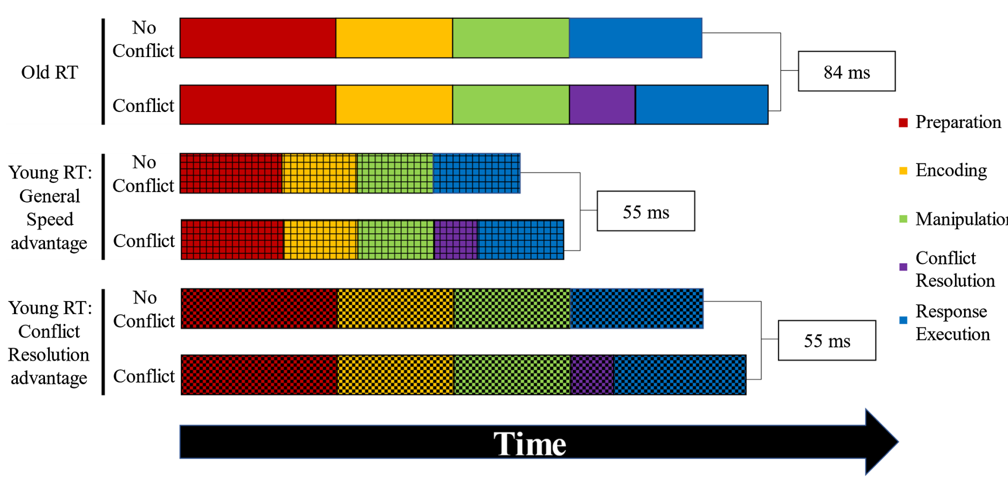
Violations of each of the subtractive methodology's assumptions are well known (see Sternberg, 1969; Townsend, 1972; Verhaeghen, 2014; Zhang et al., 2018), and although reaction time difference scores remain prominent in the literature, many alternative approaches have been proposed (see Draheim et al., 2019 for a review). One favored by many researchers interested in the speed of information processing as a correlate of intelligence has been the adoption of mathematical models, which simultaneously account for reaction time and accuracy. Mathematical models can embody theories about psychological phenomena and allow for the generation of specific quantitative predictions and stringent theoretical tests. A class of models termed *sequential sampling models* has become widely used in the study of processing speed (Heitz, 2014; Luce, 1986; Stone, 1960).

The most studied sequential sampling model is the drift-diffusion model (Ratcliff, 1978; Ratcliff et al., 2016). The drift-diffusion model consists of three main parameters. The first is a response caution/decision threshold parameter, termed "boundary separation," that dictates the amount of evidence required by the decision process before a response is decided. Setting a lower decision threshold means that less evidence is required before a participant decides to respond, hastening responding at the heightened risk of an error. As such, differential boundary separations capture differences in speed–accuracy trade-offs. The second parameter, termed "drift rate," accounts for the rate at which evidence accumulates toward a decision boundary. It is thus sometimes taken as an index of information processing speed (Hedge et al., 2022; Lerche et al., 2020). The third parameter, termed "nondecision time," accounts for nondecisional components of the total reaction time, such as those associated with stimulus encoding and response execution. The full drift-diffusion model also consists of other parameters necessary for describing many features of response time distributions, including a decision bias parameter and trial-by-trial variability in the three main parameters. In practice, however, many researchers find the quantity of data necessary for estimating these additional parameters prohibitive and instead opt for simplifications of the full diffusion model. The EZ-diffusion model (Wagenmakers et al., 2007), for instance, estimates only the main three parameters from the full diffusion model: boundary separation, drift rate, and nondecision time.

Because the drift-diffusion model simultaneously models accuracy and reaction time, it ameliorates the interpretive difficulties associated with speed–accuracy trade-offs (but see Rafiei & Rahnev, 2021). Moreover, it avoids the arbitrariness of some other proposed solutions, such as integrative speed–accuracy metrics in which researchers must decide how heavily to weight speed versus accuracy in a combined final score (Draheim et al., 2019; Vandierendonck, 2017). As such, it is

Figure 5

A Comparison of Older and Younger Adults' Processing in Two Tasks With and Without Conflict



Note. Colors denote different processing stages. The top two bars show that older adults take 84 ms longer to respond when there is conflict. The middle two bars suggest that younger adults are 65% faster than older adults at all stages. The bottom bars suggest that younger adults are faster than older adults at resolving conflict, with no difference in processing speed otherwise. Although the subtraction method shows a reaction time cost of 55 ms for young adults in both cases, it does not fully capture the differences between the two scenarios. RT = reaction time. See the online article for the color version of this figure.

unsurprising that many recent studies have opted to use parameters from the drift-diffusion model to study the relationship between speed of information processing and intelligence, with a particular focus on drift rates as reflecting processing speed. Most such studies report moderate to strong relationships between drift rates and cognitive abilities, such that faster drift rates denote higher ability ($r \approx .50$, according to the review by Lerche et al., 2020; see also Kofler et al., 2020; Schmiedek et al., 2007; Schmitz & Wilhelm, 2016; Schubert et al., 2015). Because drift rates are more interpretable than raw reaction times in that they have been dissociated from other factors affecting the decision process, these results inspire greater confidence that processing speed and intelligence are associated with one another. However, as will be emphasized, the drift-diffusion model leaves many questions about the speed–ability relationship unaddressed. For example, the model is agnostic as to the mechanisms that generate the data being modeled. Drift rates name and quantify the rate of evidence accumulation in a task, but they neither explain why individuals differ in their rates of evidence accumulation nor why these differences relate to cognitive ability.

Issues With the Cognitive-Correlates Approach

Though influential and common, cognitive-correlates research has not been without criticism. We mention two issues but direct interested readers to Stankov and Roberts (1997) for a lengthier discussion. First, it has been assumed that elementary cognitive tasks are simple and pure indicators of their target constructs, but this is not a given. The second issue is that the meaning of "speed" is often unclear and open to interpretation.

Assumptions About the Simplicity of "Elementary" Cognitive Tasks. One criticism of the cognitive-correlates approach pertains to the assumption that speed of information processing tasks are simple and factorially pure. For example, regarding his Hick paradigm, Jensen (1980) opined that the "cognitive demands … are so extremely simple that it seems almost implausible that the procedure could yield any measurements that would be correlated with IQ" (p. 109). However, Detterman (1987) highlighted several potential complications with this conjecture, noting that performance on "simple" reaction time tasks is subject to myriad influences, including task comprehension, motivation, attentiveness, and speed–accuracy trade-offs, all of which are likely to interact with ability level. Without investigation of third-variable explanations, a strong interpretation of information processing speed as the basis of intelligence is suspect.

Despite their apparent simplicity, many elementary cognitive tasks are not well understood. Even a task as "simple" as the Hick task has several competing explanations (see Proctor & Schneider, 2018), and without greater clarity as to what cognitive processes are at play, the substantive psychological meaning of "speed" remains unclear. Nettelbeck (2001) makes a similar point about the inspection time task, stressing that the task is more psychologically complex than its early proponents (e.g., Vickers et al., 1972) had suggested and that more investigation into the psychological underpinnings of inspection time would be fruitful. Speaking more pointedly, Deary (2001) has called the impulse by many researchers to pose processing speed as a fundamental cause of intelligence a "greedy reductionism." In response, one could counter that virtually no cognitive task is completely understood and that vagueness and unanswered questions provide the impetus for further research. However, the almost magical assumption of simplicity attached to "processing speed" tasks is unusual and not supported by theoretical and empirical work surrounding the tasks themselves.

The Meaning of "Speed" Is Often Unclear. A second difficulty with the cognitive-correlates approach lies in the definition of what is meant by "speed." To this point, we have assumed that a general, system-wide processing speed is a reasonable idea. The literature on processing speed, however, is equivocal in what is meant by speed, how it is defined, and what properties of the cognitive system are assumed to be reflected in the measure(s) assessed. When researchers discuss "speed," readers are often left on their own to decide what "speed" must mean and what processes underlie faster cognition.

This need not be the case. Salthouse (1996) proposed that faster processing speed could contribute to intelligence differences in two ways: simultaneity and time limitations. Simultaneity means that cognitive operations require earlier outputs as input, and faster processing leads to more successful cognition and higher test scores because more information will be available at critical information processing junctures. According to the time limitation mechanism, slower processing speed leads to incomplete outcomes and worse test performance if a test needs to be completed quickly. Although a useful distinction, researchers rarely specify which of Salthouse's (1996) mechanisms they believe to be operating in their studies. Instead, both are off-handedly cited possible explanations (see DeLuca et al., 2004; Kurtz et al., 2013; Lerche et al., 2020). This lack of specificity perpetuates conceptual vagueness about processing speed as an explanatory device.

Adding to the confusion, numerous other terms appear in lieu of "processing speed." The terms "perceptual speed" and "cognitive" or "mental speed" frequently appear in the literature, and it is difficult to understand a clear and consistent differentiation between those, or how these terms should be understood in relation to the term "processing speed." One could argue that the term "perceptual speed" should be reserved for the speed of sensory and perception-based decision making, such as in the inspection time task, Hick task, or when making same/different perceptual judgements (e.g., Salthouse & Babcock, 1991). Meanwhile, "cognitive speed" may refer to the speed of memory-based decisions, as in the Sternberg memory-scanning task or the "same name" condition of the Posner letter-matching task. Perhaps these two terms should be subsumed as subfactors under the broader "processing speed" construct.

This scheme quickly encounters difficulty, however. For example, some researchers have opted to use visual search tasks to index processing speed (e.g., Fry & Hale, 1996). Given this, should visual search tasks fall under "perceptual speed" or "cognitive speed" tasks? On the one hand, perceptual processes are clearly at play, since participants must visually scan the array for target items. On the other hand, attentional (i.e., cognitive) mechanisms also clearly have a role in driving performance (Treisman & Gelade, 1980; Wolfe, 2014).

Another term that appears in the literature is "neural speed," which would seem to have a more straightforward interpretation by way of measuring the speed of neural conduction (e.g., Reed & Jensen, 1992; Vernon, 1993). However, "neural speed" may also have several possible meanings. Does it refer to the rate with which action potentials are initiated? For instance, Goriounova et al. (2018) reported a relationship between rate of action potentials in human temporal pyramidal neurons and IQ as measured by the Wechsler Adult Intelligence Scale (cf. Anderson, 1994).[5] Or, is neural speed better conceived of as more efficient structural and/or functional connectivity between brain regions (e.g., Kocevar et al., 2019; Neubauer & Fink, 2009; Penke et al., 2012; Song et al., 2008; Wong et al., 2021)? The former is certainly more simplistic and is subject to fewer third variables and alternative causal models than the latter, but both are used in the literature and may fall under the same umbrella term.

Perhaps related to this terminological confusion, many researchers regard "speed" as a single, system-wide parameter analogous to the clock rate of a computer's central processing unit. We saw this in our earlier discussion of Brinley plots and, for expository purposes, left the assumption unchallenged. However, Perfect (1994) noted that Brinley plots provide limited support for a single speed function; the trademark high R^2 values that are so striking can be achieved even when the true data-generating process cannot be described by a single function (Verhaeghen, 2014). Confirmatory factor analysis and/or structural equation modeling would be more informative, allowing researchers to easily assess whether there are different components to processing speed and whether these components have distinct contributions to intelligence.[6]

In contrast with the elegance of Brinley plots, processing speed does appear to be multifactorial according to such factor analytic studies (Stankov & Roberts, 1997). Ackerman et al. (2002) described four subcomponents which, using confirmatory factor analysis, can be modeled under a general speed factor: scanning speed, comparison speed, memory speed, and complex speed. These subcomponents are defined by increasingly complex tasks that have progressively strengthening correlations with working memory capacity and general intelligence, with a complex speed composite measure having a sizeable unique relationship with general intelligence (a unique factor loading of .51).

