PSYCHOLOGICAL INQUIRY
2016, VOL. 27, NO. 3, 151–177
http://dx.doi.org/10.1080/1047840X.2016.1153946

Routledge
Taylor & Francis Group

TARGET ARTICLE

Process Overlap Theory: A Unified Account of the General Factor of Intelligence

Kristof Kovacs[a,b] and Andrew R. A. Conway[c]

[a]Center for Research and Development, Eszterházy Károly University, Eger, Hungary; [b]Department of Psychological Methods, University of Amsterdam, Amsterdam, The Netherlands; [c]Division of Behavioral and Organizational Sciences, Claremont Graduate University, Claremont, California

ABSTRACT
The most replicated result in the field of intelligence is the positive manifold, which refers to an all-positive pattern of correlations among diverse cognitive tests. The positive manifold is typically described by a general factor, or *g*. In turn, *g* is often identified as general intelligence, yet this explanation is contradicted by a number of results. Here we offer a new account of *g*: process overlap theory. According to the theory, cognitive tests tap domain-general executive processes, identified primarily in research on working memory, as well as more domain-specific processes. Executive processes are tapped in an overlapping manner across cognitive tests such that they are required more often than domain-specific ones. The theory provides an account of a number of findings on human intelligence. As well, it is formalized as a multidimensional item response model and as a structural model, and the neural mechanisms underlying the proposed overlapping processes are discussed.

KEYWORDS
Cognitive abilities; differentiation; factor analysis; goal neglect; individual differences; intelligence; prefrontal cortex; working memory; worst performance rule

g: A Well-Aged Puzzle

Why do people differ in their cognitive abilities? Is there a general intelligence that permeates all human intellectual activity? Or is it more reasonable to postulate specific kinds of talent? After more than a century of research, these questions are still unresolved, and the nature and origin of individual differences in mental abilities remain open to debate.

The most compelling result in this field of study is that people who perform above average on one kind of cognitive test (e.g., vocabulary) tend to perform above average on other kinds of cognitive tests as well (e.g., mental rotation). This pattern of positive correlations was first observed more than a century ago (Spearman, 1904) and is often referred to as the *positive manifold*. Indeed, because mental testing of large samples became common practice, for example, in military and academic contexts, literally hundreds of studies have revealed the positive manifold (Carroll, 1993), making it perhaps the most replicated result in all of psychology.

With the development of factor analysis, a statistical technique that aims to reduce the number of dimensions in large correlation matrices, the empirical observation of the positive correlations among diverse cognitive tests was accounted for by a general factor of intelligence, or *g*. Factor analysis is considered a data-reduction technique because a relatively small number of factors, or latent variables, identify common sources of variance across tests, which are referred to as manifest variables. In other words, the correlation between two manifest variables can be explained by their connection to a common latent variable. For example, a vocabulary test and a mental rotation test are correlated because they both correlate with the same latent variable "X."

The first factorial model of intelligence (Spearman, 1904) proposed that a single latent variable, *g*, accounts for all of the positive correlations between measures of mental ability (see Figure 1). The variance in a test not attributable to *g* was therefore explained by a test specific factor, *s*.[1] According to this initial theory, the specific factors were orthogonal, each a reflection of unique test content and, necessarily, measurement error. Spearman's idea of a latent causal variable, *g*, as the underlying reason for the correlations among different cognitive tasks, developed contemporaneously with factor analysis itself.

A general factor is indeed reliably obtained when mental test data are submitted to exploratory factor analysis. Yet the test variance that the general factor could not account for turned out not to be entirely test specific, and some groups of tests, for example, vocabulary and reading comprehension, correlate more strongly with one another than with other groups of tests, for example, mental rotation and spatial navigation. Hence Spearman's view of intelligence was quickly met with criticism and alternative accounts were proposed; the strongest competing model consisted of multiple uncorrelated group factors, representing a set of "Primary Mental Abilities" (Thurstone, 1938; see Figure 2). However, Thurstone's original model was challenged in a similar fashion as he challenged Spearman; the idea of orthogonal factors turned out to be untenable, and their correlations needed to be accounted for by a higher order general factor.

CONTACT Kristof Kovacs kristof340@gmail.com 1 Eszterházy ter, H3300, Eger, Hungary.

Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/hpli.

[1]In Figures 1 to 5 we use the contemporary notation of unique variance (delta) instead of *s*.

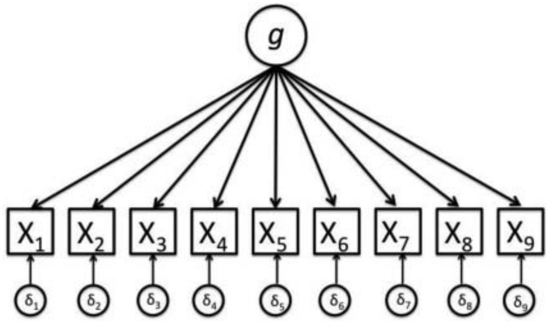

Figure 1. A model depicting Spearman's original conception of a single general factor.

The decades that followed the work of Spearman and Thurstone witnessed numerous studies of individual differences in cognitive ability as well as the development of confirmatory factor analysis (CFA). Contrary to exploratory factor analysis, CFA is a statistical procedure that enables hypothesis testing; one can specify a model of cognitive abilities and test whether observed data corroborate what one would expect based on predictions of the model. These further studies with more advanced methods gravitate toward latent variable models of intelligence that incorporate both a general factor and more specific group factors.

This has been accomplished in two ways: bifactor models and hierarchical models (see Figures 3 and 4). In bifactor models, tests correlate directly with *g* as well as with specific factors, whereas in hierarchical models no test loads directly on *g*. Instead, in hierarchical models domain-general variance is manifested in the correlations between group factors and is ultimately accounted for by the general factor, *g*, at the top level. Thus, contrary to Spearman's original conception "hierarchical *g*" explains correlations among abilities rather than correlations among tests. It arguably does a good job indeed; *g* usually accounts for about 40% (Deary, Penke, & Johnson, 2010) or 50% (Jensen, 1998) of the total variance measured in diverse sets of mental tests administered to sufficiently large samples.

Of course, instead of having uncorrelated first- or second-order factors and a general factor on top of the hierarchy, one could always have correlated first- or second-order factors in the model and no *g* (see Figure 5). Because the higher-order factor model is a nested/constrained version of the oblique first-order factor model, the latter is also usually applicable to describe the positive manifold. But the superficial impression is that the non-*g* model leaves the correlations unexplained, whereas *g*-models do explain them. Or do they?

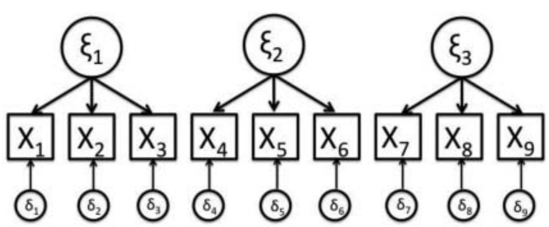

Figure 2. A model depicting Thurstone's original (but later revised) conception of orthogonal group factors.

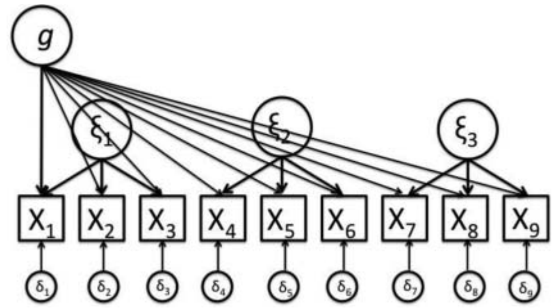

Figure 3. A bifactor model of cognitive abilities.

The problem with *g* is simply that still to this day there is no satisfactory consensus about how to interpret it: If there is a casual factor behind *g*, it has not been identified yet. Moreover, it is not only the case that there is controversy about what *g* is; there is substantial confusion about what kind of thing *g*, or indeed what any latent variable, is in the first place (Borsboom, Mellenbergh, & van Heerden, 2003; Conway & Kovacs, 2013).