Like Ackerman et al. (2002), Lerche et al. (2020) reported differentiations of speed based on task content and complexity (see also Verhaeghen, 2014). They estimated drift rates for tasks of varying complexity across verbal, numerical, and figural stimuli. Of the measurement models they tested, they found that a structural equation model with separate drift rate factors for each content type, as well as a general drift rate factor, best fits the data. Moreover, this model also included a factor capturing the variability unique to the drift rates estimated from the more complex tasks. Like the results of Ackerman et al. (2002), the general drift rate factor and the complex drift rate factor each accounted for *unique* variation in general intelligence (r = .45 and .68, respectively).

Both Ackerman et al. (2002) and Lerche et al. (2020) found strong evidence that processing speed is multifactorial. It can be grouped into isolable components, and some of these components (especially those derived from more complex measures) independently contribute to intelligence. At minimum, this conclusion warrants a more sophisticated understanding of processing speed than is offered by simple slowing accounts. For example, that reaction times from more complex tasks relate more strongly to intelligence is not a new observation (see Jensen, 1998), but this introduces ambiguity about the meaning of "speed." More cognitively complex tasks, especially when novel, likely have increased executive control demands relative to simpler tasks (Cepeda et al., 2013). The correlation between speed and intelligence may increase with task complexity because the speed measure is indexing the efficacy and efficiency of these additional executive processes.

Summary of Processing Speed and Intelligence

To this point, we have recounted some landmark conceptual and empirical developments in the ongoing attempt to characterize the nature of processing speed and its relationship to intelligence. The origins of research on processing speed can be traced back to the 19th-century mental testing movement, and like the bygone mental testing movement itself, eventually fell out of favor. When information processing began to dominate psychological thought in the mid-20th century, processing speed reemerged as a potential explanation of individual differences in intellectual abilities.

Individual Differences in Executive Attention and Intelligence

While the mental testing movement was gaining momentum, another stream of research was forming its own understanding of the elementary basis of intelligence, this one rooted in the conscious, effortful, goal-directed control of attention, or executive attention. The origins of executive attention research trace back to developmental psychology at the close of the 19th century. From there, it became linked with developments in working memory research, as experimental and differential psychology began to overlap in their quest to explain why and how goal-directed thinking and behavior contribute to individual differences in fluid intelligence and reasoning ability.[7]

Baldwin (1906) was an early developmental theorist whose influence was carried forward by the likes of Piaget (1950) and Pascual-Leone (1970, 1987; Pascual-Leone & Goodman, 2021). Baldwin argued that children's motor development proceeds by focusing their attention upon conscious movements to commit them to memory, forming a habit. Once acquired, attention can be focused to assimilate new behaviors into existing habits or to adapt old habits

[5] Note that while this correlation exists, it is doubtful even under this scenario that speed can be called the "mechanism" underlying intelligence. Goriounova et al. (2018) also report that higher IQ individuals had temporal pyramidal neurons with lengthier and more complex dendrites, suggesting that those cells were more strongly interconnected with other cells and received stronger input. These same cells also attained action potentials at higher rates. We thus argue that greater neural connectivity, not speed, is the mechanism of interest.

[6] We thank Rogier Kievit for his helpful comments on assessing the dimensionality of speed.

[7] In this section, we treat "reasoning" and "intelligence," especially "fluid intelligence," as synonyms. Many researchers fail to distinguish the terms (e.g., Kyllonen & Christal, 1990). However, we acknowledge that making this equivocation is problematic, as reasoning, while related to intelligence, is a distinct area of study. For example, Stanovich et al. (2016) argued that fluid intelligence of a certain level is often a prerequisite for reasoning well, yet intelligent individuals still make systematic reasoning errors. To reason well in a given context, they argue, also requires one to have an appropriate repertoire of learned strategies and procedures for reasoning to an acceptable answer, as well as to notice that those strategies are necessary to avoid an error. Fluid intelligence is important to reasoning, Stanovich et al. (2016) argued, because it indexes a person's ability to decouple their mental operations from reality, allowing individuals to simulate the problem-solving steps to reason toward an appropriate answer to some question. We view attention control as being critical for this decoupling operation (see Burgoyne, Mashburn, et al., 2023).

to new movement patterns via accommodation. Conversely, when children withdraw their attention or become distracted, the likelihood of new learning diminishes and the child regresses from a conscious thinker into merely "a creature of suggestion" (Baldwin, 1906, p. 454).

Following Baldwin (1906), Piaget (1950) characterized children's cognitive maturation as a progressive balancing of the processes of assimilation and accommodation. Deviating from Baldwin, Piaget had little to say directly about executive attention. However, his comments provide context for the neo-Piagetian fixation on attention as a source of developmental intelligence differences (see e.g., Case, 1985; Pascual-Leone & Goodman, 2021). For example, a child who has yet to acquire an understanding of the conservation of mass may conclude that a tall skinny glass contains more liquid than a short wide glass, even if they see the same liquid being poured from one to the other. Attention is centralized on some pertinent feature (e.g., water level), but the child cannot attend to all relevant dimensions (e.g., the glass's width) to know that the glasses hold the same volume. As the child progresses through Piaget's developmental stages, they become able to attend to the multiple dimensions, along which events may vary (Piaget, 1950).

To account for such results, Pascual-Leone (1970, 1987) proposed the concept of mental-attentional capacity (*M*-capacity), an attentional buffer capable of parsing a limited number of task-relevant information blocks (what he referred to as "schemes") from task-irrelevant ones and boosting their activation. The upper limit of *M*-capacity is a constant that increases at each stage of intellectual development (i.e., $M = a + 1$, $M = a + 2$), and its upper limit is akin to Miller's (1956) "magical number seven" ($M = a + 7$) of information processing capacity (Pascual-Leone, 1970). As *M*-capacity increases, children can attend to more information, allowing them to complete increasingly complex tasks (Pascual-Leone, 1970, 1987; Pascual-Leone & Goodman, 2021).

After the early work of Pascual-Leone and other neo-Piagetian researchers, cognitive psychologists began exploring the role of executive attention in directing cognitive processing, actions, and skill acquisition outside of a developmental perspective. Several information processing researchers (e.g., Atkinson & Shiffrin, 1968; A. D. Baddeley & Hitch, 1974; Broadbent, 1957; Neisser, 1964; Posner & Snyder, 2004; Sternberg, 1966; Treisman, 1960) had been interested in the role that selective and limited-capacity attention plays during cognitive tasks, including memory search, visual search, and dichotic listening. In some tasks, researchers noted evidence for capacity limitations, with additional cognitive processing demands leading to degraded performance, either in terms of lower accuracy or lengthened reaction times. In other tasks, no such decrements were observed.

Schneider and Shiffrin (1977) synthesized these results. Following seminal work by Posner and Snyder's (1975) differentiating automatic and controlled processing, Schneider and Shiffrin (1977) proposed a two-process theory comprised of an automatic, capacity-free mode of cognitive processing and a more controlled, capacity-limited mode characterized by the allocation of attentional resources. According to Schneider and Shiffrin (1977), an *automatic process* proceeds when a sequence of long-term memory nodes is activated by a specific pattern of input(s) in a situation or context without a person's active attention or control. By contrast, *controlled processing* involves temporary sequences of memory node activations that the participant actively attends to and controls. Since controlled processing requires active attention, the participant can only process one sequence at a time, and therefore, capacity is limited to serial processing of separate information sequences.

To test this framework, Schneider and Shiffrin (1977) conducted search and detection experiments that focused on measuring accuracy and reaction times. They contrasted performance in a *consistent mapping* condition, where memory-set items and distractors were consistently separate from one another, and a *varied mapping* condition, in which distractors could occasionally be memory-set items. There was a clear differentiation between the two. Participants in the varied mapping condition showed a large, negative effect of set size on accuracy, suggesting evidence of a controlled, serial search. The varied mapping condition also showed a set-size effect on reaction time. Schneider and Shiffrin (1977) argued that the consistent mappings fostered automaticity through the adoption of a consistent, stable, learnable cognitive set. The varied mapping condition induced control because no learnable cognitive set was possible.

Another conceptualization of the role of executive attention from this period comes from A. D. Baddeley and Hitch's (1974) multicomponent theory of working memory. According to A. D. Baddeley and Hitch (1974), working memory is a "workspace" divided among limited capacity storage and flexible processing demands. The original model included the attentional "central executive" component and two memory subcomponents, the phonological loop, and the visuospatial sketchpad. The central executive is responsible for modulating the activity of the memory subcomponents, including information maintenance and flow between memory buffers. The phonological loop is involved in processing, storing, and rehearsing verbal and written information, while the visuospatial sketchpad is involved in the storage and processing of visual and spatial information.

The starting point for Baddeley's the central executive came with Norman and Shallice's (1986) supervisory attentional system, a theoretical framework positing a set of hierarchically structured schemas that are organized based on the sequences of actions to which they belong. Schemas lay inactive unless triggered by some pertinent stimulus, and if they are activated beyond some critical threshold, the organism's thoughts and behaviors unfold according to the activated schema(s). Schemas are interconnected by what Norman and Shallice call "horizontal processing threads," whereby activated schemas facilitate other action-compatible schemas and inhibit incompatible ones in a manner commensurate with parallel distributed processing (McClelland & Rumelhart, 1981). This chaining of schemas allows even complex behaviors to be executed in an automated, stimulus-driven manner. Norman and Shallice call this process of schema selection and chaining *contention scheduling*. Once active, schemas continue to operate until they are switched off, blocked due to changes in resource allocation, or their assigned goal is executed (cf. Pascual-Leone & Goodman, 1979).

Though it is possible to perform many habitual tasks using contention scheduling alone, some acts do need deliberate control to enhance or suppress a given schema. For instance, if there is no clear "winning" action schema or if the winning schema is incongruent with current situational demands, contention scheduling is less likely to lead to the appropriate action. In Norman and Shallice (1986) model, the supervisory attentional system is responsible for biasing schema activation levels by allocating attention appropriately, exciting some schemas, and inhibiting others. It does so via connections to schemas, which Norman and Shallice term "vertical processing threads." Thus, Norman and Shallice (1986) situate executive attention as the major driving force behind flexible and adaptive behavior and cognition (cf. Baldwin, 1906; Schneider & Shiffrin, 1977). Crucially, the supervisory attentional system only acts by influencing the schema activation levels. Thus, a sufficiently potent triggering stimulus may overcome the supervisory attentional system and lead to inappropriate responding, since any schema that meets the critical threshold will be expressed. As a task becomes better learned, the precipitating schemas become more specialized and refined, reducing the risk of schema interference and the need for intervention by the supervisory attentional system. This is consistent with findings that tests of cognitive abilities such as those of working memory capacity are especially predictive early in acquiring a new skill where actions cannot be effectively guided by contention scheduling alone (cf. Ackerman, 1988).

Norman and Shallice's supervisory attention system was highly influential in the conceptualization of working memory, so much so that A. Baddeley (1986) adjusted his own model to conform more closely with the supervisory attentional system. In fact, A. Baddeley (1986; A. Baddeley, 2012) has indicated that the central executive component of his multicomponent model initially served as a useful homunculus on which to foist early theoretical and empirical ambiguities. The central executive did not begin to gain theoretical clarity until the advent of Norman and Shallice's (1986) model. Though Norman and Shallice (1986) and previous developmental researchers studied the role of attention and memory storage space in the service of complex actions, other researchers interested in individual differences wanted to better understand how executive control influences the ability to reason and solve complex problems, that is, fluid intelligence. Specifically, at this time, researchers became interested in performance on reasoning tasks, and how individual differences in working memory capacity and/or executive attention might account for differences in fluid intelligence. Because fluid intelligence and attention/working memory find their origins in different streams of research, the former being an outgrowth of psychometrics and the latter from experimental/information processing psychology, explicating how working memory and executive attention may underlie reasoning constitutes an early attempt at bridging the experimental and differential approaches to psychological science, an endeavor that has gained momentum in recent years (cf. Cronbach, 1957, 1975; Engle & Martin, 2018; Engle & Oransky, 1999; Haines et al., 2020; Hunt et al., 1975; Rouder & Haaf, 2019).

Hunt (Hunt, 1980; Hunt et al., 1975) pioneered much of the earliest work on individual differences in information processing tasks and intelligence. In his review, Hunt (1980) described two competing schools of thought about intelligence: Those who believed that so-called "general intelligence" is a collection of specialized types of intelligence and those who argued that it is a true and abiding latent construct. Specialists, particularly those arguing from a formal or computer-based model of mind, argued that intelligence is an amalgam of structural cognitive capacities and strategies dependent on acquired knowledge. Generalists appealed to the well-replicated pattern of positive correlations among cognitive assessments, that is, the positive manifold, to justify the existence of a general intellectual ability. Generalists also highlighted instances where knowledge alone is unlikely to explain differential performance across individuals. For instance, across several dual-task and easy–hard recall studies, Hunt et al. (1979; Lansman, 1978) showed that the allocation of attentional resources can explain individual differences in information processing task performance. Hunt (1980) argued that these same attentional resources may account for the positive manifold (see also Kahneman, 1973; Posner, 1978).

According to Hunt (1980), every information processing task needs some level of attention for its effective execution. If the task receives less attention than needed, the participant may still perform the task, but they may do so less successfully than if more attention was allotted. However, attention should not be treated as a single, undifferentiated process, otherwise, every task using attention would compete with one another (Hunt, 1980; Kahneman, 1973; Posner & Boies, 1971). Rather, inter-task interference depends on the specific requirements of each task. Attentional interference may arise from two sources: competing inter-task demands for common processing structures and competition for attention from some internal coordinating mechanism on how to reconcile these competing demands (Hunt, 1980). This coordinating system is what we think of and call executive attention.

Building upon the efforts of information processing psychologists, such as Hunt and Baddeley, Kyllonen and Christal (1990), were the first to expressly investigate the relationship between working memory capacity and fluid intelligence, a finding that has since been exhaustively replicated (Engle et al., 1999; Rey-Mermet et al., 2019; Schmitz & Wilhelm, 2016; van Aken et al., 2016). Kyllonen and Christal (1990) developed tests consistent with A. Baddeley's (1986) multicomponent model of working memory and administered them, along with tests of fluid intelligence, processing speed, and general knowledge, to four samples of Air Force recruits. Using confirmatory factor analysis, Kyllonen and Christal (1990) demonstrated a strong correlation (r = .80–.88) between working memory capacity and fluid intelligence across four different studies. Processing speed and general knowledge had numerically weaker relationships with fluid intelligence (r = .25–.42 and .33–.51, respectively).

Of course, the correlational models tested did not permit tests of different causal theories and could not arbitrate whether individual differences in working memory capacity gave rise to individual differences in fluid intelligence or vice versa. Even so, the two were shown to have what at the time was considered a surprisingly strong relationship, leading to a proliferation of studies seeking to clarify why the two constructs were so closely linked. Kyllonen and Christal (1990) conjectured that the availability of "attentional resources" may explain individual differences in cognitive ability, particularly when tasks are novel (cf. Ackerman, 1988). If this was the case, one might expect variation in the central executive component of the working memory system to be especially important in the prediction of fluid intelligence and reasoning.

Engle et al. (1999) attempted to investigate this hypothesis directly. They parsed the functions of working memory capacity and short-term memory to further explicate working memory capacity's strong relationship with fluid intelligence. Using confirmatory factor analysis, Engle et al. (1999) showed that working memory capacity and short-term memory could load onto separable but strongly correlated (r = .68) latent variables (see also Conway et al., 2002; Kuhn, 2016). Furthermore, accounting for this correlation in a structural equation model revealed that working memory capacity is uniquely related to fluid intelligence, while short-term memory is not (compare $\beta = .59$ to $\beta = -.13$). As previously mentioned, and in broad agreement with A. Baddeley (1986; A. Baddeley, 2012; A. D. Baddeley & Hitch, 1974), Engle et al. (1999; Mashburn et al., 2021) viewed working memory as an interaction of executive attention and temporary short-term memory storage processes (see also Cowan, 1988; Oberauer et al., 2007). Engle et al. (1999) argued that the unique relationship between working memory capacity and fluid intelligence is evidence for a particularly strong relationship between executive attention and fluid intelligence.

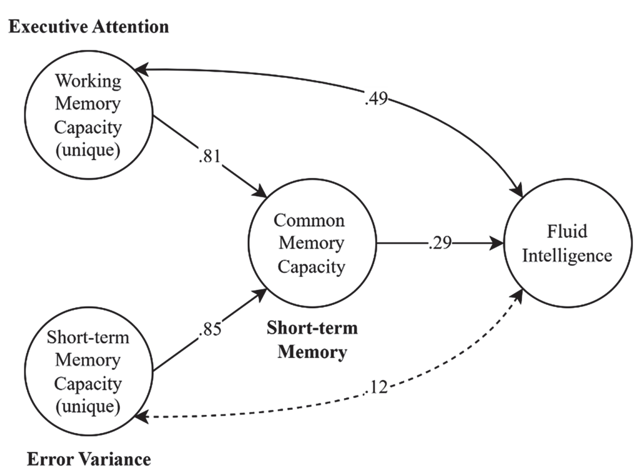
In support of this view, another structural equation model (see Figure 6) revealed that, while the variability shared by working memory capacity and short-term memory tests was related to fluid intelligence ($\beta = .29$), there remained a unique relationship between the working memory capacity residual factor (thought to measure executive attention) and fluid intelligence ($r = .49$). Engle et al. (1999) concluded that both working memory capacity and fluid intelligence require deploying attention to keep representations active in the face of distraction (see also Kane & Engle, 2002; Rueda, 2018). Short-term memory, by contrast, is a mere storage component that has little unique relation to fluid intelligence (Engle et al., 1999). Subsequent studies suggest that the correlation between working memory capacity and fluid intelligence stems from both executive attention and short-term memory processes, including retrieval from long-term memory (Kuhn, 2016; Shipstead et al., 2014; Unsworth et al., 2010).

Recently, Burgoyne et al. (2022) published a reanalysis of data originally published by Tsukahara et al. (2020), which further supports a close link between executive attention and intelligence. They derived a second-order general intelligence factor defined by the variability common to working memory capacity, attention control, and auditory discrimination ability factors. These lower order factors were strongly related to one other, as indexed by substantial loadings on a general intelligence factor (the average loading was .82). However, of the lower order factors, attention control contributed the most shared variance, as indicated by a second-order factor loading of .98. Thus, attention control shared virtually all its reliable variance with general intelligence in these data.

In summary, research on executive attention is rooted in developmental and information processing approaches to psychology, particularly working memory research. It has been characterized as a fundamental driving force underlying complex, goal-directed behavior and has long been suggested to contribute to developmental and individual differences in various aspects of cognitive ability, including working memory capacity, fluid, and general intelligence. In the following section, we offer some current theoretical perspectives on the nature of executive attention.

Figure 6

A Structural Equation Model Illustrating the Relationships Among Short-Term Memory, Working Memory, and Fluid Intelligence According to Engle et al. (1999)



Note. The constructs thought to be reflected by each latent memory factor are given in bold.

Contemporary Views on Executive Attention

Several theories explaining the relationship between executive attention and fluid intelligence have been proposed. We present three theories below: the unity and diversity model of executive functions (Friedman & Miyake, 2017; Miyake & Friedman, 2012; Miyake et al., 2000), the maintenance and disengagement theory (Shipstead et al., 2016), and process overlap theory (Kovacs & Conway, 2016, 2019).

Unity and Diversity of Executive Functions

Friedman, Miyake, and their colleagues have proposed the unity and diversity of executive functions model, a profoundly influential account of the control of goal-directed behavior by higher order executive processes (Friedman & Miyake, 2017; Friedman et al., 2006; Miyake & Friedman, 2012; Miyake et al., 2000). The original model (see Panel A of Figure 7) consisted of three correlated yet distinct executive functions (i.e., functions of the central executive) derived from batteries of executive tasks. These executive functions include mental set shifting (Shifting), the monitoring and updating of information in working memory (Updating), and the control of interference and inhibition (Inhibition; Miyake et al., 2000). In more recent research, however, Friedman and Miyake (2017) prefer a bifactor model that includes one unitary executive function that accounts for correlations across Updating, Shifting, and Inhibition tasks and separable Updating-specific and Shifting-specific factors (see Panel B of Figure 7).

The unity and diversity model was not initially articulated to explain intelligence, although different relations with intelligence have been observed between the two versions of the model. Friedman et al. (2006) found that the only reliable predictor of intelligence in the correlated functions model was Updating and that any relationship between intelligence and Shifting or Inhibition was explained by their correlation with Updating. Conversely, in the bifactor model, both the common executive functioning and Updating-specific factors, and, to a lesser degree, the Shifting-specific factor, have been found to predict individual differences in intelligence (Friedman et al., 2011; but see Wang et al., 2021).

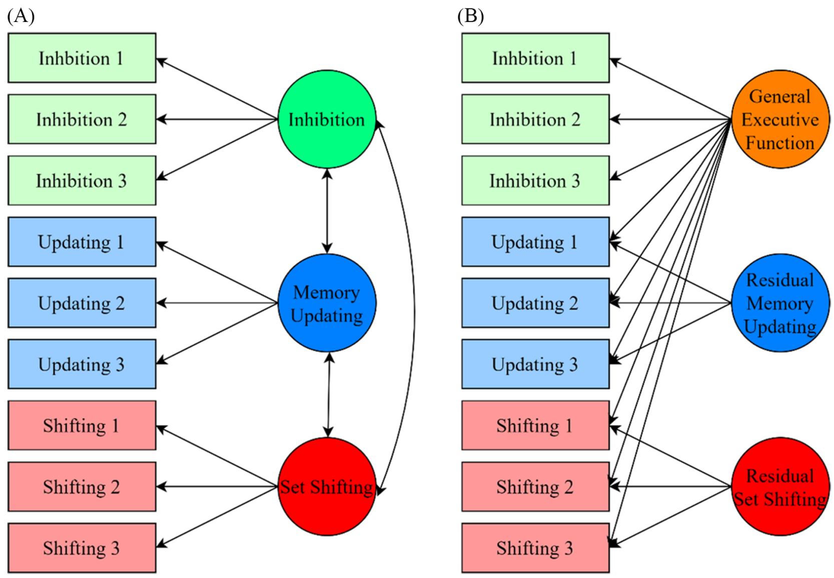
Maintenance and Disengagement Theory

It is commonly argued that working memory capacity determines reasoning ability because working memory holds relevant information in an active, accessible state (e.g., Carpenter et al., 1990; Cowan et al., 2005; Engle et al., 1999). However, Shipstead et al. (2016) have pointed out that much of the working memory capacity/fluid intelligence research is correlational, meaning that the field lacks strong evidence of such a one-way relationship.