Here we propose a novel solution to this well-aged puzzle, which we refer to as process overlap theory. The primary aim of process overlap theory is to explain the positive manifold, yet the theory also provides a comprehensive account of established findings on individual differences in intelligence. It is important that process overlap theory explains interindividual differences in behavior in terms of intraindividual psychological processes and neural mechanisms. There have been other approaches, discussed later on, that question the latent cause interpretation of the positive manifold and have offered alternatives. However, in our view, process overlap theory is unique in the sense that it integrates psychometrics, cognitive psychology, and neuroscience.

Such an ambitious integrative approach requires a solid theoretical foundation, which we describe in detail next. To preview, here we consider three axioms, or fundamental premises of the theory:

1. *g* is a necessary consequence of the positive manifold; whenever there are only positive entries in a correlation matrix, it is always possible to extract a single general factor via factor analysis, and this factor will correlate positively with all of the manifest variables or, in the case of hierarchical models, with all of the first- or second-order factors. Of importance, this is not an empirical finding but a mathematical necessity, of which there

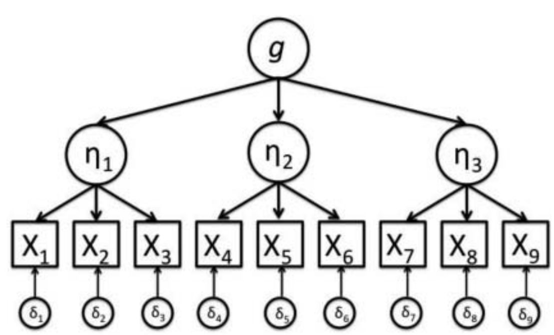

Figure 4. A hierarchical model of cognitive abilities.

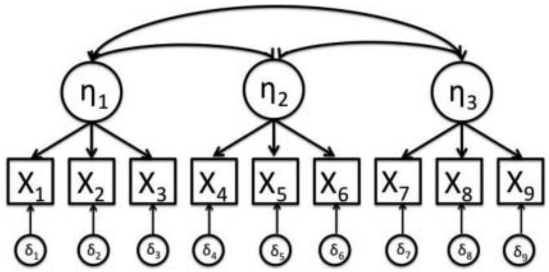

Figure 5. An oblique model of cognitive abilities.

exists adequate algebraic proof (Krijnen, 2004). That is, in a technical sense, *g* is no more, no less, than a reflection of the positive manifold. Hence, "it is always important to remember that it is the positive manifold, not *g* as such, that needs explanation" (Mackintosh, 2011b, p. 165).

2. An ontological stance of entity realism is required if one is to seriously evaluate the theoretical status of latent variables[2] (Borsboom et al., 2003). Theorizing about a latent variable must transcend the world of mathematical abstractions and pinpoint a real entity, which plays a causal role in the correlations among manifest variable—regardless of whether this entity is a process, a set of processes, or some common property/characteristic of processes.
3. Latent variables are *differential* constructs that do not directly translate to within-individual processes or mechanisms (P. C. M. Molenaar & Campbell, 2009; Voelkle, Brose, Schmiedek, & Lindenberger, 2014). Also, latent variables exist because of individual differences, and without variation in mental abilities there would be no latent variables—the last survivor of a meteor collision with Earth would still have cognitive abilities and mental limitations but would not have *g*. Naturally, this stems from the fact that the positive manifold, being a correlation matrix with only positive entries, is itself a between-individual phenomenon. Hence the scope of any explanation of the positive manifold, including but not restricted to latent variables, is not necessarily directly applicable to single individuals.

The structure of the article is as follows. First we discuss the relation between within-individual processes and sources of between-individual variance and provide a critique of the interpretation of *g* as a within-individual construct. A few important characteristics of the general factor that any theory of the positive manifold should probably take into account are surveyed next. The following two sections discuss working memory, first as a within-individual construct and then as a latent variable that is strongly related to variation in fluid reasoning. The reason for discussing working memory is detail is that there is a positive manifold and a general factor obtained in such tasks as well; not only is it strongly related to the positive manifold in intelligence but it is quite likely that there is a similar explanation of these two positive manifolds.