Shipstead et al. (2016) instead proposed the maintenance and disengagement theory, depicted in Figure 8, which suggests

Figure 7

Two Conceptualizations of the Unity and Diversity Model

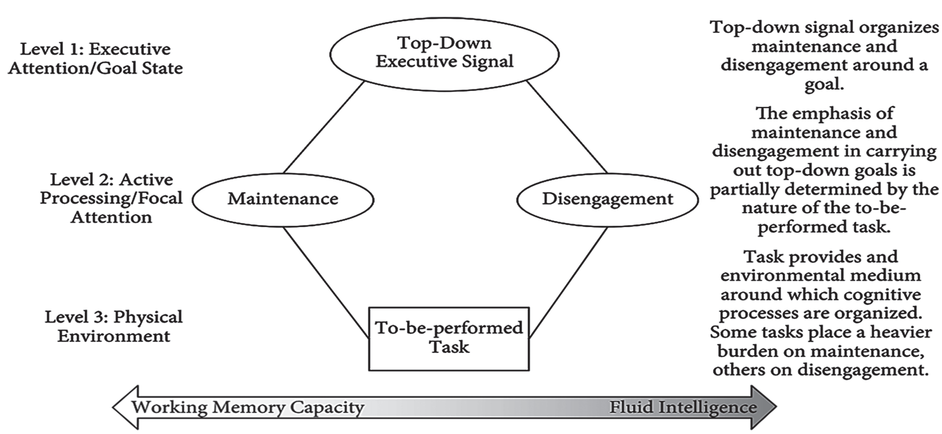


Note. The first diagram, panel A, is consistent with Miyake et al.'s (2000) model of the correlated but separable executive functions of Updating, Shifting, and Inhibition. The second, panel B, depicts a model consistent with their more current thinking (Friedman & Miyake, 2017), with a unifying latent executive functioning variable among all measures and updating-specific and shifting-specific factors. See the online article for the color version of this figure.

working memory capacity and fluid intelligence have distinct yet related cognitive underpinnings because they both depend on an executive attention and goal signaling system. The model has three levels. Level 3 represents a given behavioral task, while Levels 1 and 2 both represent underlying cognitive processes that performance on that task might reflect. Level 2 illustrates two ways executive attention can be deployed while performing a task, through maintaining relevant information or disengaging from irrelevant information. Working memory capacity and fluid intelligence become distinct constructs at Level 2, with working memory tasks placing more emphasis on maintenance and fluid intelligence tests having stronger disengagement demands (Shipstead et al., 2016). Executive attention exists at Level 1 of the model; while attention may be flexibly deployed to either maintain or disengage

Figure 8

A Diagram for the Maintenance and Disengagement Theory



Note. Adapted from "Individual Differences in Attention Control: Implications for the Relationship Between Working Memory Capacity and Fluid Intelligence," by C. A. Mashburn, J. T. Tsukahara, and R. W. Engle, in R. H. Logie, V. Camos, and N. Cowan (Eds.), *Working Memory: State of the Science* (pp. 175–211), 2021, Oxford University Press (https://doi.org/10.1093/oso/9780198842286.003.0007). Copyright 2021 by Oxford University Press. Adapted with permission.

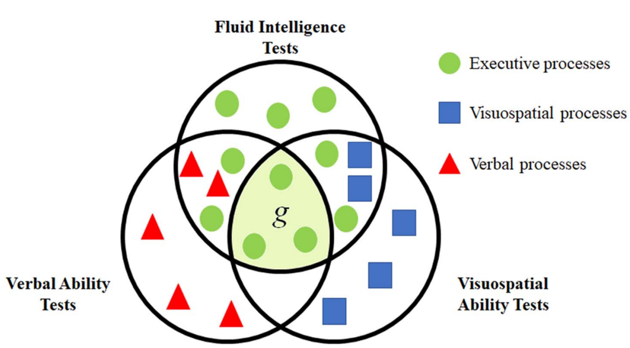
from items in memory depending on current needs, the ability to coordinate attention is unitary and task-general (cf. Hunt, 1980).

Process Overlap Theory

Kovacs and Conway (2016, 2019) noted that the ubiquitous pattern of positive correlations among cognitive tests, referred to as the positive manifold, has traditionally been explained by Spearman's *g*, the general factor of intelligence (Spearman, 1904). However, it is unclear whether *g* should be understood as a genuine psychological phenomenon or as a statistical artifact (Burgoyne et al., 2022; Hunt, 1980; Kovacs & Conway, 2016, 2019; Spearman, 1904; Thomson, 1916; Thurstone, 1938). Kovacs and Conway's (2016, 2019) process overlap theory attempts to explain the positive manifold while dispensing with the general factor. In process overlap theory, cognitive tests are thought to tap both domain-general executive processes and domain-specific (e.g., verbal, visuospatial) processes. Domain-general executive processes are tapped in an overlapping manner across a variety of cognitive tests, making them more heavily utilized than domain-specific processes. For example, an executive control process may be required by both verbal and visuospatial ability tests.

Process overlap theory suggests that the positive manifold and, by extension, *g*, is an emergent phenomenon based on overlapping samples of different cognitive control processes coming into play across diverse tasks (Kovacs & Conway, 2016, 2019; Thomson, 1916). In other words, *g* is evidence of cognitive control (i.e., executive attention) being broadly helpful for cognition but is not evidence for a single, common causal process. Following Borsboom et al. (2003, 2004), Kovacs and Conway (2019) suggested that *g* is a *formative* rather than a *reflective* latent variable, since it is not easily mapped onto latent causal processes (see Figure 9; see also S. B. Kaufman et al., 2009). Process overlap theory thus defines *g* as a domain-general latent factor for which executive attention is responsible, yet the general factor is neither psychologically necessary nor adequate for explaining the positive manifold (Kovacs & Conway, 2019).

Figure 9
Process Overlap Theory



Note. The general factor (*g*) is defined by the correlation among verbal ability, fluid intelligence, and visuospatial ability tests. This correlation is determined by the executive processes recruited (green circles) by all three task types. See the online article for the color version of this figure.

Evaluating Current Views on Executive Attention

Given these multiple ways of conceptualizing executive attention, we should ask whether one view is preferable. Of the three mentioned, the unity and diversity of executive functions has been the most influential by far, the original Miyake et al. (2000) article having been cited almost 18,000 times as of this writing. However, the framing has recently come under scrutiny. Karr et al. (2018) reanalyzed published data sets ($N = 9{,}756$) and evaluated model fit and convergence rates for different variations of the unity and diversity of executive functioning model, including the formulations presented in Figure 7. While their analysis did not disconfirm the unity and diversity framework, Karr et al. (2018) found poor rates of model acceptability and convergence. They suggested that many of the published studies using the unity and diversity model are underpowered, leading to well-fitting but ungeneralizable statistical models (Karr et al., 2018). Despite its ubiquity, the foundations of the unity and diversity view are not well established. We thus suggest that the other perspectives be given more attention.

Both process overlap theory and maintenance and disengagement theory argue that executive attention is a general constraint on information processing. Unsurprisingly, some studies expressing support for one theory would also be consistent with the other (e.g., Schubert et al., 2021). The theories differ in how they characterize executive attention, though. Process overlap theory suggests that executive attention is a set of independent or nearly independent processes, which are sampled across tests of different domains, modalities, formats, and contents (Kovacs & Conway, 2016, 2019). Maintenance and disengagement theory takes a more unitary view, at least of attention control (Martin et al., 2020; Shipstead et al., 2016).

The unitary nature of attention control has been much debated and difficult to establish (Draheim et al., 2021; Rey-Mermet et al., 2019; Weigard et al., 2021). This difficulty could be taken as support for process overlap theory, though recent evidence of attention control's generality is encouraging for the maintenance and disengagement view (Burgoyne et al., 2022; Burgoyne, Tsukahara, et al., 2023). Robinson and Steyvers (2023) substituted an attentional weight parameter from a computational model of a flanker task into a computational model of a switching task and vice versa. They found that attentional weights from the two models were interchangeable: participants' flanker performance could be predicted from their switching parameter and their switching performance from their flanker parameter (Robinson & Steyvers, 2023). This is particularly notable because flanker and switching tasks are thought to measure distinct functions (inhibition and set switching, respectively). This is consistent with a task-general ability to selectively prioritize relevant information and would be readily predicted by maintenance and disengagement theory, but not necessarily process overlap theory.

Another recent line of evidence comes from positively and negatively cued visual search tasks (see Carlisle, 2023, for a review). In a positively cued visual search, participants are told which items in a search array will contain a target (e.g., the target *will be* one of the green items). In a negatively cued visual search task, participants are told which items will not contain the target (e.g., the target *will not be* one of the red items). Both positive and negative cues lead to higher target identification accuracy and shorter reaction times than uncued visual search. Interestingly, participants who receive the largest performance benefits from the positive cue also benefit most from the negative cue (see Beck & Hollingworth, 2015; Carlisle, 2023). This again suggests that executive attention exerts a general influence across different task demands; attentional selection of targets is related to attentional suppression of distractors. These results align more closely with maintenance and disengagement theory than with process overlap theory, though it would be interesting to see whether positively and negatively cued visual search tasks relate differentially to measures of working memory (maintenance) and fluid intelligence (disengagement).

Measuring Attention Control

While findings like those of Robinson and Steyvers (2023) or Carlisle (2023) suggest that attention control is a general construct, poor measurement has made delineating its precise nature difficult. Despite a long history, the recent psychometric literature surrounding executive attention has witnessed much controversy. This stems from difficulty establishing psychometric models for individual differences in attention control (Karr et al., 2018; Rey-Mermet et al., 2019). There are several interrelated reasons for this, including the field's overreliance on conflict tasks imported from experimental cognitive psychology (Draheim et al., 2019).

Conflict tasks such as the Stroop, flanker, and Simon typically require participants to respond to multiple trial types, with some trials involving a degree of conflict between stimuli and/or responses. On other trials, such conflict is absent. The difference between mean reaction times in the conflict and no-conflict conditions is taken to indicate the efficiency of participants' inhibitory control. A smaller difference suggests a greater ability to reduce the influence of cognitive processing inconsistent with the current task goal. These difference scores are then included in correlational latent variable models to measure attention control.

This approach has theoretically and methodologically stifled progress on understanding individual differences in attention control and cognitive abilities. One reason for this is that the difference scores derived from conflict tasks are ill-suited for individual differences research. With few exceptions (e.g., Rey-Mermet et al., 2019), interference effects demonstrate low reliability estimates (see Ackerman & Hambrick, 2020; Draheim et al., 2019; or Goodhew & Edwards, 2019, for reviews). Understanding the reason for this requires an understanding of how the reliability of a difference score is calculated and the psychometric properties of conflict tasks. The reliability of a difference score is a function of the reliability of each of the component scores (e.g., mean reaction times from both the conflict and no-conflict trials) and the correlation between those scores. More reliable component scores produce a more reliable difference score. Reliability is diminished, however, when the correlation between component scores is large, as is the case in most conflict tasks (see Cronbach & Furby, 1970; Draheim et al., 2019; Hedge et al., 2018; Rouder et al., 2019). This creates a difference score containing mainly unsystematic error variance (Hedge et al., 2018; Rouder et al., 2019). Since validity is constrained by reliability, using these difference scores results in weak correlations between theoretically similar tasks and poorly performing psychometric models. The fact that these difference scores are contrasts between reaction times adds further complexity due to possible individual differences in speed–accuracy trade-offs, which may interact with cognitive ability (Draheim et al., 2016, 2019; Miller & Ulrich, 2013). We and others (Ackerman & Hambrick, 2020; Cronbach & Furby, 1970; Draheim et al., 2019; Goodhew & Edwards, 2019) thus caution against using difference scores for psychometric research.[8]

There have been several proposed solutions to these problems, including developing new tasks (Burgoyne, Tsukahara, et al., 2023; Draheim et al., 2021), explicitly modeling trial-level variability (Rouder & Haaf, 2019), expanding the focus of quantitative investigations beyond measures of central tendency (e.g., Haines et al., 2020), integrating behavioral performance with neurophysiological data (e.g., Schubert et al., 2022), and utilizing cognitively informed computational modeling (Frischkorn & Schubert, 2018; Robinson & Steyvers, 2023). These efforts are unlikely to dispel all difficulties facing attention control researchers (e.g., there are conceptual weaknesses that pose their own issues; see MacLeod et al., 2003; Weigard et al., 2021; Werner et al., 2022), but these novel approaches promise to help advance the field.

In addition, we urge researchers not to treat conflict tasks as the crucible for testing theories about executive attention. Doing so is too narrowly focused, and it makes unrealistic assumptions about the situations in which executive attention is engaged. Not only does executive attention operate in nonconflict situations (Fox et al., 2009; Schubert et al., 2017), conflict resolution may not even be the active mechanism in some "conflict" tasks. For instance, Meier et al. (2018) found that goal instantiation, not conflict resolution, helped explain the relationship between working memory capacity and antisaccade task accuracy, a measure often used to assess inhibition. Similarly, participants' pupillary responses in the preparatory period of an antisaccade task help to explain working memory advantages in antisaccade performance (Unsworth et al., 2023). This finding suggests that higher working memory capacity participants control their attention in the antisaccade task to prepare for upcoming events in the antisaccade task, not merely to resolve conflict (Unsworth et al., 2023; see also Mashburn & Engle, 2023). While we do not abjure studying conflict tasks per se, adopting a broader view of executive attention may prove useful to all those conducting work in this area, particularly when taken in conjunction with some of the other recommendations mentioned.

Summary of Executive Attention and Intelligence

Early developmental psychologists postulated the development of controlled, focused attention as a fundamental aspect of intellectual maturation. With time, information processing psychologists began to incorporate it into their work, most notably theories of working memory. There are currently several competing theories about the relation between executive attention, its aspects, and intelligence, as well as intense discussion about the nature and measurement of individual differences in the control of attention. Of these theories, we suggest that process overlap theory and maintenance and disengagement theory warrant more attention from the field, especially maintenance and disengagement theory.

[8] Some researchers have instead chosen to use structural equation modeling to isolate conflict resolution-related variability in one latent variable and all other task-related variability in another (e.g., Frischkorn et al., 2019). However, the strong correlation between congruent and incongruent trials means there is simply not much variance to be modeled under the "conflict" latent variable. Difference scores thus accentuate the problem with conflict tasks, but avoiding them will not remedy the psychometric difficulties of conflict tasks. The problem runs deeper.

Speed Versus Executive Attention in the Prediction of Intelligence

Thus far, we have chronicled major developments in the study of processing speed and, separately, executive attention as they pertain to explaining intelligence. The former finds its origins in the mental testing movement but received more emphasis when information processing began to dominate mainstream psychology. The latter is rooted in developmental psychology and is both a precursor and consequence of developments in working memory research. Executive attention and processing speed appear, at surface, to embody quite different constructs, the former being brought to bear in situations of high cognitive demand and the latter embodying parameter(s) of cognition more generally. However, closer examination of the two constructs reveals that they are at times difficult to parse and may not be as distinct as some researchers have asserted. For instance, many tests thought to reflect speed likely rely on executive attention, particularly in more complex speed tests (Ackerman et al., 2002; Cepeda et al., 2013; Lerche et al., 2020).

To make this case, we describe findings from several lines of research. First, we contend that both executive attention and processing speed vary concomitantly across the life span. We then turn to studies on the *worst performance rule*, the finding that the slowest tail of an individual's reaction time distribution is more diagnostic of their intelligence than other components of the reaction time distribution. Next, we consider evidence that undifferentiated speed is insufficient to describe the relationship between speed and ability and that the speed of neurocognitive processes related to executive attention may be especially important for explaining cognitive ability differences. Finally, we discuss studies that attempt to manipulate executive attention and/or speed to assess claims of causality in determining intelligence.

Attention, Speed, and Intelligence Covary Across Development

Processing speed and executive attention are thought to follow similar life span developmental trajectories. Childhood is marked by a quickening of responding until adolescence, while old age is marked by a progressive slowing (Fry & Hale, 1996; Gilbert, 1894; Kail & Salthouse, 1994). Additionally, children are thought to have increasingly strong attention capabilities as they age and adults tend to experience declines in these same abilities in late life (Blankenship et al., 2019; Case, 1985; Kang et al., 2022; Pascual-Leone & Goodman, 2021; Reuter-Lorenz & Cappell, 2008). In their review of age-related cognitive decline, Zanto and Gazzaley (2019) argued that these latter decrements stem in part from age-related changes in the morphology and functioning of the prefrontal cortical areas related to attention and executive functioning.

Importantly, researchers have linked both processing speed and executive attention to developmental changes in cognitive abilities. Kail and Salthouse (1994) reviewed evidence for a general speed of processing that varies across development and reiterated that there is often a systematic, highly lawful relationship between age groups' performance on speeded tasks: older children perform tasks more quickly than younger children and older adults perform tasks more slowly than younger adults. Moreover, accounting for performance on processing speed attenuates age effects on cognitive tests. For matrix reasoning alone, accounting for processing speed attenuated age effects by approximately 85% (see Table 2 in Kail & Salthouse, 1994), suggesting substantial overlap between age, processing speed, and cognitive ability. Analogously, Stankov's (1988) factor analyzed a battery of cognitive tests, finding three factors corresponding to facets of attention, namely flexibility, concentration, and search. Stankov (1988) reported that statistically controlling for any of these attention factors, especially flexibility, eliminated age differences in fluid intelligence. Additionally, in a longitudinal study of 157 children, Blankenship et al. (2019) found that better attention in 5-month-olds predicts later executive functioning. Moreover, these longitudinally measured executive advantages predict IQ and reading ability at age 6 (Blankenship et al., 2019). Thus, it appears that either speed or attention may account for developmental changes in intelligence.

To reiterate this point, McCabe et al. (2010) found that age differences in retrieval from episodic memory can be statistically explained by executive attention, as evidenced by a full mediation of the effect of age on memory retrieval. A full mediation was also obtained when the effect of age was routed through processing speed. The effect of processing speed on memory retrieval was, in turn, fully mediated by processing speed's relationship with executive attention. Thus, either processing speed or executive attention could account for age effects on episodic memory retrieval, but accounting for executive attention eliminated the effect of speed on memory. This finding warrants some qualification. First, although mediation models theoretically assume a causal direction, they do not constitute tests of causal claims, as several statistically equivalent models (which all assume causality) are possible (Thoemmes, 2015). Second, McCabe et al. (2010) investigated episodic memory retrieval, not intelligence. However, their findings do suggest that executive attention and processing speed share much of the same age-related variability.

The Worst Performance Rule

Theories that explain differences in intelligence by appealing to differences in speed *must* assume that faster cognition leads to better performance on intelligence tests. Furthermore, some have argued that if speed causes intelligence differences, then an individual's fastest reaction times should be most diagnostic of intelligence differences (Ellingsen & Engle, 2020; Unsworth et al., 2010). However, the worst performance rule appears to conflict with this view (Ellingsen & Engle, 2020; Unsworth et al., 2010; Unsworth & Redick, 2017). Reaction times famously tend to have a right-skewed distribution, and less intelligent individuals who score lower on intelligence tasks have distributions with especially lengthy tails (Larson & Alderton, 1990; Unsworth et al., 2010). The worst performance rule refers to the finding that reaction times in the slower tail of the distribution most strongly (negatively) predict intelligence. The worst performance rule is thus difficult to square with a pure speed-based account but appears friendlier to an account of intelligence differences rooted in executive attention. Attentional lapses directly account for slowed reaction times on some trials, and those more prone to such lapses (i.e., those with worse attention control) experience longer and more frequent lapses (e.g., Unsworth et al., 2010), leading to more severely skewed distributions.

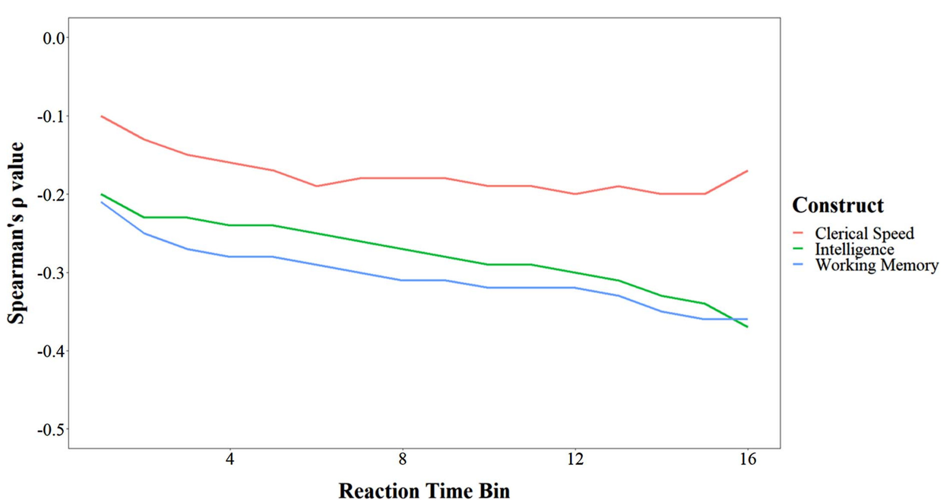
Larson and Alderton (1990) were the first to assign importance to this finding, though the pattern had been previously observed (see Baumeister & Kellas, 1968; Jensen, 1982). Noting that reaction time variability is a function of a participant's slowest trials, Larson and Alderton (1990) rank-ordered individual responses on a switching task, and partitioned them into 16 bins of five trials each. They then averaged the reaction times in each bin and correlated these mean reaction times with composite scores representing general intelligence, working memory, and clerical speed. They found that the correlations between reaction time bin scores and cognitive abilities grew stronger at slower reaction times, especially for intelligence and working memory (see Figure 10). Moreover, they found a very strong correlation between an individual's overall reaction time variability and their slowest bin score ($\rho = .95$), confirming that individuals' reaction time variability is primarily a function of their propensity for occasional slow responding, to which low-ability participants were especially prone.

Spieler et al. (1996) adopted a complementary approach. Rather than dividing individual responses into reaction time bins, they capitalized on the fact that hallmark reaction time distributions resemble an ex-Gaussian distribution, which can be created by summing a standard Gaussian and an exponential distribution. This allows researchers to decompose reaction time distributions into three components: mu and sigma (the mean and standard deviation of the Gaussian component, respectively), and tau, the mean and standard deviation of the exponential component. Tau captures the hallmark right-skew (see Heathcote, 1996). Spieler et al. (1996) administered a color Stroop task to a sample of undergraduates, healthy older adults, and older adults diagnosed with Alzheimer's disease. They noted an increase in the classic Stroop interference effect for healthy older adults as compared to undergraduates and a further increase for older adults with Alzheimer's disease. This is not especially informative, as increases in interference effects can be produced by either age differences in global speed or interference-reduction processes (see Figure 4; Verhaeghen, 2014). However, their ex-Gaussian analysis suggested that the primary source of this increased interference effect came from the tau parameter. Older adults, and especially those with Alzheimer's disease, had more skewed distributions than younger adults, which Spieler et al. (1996) interpreted as older adults experiencing greater interference from the irrelevant color word relative to their younger counterparts, but only for some trials. In short, Spieler et al. (1996) replicated and extended Larson and Alderton's (1990) original findings: Slower trials were most diagnostic of an individual's cognitive ability (here indexed by age and dementia diagnosis), with older adults showing increased interference effects because of their reduced ability to *consistently* attend only to the relevant Stroop features.

In the intervening years, there have been two major reviews of the worst performance rule, each attempting to summarize evidence to date and to address attempts to explain the pattern. The first was conducted by Coyle (2003). Of the studies conducted to that date, most found evidence supporting the worst performance rule. Coyle (2003) made several other useful observations concerning the validity of this finding, of which we note two. First, he noted that measurement unreliability cannot account for the worst performance rule. In theory, extreme scores contain much unsystematic error variance. However, this cannot explain the worst performance rule, since under this explanation, the unreliability of extreme scores should preclude observing sizable correlations (Coyle, 2003). Reliability should be lowest for the slowest responses, yet that is where the highest correlation is found. Second, reaction time outliers cannot explain the worst performance rule; there are two reasons for this. First, and related to the unreliability issue, outlying scores should be random and unsystematic, reducing the likelihood of a strong and reliable correlation, which

Figure 10

The Spearman's ρ Rank-Order Correlations Between Individual Reaction Time Bins and Cognitive Ability Composites



Note. Adapted from "Reaction Time Variability and Intelligence: A 'Worst Performance' Analysis of Individual Differences," by G. E. Larson and D. L. Alderton, 1990, *Intelligence*, *14*(3), pp. 309–325 (https://doi.org/10.1016/0160-2896(90)90021-K). Copyright 1990 by the American Psychological Association. Larger bin numbers contain slower reaction times. Figure adapted from their Table 4. See the online article for the color version of this figure.

is not the case. The second problem with the outlier account is that the correlation between reaction time and cognitive abilities increases over the course of the entire distribution, not merely at the very tail where outliers should be clustered (Larson & Alderton, 1990).