This is followed by a discussion of goal neglect and prefrontal function, and how they are related to both working memory and fluid reasoning, highlighting the importance of cognitive processes in fluid intelligence that we believe to be crucial in causing the positive manifold. Having surveyed a large bulk of empirical evidence that function as the grounds of our theoretical framework, we turn to outlining process overlap theory as both a cognitive and a structural model of human intelligence, accompanied by a mathematical (psychometric) model. The next section covers studies that employed a network approach to brain functioning; such studies highlight a functional overlap of neural circuitry that corresponds to the overlap of psychological processes hypothesized by our theory. This is followed by a comparison of our theory with previous attempts to explain the positive manifold without a single underlying causal dimension, and we close the article with a few concluding remarks.

The *g* Within?

A parsimonious interpretation of the general factor, based solely on the statistical evidence, is that it represents a single, general ability ("general intelligence" or "general cognitive ability") that manifests itself in all kinds of different tests. However, this is not the only possible explanation of the positive manifold. Thomson (1916) demonstrated that a general factor could appear as the result of a large number of independent, uncorrelated psychological processes, "sampled" by a battery of tests. Thomson's "sampling theory" proposed that every mental test randomly taps a number of "bonds" from a shared pool of neural resources, and the correlation between any two tests is the direct function of the extent of overlap between the bonds, or processes, sampled by different tests.

Because its original formation, there have been statistical elaborations and extensions of the sampling model (Bartholomew, Allerhand, & Deary, 2013; Bartholomew, Deary, & Lawn, 2009; Maxwell, 1972; McFarland, 2012) as well as substantial ones, claiming that the overlap takes place at the genetic (Anderson, 2001) or neural (Hampshire, Highfield, Parkin, & Owen, 2012; Rabaglia, Marcus, & Lane, 2011) level. A developmental account based on mutually beneficial interactions has been proposed that also provides a mathematical explanation of the positive manifold without assuming the causal action of a single general factor (van der Maas et al., 2006). Crucially, with regard to the distinction between sampling models and *g*-models, it has been mathematically demonstrated that "there is no statistical means of distinguishing between the two" (Bartholomew et al., 2009; see also Maxwell, 1972). The conclusion from these studies is that general intelligence, a single common cause of the positive correlations between mental tests, is surely a sufficient, but definitely not a necessary explanation of the positive manifold.

A crucial thing to notice is that the concept of general intelligence interprets *g* as a within-individual mental ability, the involvement of which, in all kinds of cognitive activity, is *causally* responsible for the positive manifold. Therefore, if the concept of general intelligence is correct, then the following

[2]More precisely: to evaluate the theoretical status of *reflective* latent variables, see "Process Overlap Theory."

statement is valid: “John used his general intelligence to correctly answer items on both the vocabulary test and the mental rotation test.” This, however, is substantially different from the statement: “If John performs better on the vocabulary test than most people, it is likely that he will perform better on the mental rotation test as well,” because the latter statement leaves the possibility open that John in fact did not use the same general cognitive ability to solve items in the vocabulary test and the mental rotation test, respectively. Nevertheless, the statistical evidence based on between-subject data validates only the second statement, not the first. To validate the first statement, one has to review other kinds of evidence, and the result is far from convincing.

First, there is a substantial amount of neuropsychological evidence contradicting the idea that people use the same general cognitive ability to perform tests with different content. Damage to different areas of the brain results in the double dissociation of various cognitive abilities. In particular, spatial and verbal abilities can be dissociated this way, as well as fluid reasoning from crystallized abilities (Duncan, Burgess, & Emslie, 1995). Similarly, specific developmental disorders result in impaired spatial abilities, whereas certain verbal skills remain intact, or vice versa (e.g., Vicari, Bellucci, & Carlesimo, 2007; Wang & Bellugi, 1994). This provides strong evidence against the explanation of the positive manifold by a general cognitive ability operating within individuals. For if John excels in both vocabulary and mental rotation because he uses the same single general ability for both, it would not be possible for his performance to deteriorate on only one of these tests following damage to specific areas of his brain. Similarly, there is ample evidence for the dissociation of verbal and spatial tests as a result of various experimental manipulations; such results are also incompatible with the notion that both tap a single general ability (Jonides et al., 1996).

Sex differences can also be a means toward fractionating human intelligence (Mackintosh, 2008); a large number of studies indicate that on average, male and female individuals have somewhat different cognitive profiles, with female participants outperforming male participants in most verbal tests, as well as tests measuring perceptual speed, whereas male participants excel in three-dimensional spatial skills.