More recently, Schubert (2019) conducted a meta-analysis on the worst performance rule, with mixed findings. Although she found robust evidence for the worst performance rule across tests of memory, general intelligence, fluid intelligence, and clerical speed, the pattern of increasing correlations violated linearity, contradicting the original study by Larson and Alderton (1990). That is, the slowest reaction times consistently prevailed as the best predictors of cognitive ability, but the correlations increased logarithmically from the fastest, to the mean, to the slowest trials; mean reaction times predicted ability better than the fastest reaction times, and slowest reaction times predicted ability better than mean reaction times, but the difference in prediction was larger between the fastest and mean reaction times than that between mean reaction times and slowest reaction times. The importance of this logarithmic increase for arbitrating between executive attention and processing speed is difficult to appreciate, as most accounts make no explicit prediction as to what the shape of this function ought to be. More troubling is the finding that the worst performance rule was stronger for clerical speed tests than for the intelligence and memory tests included in the analysis (Larson & Alderton, 1990; Schmiedek et al., 2007; Schubert, 2019). This might suggest a closer relationship between speed and the worst performance rule than suggested previously by others (e.g., Ellingsen & Engle, 2020; Unsworth & Redick, 2017), and a closer examination of speed is warranted.

Evidence that the worst performance rule can be explained by individual differences in processing speed comes from several other sources. Ratcliff et al. (2008) conducted a study in which they simulated plausible participant reaction times and accuracy rates according to different diffusion modeling parameters. They then correlated their simulated participants' drift rates with accuracy rates and overall mean reaction times. They also binned trial-level reaction times by decile and obtained correlations between the mean of each reaction time bin and drift rates. Ratcliff et al. (2008) reported two crucial findings. The first is that slower drift rates tended to produce more strongly right-skewed reaction time distributions. The second is that the correlations between the binned reaction times and drift rates conformed to the worst performance rule. While Ratcliff et al. (2008) did not collect empirical data, their results show that diffusion model parameters can create patterns consistent with the worst performance rule, with high drift rates being necessary to avoid a strongly skewed reaction time distribution.

Further empirical evidence comes from studies that have applied the drift-diffusion model alongside the ex-Gaussian model to the same reaction time data. Recall that the mean/standard deviation of the exponential component of the ex-Gaussian decomposition, tau, has often been interpreted as reflecting attentional lapses (e.g., Spieler et al., 1996; Unsworth et al., 2010). Studies show that the diffusion model parameter most strongly correlated with tau is drift rate (Schmiedek et al., 2007; Schmitz & Wilhelm, 2016). Moreover, both the drift rate and tau parameters most strongly and consistently correlate with working memory capacity and fluid intelligence. Thus, both tau and drift rates are especially sensitive to occasional, extremely slow reaction times and are related to cognitive ability constructs, suggesting that both parameters may be sensitive to similar properties of the neurocognitive system.

The fact that slower drift rates (evidencing slower processing speeds) produce severely skewed reaction time distributions conflicts with the notion that the worst performance rule is necessarily incompatible with processing speed as an explanation of intelligence differences. However, that drift rates can reproduce the worst performance rule does not refute the claim that lapses of attention control can explain the worst performance rule or individual differences in intelligence.

It is important to keep in mind that the drift-diffusion model is fundamentally a mathematical description of a decision-making process. For instance, the EZ-diffusion model requires three pieces of information to estimate a participant's drift rate, boundary separation, and nondecision time: the proportion of the participants' correct responses, the participant's mean reaction time, and the variance of their reaction times (Wagenmakers et al., 2007). All binary choice tasks, irrespective of their psychological underpinnings, provide the requisite information to estimate the EZ-diffusion model's parameters. The diffusion model is thus not, in and of itself, a satisfactory psychological theory, since it is agnostic to the data-generating processes it models.

Relatedly, it is not always clear what psychological processes are reflected by the diffusion model's parameters, although the parameters can be selectively manipulated to some extent (Voss et al., 2004; but see Rafiei & Rahnev, 2021). For example, any neurocognitive process that affects the rate of evidence accumulation should affect drift rates. Moreover, finding that drift rates from different cognitive tasks strongly correlate does not necessarily imply that "speed" determines performance across diverse sets of tasks. It may suggest that rates of evidence accumulation across cognitive tasks are affected by similar psychological processes. A useful line of research would thus be to understand the cognitive basis of individual differences in drift rates across different tasks, which may include executive attention (cf. Boehm et al., 2021).

To illustrate, Löffler et al. (2022) recently explored the attentional lapses account of the worst performance rule. In one study, they confirmed the presence of the worst performance rule in reaction times from a switching task and scores from the Berlin Intelligence Structure Test. They also collected several indices of attentional lapses, including self-reported task-unrelated thoughts, propensity for mind-wandering, several event-related potential (ERP) signatures, and reaction time variability in a behavioral task meant to index sustained attention. Jointly controlling for the attentional lapse metrics eliminated the worst performance rule pattern, although each attentional lapse metric accounted for only a small portion of the total effect. Löffler et al. (2022) replicated this finding in a reanalysis of a different data set (Kane et al., 2016), this time using reaction times from four cognitive tasks and working memory capacity as the criterion construct rather than intelligence. Evidence for the worst performance rule was found for each task and controlling for task-unrelated thoughts attenuated the worst performance rule in each case.

The analyses reported by Löffler et al. (2022) support the notion that the worst performance rule is related to the control of attention and is not merely an artifact of information processing speed. Furthermore, these results allow that attentional processes may help explain some results surrounding the speed–intelligence relationship by mapping drift rates onto plausible cognitive mechanism(s); drift rates may be sensitive, among other things, to the lapsing of attention. This correspondence gives drift rates psychological meaning and not mere mathematical utility. However, it remains an open question to what extent drift rates are determined by the lapsing of attention, or if other temporal aspects of attention (e.g., the average rate of attentional engagement/selection, trial-by-trial variability thereof) also affect drift rates and, the skew of individual reaction time distributions, and perhaps even other aspects of the distribution as well.

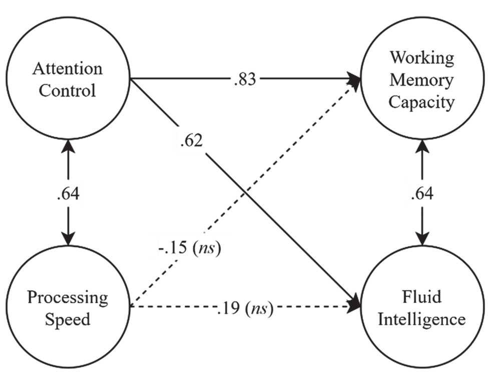
Does the "Speed of *What* ?" Matter ?

Rather than a global, general speed advantage that generalizes across cognitive processes, those higher in cognitive ability may have speed advantages in particular cognitive processes (cf. Rabbitt, 1996). Some evidence suggests that the speed of attention and cognitive control processes may be closely related to intelligence and complex cognition. Draheim et al. (2021), for example, found that a latent variable thought to measure attention control was strongly correlated with a processing speed latent variable, such that those with better attention control also performed better on several computerized speed tests. However, when accounting for this correlation, only attention control predicted working memory capacity and fluid intelligence; the predictive paths from processing speed to working memory capacity and fluid intelligence were smaller and nonsignificant (see Figure 11). This indicates that whatever prediction processing speed had for working memory capacity and fluid intelligence was subsumed under and superseded by attention control.

The results of Draheim et al. (2021) suggest substantial overlap between the processes measured by tests of processing speed and attention control. Still, a more molecular, experimental approach would be informative. Heitz and Engle (2007) provided one such demonstration of the specificity of speed advantages in individuals of varying cognitive ability. The presence of incongruent distractors

Figure 11

Structural Equation Model With Attention Control and Processing Speed Predicting Working Memory Capacity and Fluid Intelligence



Note. Adapted from "A Toolbox Approach to Improving the Measurement of Attention Control," by C. Draheim, J. S. Tsukahara, J. D. Martin, C. A. Mashburn, and R. W. Engle, 2021, *Journal of Experimental Psychology: General*, *150*(2), pp. 242–275 (https://doi.org/10.1037/xge0000783). Copyright 2021 by the American Psychological Association. *ns* = nonsignificant.

in flanker tasks delays reaction time and increases the number of errors, but high working memory participants (high-spans) often show smaller performance decrements than those with lower working memory (low-spans). Heitz and Engle (2007) hypothesized that this could occur because high-spans are more efficient at constraining their attention to the central target item (cf. Eriksen & St. James, 1986). Participants categorized as high- or low span completed a letter flanker task in which they identified a central letter in a string of five letters. The letters could all be the same (e.g., HHHHH; also called congruent trials) or the central letter could differ (e.g., SSHSS; also called incongruent trials). Participants were encouraged to respond quickly via the use of increasingly stringent response deadlines as they progressed through the task. Reaction times on correct trials were then binned and plotted against accuracy rates to create conditional accuracy functions. This was done separately for congruent and incongruent trials and for high- and low-span participants. The goal was to assess at which time point high- and low-span participants obtain asymptotic accuracy levels. If high-spans are faster at constraining the focus of their attention to the target letter, they should obtain asymptotic accuracy levels faster than low-spans, but only on incongruent trials. However, if there is a general speed advantage, high-span participants should reach asymptote faster, regardless of the condition.

Consistent with their expectations, Heitz and Engle (2007) found no span differences for congruent trials, but high-spans reached asymptotic accuracy levels on incongruent flanker trials more quickly than low-spans. Therefore, Heitz and Engle (2007) concluded that working memory capacity is related to the rate of attentional constraint. That is, higher working memory capacity individuals can shrink their focus to the target faster than low working memory capacity individuals. Their results are inconsistent with a general speed advantage explanation of working memory capacity differences, but compatible with some localized, attention-related speed explanations.

Several recent neurophysiological studies further support the conclusion that more intelligent individuals possess specific advantages in processes related to executive attention. Schubert et al. (2017) asked whether more intelligent participants have a general speed advantage evident in all task-evoked ERP components or whether they differ in specific ERP latencies (i.e., the time from ERP onset to peak amplitude). They measured the time course of different poststimulus ERP signals during three processing speed measures: a Hick task, a Sternberg memory-scanning task, and a Posner letter-matching task. They then related these different ERP signals to general intelligence as measured by the Berlin Intelligence Structure Test and Raven's Advanced Progressive Matrices. If there is a general speed advantage, then the different ERP components should relate uniformly to intelligence, whereas if high-intelligence individuals have speed advantages in specific processes, then some ERP components should relate more strongly than others.

The latter result obtained; latencies of ERP components occurring later in the stream of information processing, particularly the P300 signal, were strongly related to general intelligence ($r = -.78$). Because the P300 waveform is thought to index processes related to the regulation of attention and working memory (Kala et al., 2023; Linden, 2005; Picton, 1992), this finding bridges the divide between processing speed and executive attention explanations of cognitive ability differences, where the efficiency of neurocognitive processes underpinning attention control provide the basis for individual differences in intelligence (for a similar finding using functional magnetic resonance imaging and the Hick task, see Wu et al., 2018; see also Wong et al., 2021).

In another study, Schubert et al. (2021) investigated whether functional connectivity during a cognitive control task was related to individual differences in intelligence. They were interested in whether theta-band activity in the midfrontal brain region during a switching task predicted intelligence, where midfrontal theta-band activity is construed as an ERP signature of cognitive control (see Cavanagh & Frank, 2014). They also assessed whether the time course of this functional connectivity affected the relationship with intelligence. They found that increased functional connectivity in the midfrontal theta band, particularly in later processing stages, was related to intelligence ($r \approx .80$). Importantly, the relationship was specific to the theta band and did not generalize to other, non-control-related ERP wavelengths. Again, these results are consistent with the notion that executive attention is a critical determinant of individual differences in intelligence.

These results contradict explanations of cognitive ability differences rooted in a general processing speed. Rather, they suggest that researchers should reorient away from studying "general" speed to studying the speed and efficiency of processes related to the focusing and control of attention, enumerating those processes, and explaining how and why those specific speed advantages occur. That neural markers of executive attention are found in speed tasks with no explicit conflict component suggests that clinging to conflict tasks as the crucible for theorizing about executive attention is predicated on unrealistically narrow views on the nature and role of executive attention as a component of complex cognition.

Manipulations of Executive Attention and/or Speed

At the outset of this article, our stated goal was to compare executive attention and information processing speed as contributors to intelligence differences. Of course, establishing causation requires painstaking attempts at control and disconfirmation, which can be especially difficult in the context of individual differences studies. Nonetheless, there have been several attempts to directly manipulate demands for attention and/or speed of information processing.

Following concerns about spatial attention confounds in Jensen's apparatus for studying Hick's law (Bors et al., 1993; Longstreth, 1984), Bates and Stough (1997) assessed whether the spatial distribution of stimuli and responses affected the relationship between reaction times and intelligence. They administered one- and two-bit conditions of a Hick task in either a spatially condensed or distributed configuration. They also administered Raven's Advanced Progressive Matrices as a measure of intelligence. Reaction times in each condition of the task were negatively correlated with Raven's scores. However, after dividing the participants into high- and low-intelligence groups, Bates and Stough (1997) submitted their reaction time data to a 2 (intelligence group) × 2 (bit condition) × 2 (spatial configuration) analysis of variance, revealing a three-way interaction: High-ability participants showed faster reaction times in the spatially condensed condition of the one-bit task relative to the spatially dispersed condition, while lower ability participants showed no such advantage. This suggested that more intelligent participants had particular advantages in task conditions conducive to focused attention (Bates & Stough, 1997). Thus, manipulating spatial attention demands modulated the relationship between choice reaction time and cognitive ability.

Bates and Stough (1997) manipulated attentional demands (i.e., attentional breadth) to observe the effect it had on the relationship between reaction time and intelligence. Fox et al. (2009) achieved a similar result by introducing an auditory shadowing dual task to a visual inspection time task. Participants underwent a thresholding procedure to estimate their inspection time. In a first study, they confirmed that inspection time was related to performance on a short form of Raven's Advanced Progressive Matrices, where shorter inspection time estimates predicted higher intelligence test scores. In a second study, participants were instructed to repeat text read to them via headphones and to prioritize this as their main task. Of secondary importance, they were instructed to do the visual inspection time task. This manipulation tested whether the inspection time task depends on attention allocation. If, as has been speculated, the inspection time task is a pure, "precognitive" measure of speed (Jensen, 1998; Nettelbeck, 1987), it should be unaffected by the presence of an unrelated distractor task, both in terms of average performance and its correlation with intelligence. In contrast, if the ability to maintain focused attention is important to the inspection time task, there should be a decrement in inspection time estimates and, to the degree that they conform to instructions and attend the primary shadowing task, more intelligent participants should perform more poorly on the inspection time task.

Consistent with the attention account, inspection time estimates were significantly longer with the introduction of the shadowing task. Most strikingly, the direction of the correlation reversed, such that worse performance on the inspection time task now predicted higher scores on the Raven's Advanced Progressive Matrices. This would be expected if more intelligent participants were better at prioritizing the auditory shadowing task as their main objective, diverting attention from the inspection time task.

Unfortunately, both Bates and Stough (1997) and Fox et al. (2009) are limited by small sample sizes ($N < 40$ in each case, except for Study 1 of Fox et al., where $N = 77$) and limited task batteries, so the robustness of their findings is difficult to assess without replication with larger samples and more tasks. Tentatively, they both suggest that the relationship between measures of speed and intelligence can be affected by attentional manipulations.

While both Bates and Stough (1997) and Fox et al. (2009) manipulated attentional demands within speed tasks, Chuderski (2013) investigated what effect different time constraints have on the construct validity of fluid intelligence tests. He administered measures of working memory capacity (a change detection task and a relation monitoring task). His participants also completed Raven's Advanced Progressive Matrices and a figural analogy test under their standard time limits (i.e., 40 min for Raven's Advanced Progressive Matrices and 30 min for the figural analogy test), with half the recommended time, or with a lenient time constraint of 1 hr. The correlation between working memory capacity and fluid intelligence factors strengthened as time constraints became more severe, increasing from .62 in the unspeeded group to .83 in the standard time group to an astonishing 1.00 for the speeded group (Chuderski, 2013). Depending on how it was measured, fluid intelligence was either moderately related to working memory, sharing as little as 38% (i.e., $.62^2$) of its variance, or completely indistinguishable from it.

Clearly, administering intelligence tests under different time constraints can change what test scores reflect. It is less clear how we should interpret Chuderski's (2013) findings. One interpretation of this pattern of results is that the speeded nature of the time-limited tests created an opportunity for individual differences in processing speed to dominate test performance, perhaps according to Salthouse's (1996) time limitation mechanism. One might argue this increased reliance on speed strengthened the working memory capacity–intelligence correlation. However, Chuderski (2013) favored an interpretation whereby performance on intelligence tests with liberal time constraints is more multiply determined than that of time-limited tests. Severe time constraints might require participants to solve items using working memory processes alone, whereas less-speeded tests allow for more reasoning-specific factors to influence responding, diluting the correlation. Time constraints would appear to be a plausible speed manipulation, but a more direct approach is needed to establish a role for speed in determining intelligence.

An example of this comes from Schubert et al. (2018), who pharmacologically manipulated participants' speed of information processing. They did so via a transdermal nicotine patch in a pretest–posttest design. In one session, participants completed a Sternberg memory-scanning task and a matrix reasoning task, after which they were either administered a nicotine patch or a placebo. Later in the day, participants underwent a second round of testing, completing a second memory-scanning task and another matrix reasoning task, this time with ERPs recorded to index neural speed. One week later, the procedure was repeated under the other nicotine treatment.

While the nicotine patch hastened behavioral responding on the memory-scanning task and reduced the latency of N200 and P300 ERP signatures, there was no evidence that these increases in speed led to any differences in performance on the intelligence tests. Thus, Schubert et al. (2018) suggest that, rather than speed being a causal factor in intelligence differences, processing speed and intelligence are both consequences of some other property of the neurocognitive system. Long-range functional connectivity in the frontoparietal and salience networks are promising candidates, again suggesting that the efficiency of attentional processes may help explain the speed–intelligence relationship (Rueda, 2018; Yuan et al., 2012).

Finally, a study conducted by Kofler et al. (2020), while not related to intelligence, jointly manipulates both speed and working memory load and suggests a causal direction between the two. In the low-load condition, participants merely completed the processing components of the working memory tasks. This involved identifying visual stimuli (i.e., animals or emotional faces) and then judging the veracity of simple sentences. In the high working memory load condition, participants also recalled the animals/emotions that they had identified during that set of items in their correct serial position. Information processing speed was manipulated by varying whether the animals and faces were presented directly or whether the identity of the stimulus needed to be inferred from contextual information (e.g., a photo of a man with a leash walking an unseen animal should prompt the response DOG). The contextual versions of the tasks were intended to slow the speed of information uptake, as measured by drift rates in a linear ballistic accumulator model (a sequential sampling model related to the drift-diffusion model). For present purposes, the most critical result is that increasing working memory load also slowed drift rates. However, slowing drift rates had no substantial effect on working memory performance. These results occurred despite their manipulations having the intended effects; accuracy was higher in the low-load conditions of the working memory tasks and drift rates were slower in the infer-from-context conditions. This suggests directionality in the relationship between processing speed and working memory performance, with speed being a consequence, not a cause, of working memory processes.

The emerging picture is favorable to executive attention as a basis for individual differences in intelligence. Manipulating the demands for executive attention and related constructs (i.e., working memory) affects the relationship between speed and intelligence, but the reverse is untrue (Bates & Stough, 1997; Fox et al., 2009; Kofler et al., 2020). Moreover, directly manipulating speed of neural processing has no discernible effect in intelligence test performance, undermining claims that speed is the functional basis for intelligence (Schubert et al., 2018).

Conclusion to Speed Versus Executive Attention

In this section, we have compared processing speed and executive attention as candidate causes of intelligence differences. There are some similarities between the two constructs. Both abilities improve in childhood and degrade in old age. Moreover, both have been implicated in age effects on intelligence tests. However, we have also pointed to some important differences. We have argued that while drift rates, often taken as markers of processing speed, may offer a mathematical description of the worst performance rule, researchers should not be satisfied with them as a psychological explanation of the effect. A vital next step is exploring the cognitive basis of individual differences in drift rates and linking these cognitive processes to intelligence. Executive attention, particularly the ability to maintain task focus and flexibly generate novel stimulus–response sets, is a logical starting point (Löffler et al., 2022; Oberauer et al., 2007; Weigard et al., 2021).

We have also contested a general speed advantage as the primary basis for individual differences in intelligence. We have done so on two fronts. First, ability differences are most pronounced on tasks that demand executive attention; even in speeded tasks not normally conceived of as having strong attention demands, cognitive ability differences are most localized to neurophysiological signatures of cognitive control (Schubert et al., 2017, 2021; see Wu et al., 2018). Second, attempts to manipulate speed or attention suggest a one-way relationship, such that manipulating attention demands affects performance on speed tasks and their relationship with intelligence test scores. Conversely, manipulating speed has little effect on intelligence test performance or on constructs thought to be related to executive attention (i.e., working memory). Rather than speed being the basis of individual differences in intelligence, we argue that executive attention may be a fundamental mechanism for understanding processing speed, intelligence, and their association.

Executive Attention and the Meaning of the *g*-Factor

We have delineated major historical developments in the study of processing speed and executive attention as they pertain to intelligence and compared executive attention and processing speed explanations of general intelligence and related phenomena. We have argued that executive attention is a more fundamental process to the understanding of intelligence and that the speed of executive attention-related processes may help to explain the processing speed–intelligence association. In doing so, we have frequently invoked the idea of the positive manifold and the resultant general factor of intelligence. Our use of these terms as explanandum belies considerable disagreement about the nature and meaning of the general factor of intelligence, which we can group into at least three viable approaches.[9]

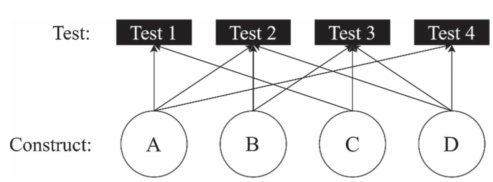
The first approach regards the general factor as indicating a general-purpose latent psychological trait or process (e.g., Jensen, 1998; Spearman, 1904). Attempts to identify specific neurocognitive traits/processes, such as processing speed or executive functioning with general intelligence often fall into this camp. Henceforth, we refer to this as the single-cause view.

A second approach, classically exemplified by Thomson's (1916) sampling theory, argues that the g-factor is a statistical phenomenon stemming from a failure to isolate discrete psychological mechanisms. Sampling theory supposes that every test reflects some subset of latent processes, and its major insight is that no process need to be shared across all tests for the positive manifold to emerge. To illustrate, Figure 12 depicts four psychological tests, which reflect four latent constructs. Each test measures some of the same constructs as other tests, so each test will be positively correlated with the others. This uniform pattern of positive correlation is computationally consistent with a general factor, yet no task-general latent variable exists, since no construct is reflected across all tests. Theoretically, with sufficiently precise measurement of each individual latent construct, one could eliminate the positive manifold entirely, explaining *away* the general factor.

A third perspective on the meaning of the general factor, mutualism, contends that the positive manifold emerges from a developmental interdependence of cognitive processes over the course of early life (van der Maas et al., 2006). Suppose that, at birth, all the different cognitive functions a child can display are statistically unrelated to one another. Despite being initially uncorrelated, multiple cognitive processes are engaged in nearly any situation a child may find themself. This creates a functional interdependence, where growth in one cognitive capacity enables growth in other capacities. In turn, growth in these other cognitive capacities enables growth in the first in a positive, mutually beneficial feedback loop. This continues until asymptotic cognitive capacities are reached. For example, a child's ability to recognize written words will depend on their knowledge of words in a language. As their vocabulary grows, their word recognition will also improve. Their improved word recognition will, in turn, help grow their vocabulary, and so on. In this way, capacities that did not initially correlate come to be correlated over the course of development (van der Maas et al., 2006).

Much of our review has focused on comparing executive attention and processing speed as latent variables undergirding performance across many different cognitive tests, that is, as the basis of the positive manifold, general intelligence, and the g-factor. As such, our article has, to this point, been reminiscent of the single-cause approach, and we might be expected to conclude that executive

Figure 12
An Illustration of Sampling Theory



attention is equivalent to g (Burgoyne et al., 2022). However, the three perspectives on the positive manifold outlined above are difficult, if not impossible, to statistically distinguish. As such, it is important to consider whether our argument that the speed of attention-related processes causes the positive manifold hinges on how general intelligence is conceptually defined.

We argue that our conclusions about the importance of executive attention to understanding the positive manifold are not specific to any one approach. Beginning with sampling theory, we need not assume that executive attention is sampled across all tests for it to deserve special emphasis as a cause of the positive manifold. Rather, we merely need to assume that processes related to executive attention are overrepresented relative to other cognitive mechanisms across the range of cognitive tests. This view mirrors process overlap theory very closely (Kovacs & Conway, 2016, 2019).

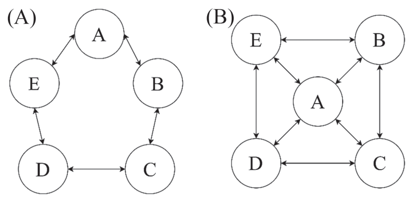
A similar argument can be made for mutualism. Like sampling theory, mutualism does not assume that the positive manifold results from the common influence of a causal latent variable.[10] Rather, the positive manifold is a result of reciprocal relationships between the growth of various cognitive capacities. However, van der Maas et al. (2006) noted that some psychological tests have higher g-loadings (i.e., share more of their variance with the general factor of intelligence) than others. Mutualism can account for this by allowing for some constructs to be more densely interconnected than others; if growth in a construct has an especially broad effect on other constructs, or if a construct benefits from growth in many other constructs, then that construct will load more highly on the general factor of intelligence. For example, in Figure 13, one would expect measures of each construct in Panel A to correlate and to load uniformly onto a general factor. By contrast, in Panel B of Figure 13, we would expect measures of all constructs to form a general factor, but measures of Construct A should load most highly onto that factor. By implication, we predict that executive attention occupies a position in the web of cognitive processes akin to that of Construct A in Panel B. Indeed, executive attention has been argued to have such diffuse effects (see, e.g., Burgoyne & Engle, 2020; Gazzaley & Nobre, 2012).

Executive attention may thus cause the positive manifold no matter which view we take of the general factor. While we have found it convenient to discuss executive attention as a latent variable in accordance with the single-cause framing, our aim in this article was not to advocate for any one perspective on g. In fact, we find the single-cause view improbable. The executive attention literature suggests that the construct can likely be broken into capacity and

[9] A fourth possibility is that the general factor should not be considered as something that needs explaining but rather something that is best thought of as an explanation; it may be that the g-factor causes individual differences in a host of abilities, including working memory capacity, processing speed, executive attention, and so forth. We find this position unappealing for understanding intelligence because it insists on not saying anything specific about how or why the positive manifold emerges. This position also fails to convincingly distinguish itself from the single-cause view that the positive manifold emerges because of a common latent variable. It is a poor imitation, however, because it dismisses investigating the nature of that latent variable. Rather than evaluating candidate traits or processes that could be identified with the g-factor, this approach maintains that intelligence is intelligence, and no further thought need be given to the matter. As such, we do not mention it further.

[10] Accordingly, both sampling theory and mutualism take a formative rather than a reflective view of g (see Borsboom et al., 2004).

Figure 13
Two Versions of a Mutualistic Relationship Among Psychological Constructs



Note. In Panel A, there is no "central" construct, so all measures should relate uniformly to a general factor. In Panel B, Construct A is more densely interconnected so should have higher factor loadings onto a general factor.

control aspects (Hakim et al., 2020; Schor et al., 2020) and some have suggested differentiating attentional consistency and intensity (Unsworth & Miller, 2021). It is conceivable that different tasks may place a larger emphasis on one facet than the other, perhaps consistent with sampling theory. Moreover, and consistent with mutualism, executive attention almost certainly has reciprocal relations with other cognitive processes, including memory (see Gazzaley & Nobre, 2012; Hubbard et al., 2017). Accordingly, we prefer to treat general intelligence as a global summary statistic for the efficacy of cognition, where executive attention has an outsized effect on the quality of cognitive performance rather than as a single, undifferentiated trait.

This claim has implications for how we might situate executive attention within the HCHC taxonomy of cognitive abilities (refer to Figure 1). If our characterization is accurate, we would not represent executive attention as one among several broad cognitive abilities. Instead, executive attention ought to be distributed among the model's broad cognitive abilities. Furthermore, the broad cognitive abilities that most strongly rely on executive attention ought to relate most strongly to the general factor. This might explain why some studies report that fluid intelligence, an ability closely linked to executive attention, is sometimes found to be indistinguishable from the general factor (Gustafsson, 1984; see also Kovacs & Conway, 2019).

Conclusions and Future Directions

We have delineated major historical developments in the study of information processing speed and executive attention as they pertain to intelligence. We have also attempted to directly compare executive attention and speed explanations for individual differences in intelligence. We conclude that processing speed and executive attention are similar notions, under some definitions. Higher ability individuals possess speed advantages in particular cognitive processes, especially those related to executive attention, a reasonable view irrespective on how the general factor is conceptualized.

There are several advantages to this view. First, viewing individual differences in processing speed through the lens of executive attention suggests specific neurocognitive mechanisms for researchers to investigate. This adds nuance and depth to the study of processing speed. Even if it proves incorrect, our linking of executive attention and processing speed discourages unwarranted assumptions about the nature of speed advantages, stressing that psychologists should refrain from conflating dependent measures (e.g., fast reaction times, high drift rates) with the mechanisms that give rise to them. By analogy, a central processing unit with a faster clock rate will, all else being equal, outperform one with a slower clock rate. However, while a useful specification to know, a computer's clock rate reveals little about how the central processing unit works nor about its precise role in the operations of a computer. If we would be dissatisfied with regarding clock rate as the *cause* of performance differences in computers, it surely makes sense to ask more of processing speed explanations of intelligence as well.

A second advantage is that our view suggests guardrails for theorizing about executive attention. For instance, as we have stressed, part of the guiding logic behind the use of conflict tasks in differential cognitive psychology is that attention control is thought to be selectively engaged in conflict situations (cf. Weigard et al., 2021). The fact that neurophysiological markers of cognitive control are present in hallmark processing speed tasks devoid of overt conflict and that these markers relate strongly to individual differences in intelligence suggests that the conflict assumption is unjustified and should be abandoned (Schubert et al., 2017). Rather, executive attention may be more strongly engaged by situations with more uncertainty about upcoming stimuli and/or responses (e.g., Schneider & Shiffrin, 1977; Wu et al., 2018). If true, this view of executive attention further stresses the theoretical closeness between executive attention and speed of information processing, making an explicit conceptual link between executive attention and classic information processing notions such as bit values.

Pursuing such claims has the potential to unite adversarial hypotheses into a coherent and productive program of research. For this to come to fruition, increased conceptual and methodological clarity are necessary. Researchers working in this area should be specific and explicit in their hypotheses, interpretations of results, and conjectures, especially where processing speed is concerned. Rather than relying on vague terminology or decontextualized mathematical parameters, researchers should interrogate their own usage of "processing speed" and related terms. Why is speeded processing in a measure beneficial for performing that measure? Furthermore, what neurocognitive operations are reflected by individual differences in the speed metric(s) under consideration? Answering such questions is a basic but critical first step in achieving greater conceptual clarity so that individual differences in processing speed can be understood more richly. This step alone could prove tremendously generative for future work. Clarifying what different researchers mean to convey about individual differences in "processing speed" would reveal differences between similar-sounding positions that could then be investigated.

Relatedly, researchers should be mindful of how their preferred explanations of intelligence and the positive manifold might be translated into competing explanations. For example, drift rates from sequential sampling models may reflect basic, fundamental differences in processing speed. An alternative view might be that drift rates reflect an individual's ability to consistently select and prioritize information that leads to a correct response. Weigard et al. (2021), for instance, suggest "that [the] measurement of cognitive efficiency through drift rates is not an alternative to measurement of top-down control. Instead, the drift rate might reliably measure both constructs, which may be closely related or identical." Of course, this interpretation of drift rates (or whatever metric one would like to adopt) is itself a claim warranting empirical scrutiny. To assess it, one could ask whether manipulating executive attention demands in simple tasks selectively affects drift rate estimates, both in terms of their point estimates and in their correlations with intelligence. This kind of work is important because it would build connections between mathematical models and the constructs routinely discussed in mainstream cognitive psychology (e.g., in a drift-diffusion model, where might we observe executive attention?). Extending such manipulations beyond the study of overt conflict to less explored areas such as learning (cf. Crawford et al., 2020) or sensory discrimination (Jastrzębski et al., 2021; Tsukahara et al., 2020) would be especially valuable.

Longitudinal studies of speed and executive attention that incorporate these recommendations would also be informative on several fronts. Jointly measuring speed, executive attention, and intelligence in a developing sample could help arbitrate whether one factor or the other is a more primal cause of intellectual development. This would also help determine whether individual and developmental differences in speed and/or executive attention share a common basis (cf. McCabe et al., 2010). Finally, such longitudinal studies could help arbitrate between perspectives on the *g*-factor. We have argued that executive attention is a cause of the positive manifold. If executive attention's importance emerges according to the principles of mutualism, then measures of executive attention should relate more strongly to other measures as children develop. They should also occupy a more central position in the nomological network of cognitive tests as children mature. One way to assess this hypothesis might be to examine centrality statistics from network analyses of longitudinally administered task batteries. If measures of executive attention become more central as children develop, this would provide confirmatory evidence both for our main hypothesis and for a mutualistic view of *g*.

Limitations of the Present Review

The expansive nature of this review comes with several limitations. There were many relevant contributions which, while warranting mention, were not included in detail (e.g., Broadbent, 1957; Carroll, 1980; Case, 1985; Cowan, 1988; Jensen, 1998, 2006; Kahneman, 1973; Neely, 1977; Posner & Snyder, 2004). Our goal was not to overlook or minimize these works and their relevance to the topics reviewed, but only to be brief relative to the totality of what could be written. Similarly, we privilege a sparse number of possible relationships between the constructs we discussed in that we assume some degree of causality between them. In doing so, we ignore other possibilities, including the possibility that speed, executive attention, and intelligence are common consequences of underlying genetics or other low-level biological properties and do not cause each other (cf. Geary, 2018; Luciano et al., 2005). We are also limited in that much of the work reviewed samples within a very narrow demographic pool, occurring in predominately Western, educated, and industrialized contexts. All psychological scientists hope that our conclusions extend to the generalized human population, but this cannot be assumed, and more diverse, globally representative samples are clearly needed (Apicella et al., 2020). Despite these limitations, our hope is that this review provides some historical orientation to a highly contentious research issue, alerts researchers to overlap between their own theoretical orientation and ones they may find objectionable, and paves the way forward for productive dialogue about the sources of individual differences in human cognitive abilities.

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