Finally, the Flynn-effect, which refers to the secular increase in IQ across generations, also contradicts the within-individual notion of general intelligence. In tests requiring fluid inductive reasoning (see “Understanding *g*: Characteristic Features,” particularly “Figure 1: *g* and Gf Are Very Strongly Correlated”), such as Raven’s Progressive Matrices, the gains per generation have been as high as 15 IQ points, whereas in tests measuring crystallized abilities, such as vocabulary and mental arithmetic, the gains have been negligible; 2–3 IQ points over half a century (Flynn, 2007).

To be fair, *g*-theories of intelligence could account for all these phenomena by assuming that all fractionation and dissociation occurs only in lower order specific abilities. Because sex differences appear in specific abilities, that argument does indeed seem valid. Similarly, claims have been made that the Flynn-effect is independent of *g* (e.g., Rushton, 1999), even though this conclusion is controversial (see Flynn, 1998). However, the neuropsychological evidence is harder to dismiss; it appears as if there is simply no place in the brain for general intelligence (see “Overlapping Networks in the Brain” for details). Also, taken together, these converging lines of evidence point to the elusive nature of general intelligence. With all different lines of fractionating evidence taken into account, there is hardly any space left for a general cognitive ability that permeates all human cognition.

It is also important to point out that not all *g*-theorists equate the general factor with a general ability. Actually, one of the leading *g*-theorists, Arthur Jensen, opposed such an interpretation: “It is important to understand that *g* is not a mental or cognitive process or one of the operating principles of the mind, such as perception, learning, or memory” (Jensen, 1998, p. 94–95.). More generally, our emphasis on *g* being a differential construct is in perfect agreement with his theorizing about the general factor: “A simple distinction between process and factor is that a process could be discovered by observing one person, whereas a factor could be discovered only by observing a number of persons” (Jensen, 1998, p. 95; see also Jensen, 2000).

So how does Jensen, and other *g*-theorists, interpret *g* other than a general cognitive ability? They hypothesize that it is a common parameter that influences all of the specific abilities or modules. For instance, Jensen proposed that *g* reflects individual differences in the speed of mental operations, whereas Eysenck emphasized the role of the efficiency of neural transmission (e.g., Eysenck, 1998). There is indeed valuable contemporary research exploring the link between such phenomena and the general factor; for instance, white matter tract integrity appears to be a promising candidate for such a parameter (Penke et al., 2012). However, even this explains only 10% of the variance in the general factor. Speed and efficiency, even though they surely have explanatory power, only explain a portion of the across-domain variance in mental tests.

Moreover, there are other problems with the theory of mental speed: Among others, attention seems to be responsible for much of the speed–IQ relationship (e.g., Conway, Kane, & Engle, 1999), and it is also most pronounced on psychometric tests of perceptual speed (e.g., Mackintosh & Bennett, 2002). It is not the aim of this article to do justice on the mental speed hypothesis of *g*, so we stop here by saying that this line of explanation has not been sufficient, and we kindly refer the interested reader to Chapter 3 of Mackintosh’s (2011b) textbook for an extansive elaboration on why not

Not a within-individual general cognitive ability, and probably much more than mental speed, the general factor of intelligence remains an unsolved puzzle, and so does the positive manifold. Although several candidates have been offered, there is still no consensual explanation of why there are substantial correlations between cognitive tests that appear to measure very different things.

From a cognitive perspective, the puzzle itself can be summarized as follows: *Why does the variation between people in test performance appear massively domain-general if the abilities they employ to solve such tests are largely domain-specific*? To answer this question, we provide a cognitive account of item response processes and a corresponding structural model, which are compatible with current research in cognitive psychology and neuroscience as well as with a century of research on the structure of individual differences in intelligence.

Understanding *g*: Characteristic Features

The positive manifold and, consequently, the general factor of intelligence have a number of important characteristics, which process overlap theory attempts to explain. We list four such features of *g*:

Feature 1: g *and Gf Are Very Strongly Correlated*

The first feature to consider is *g*'s relationship with various group factors, or specific abilities. To fully understand this feature, a brief review of the fluid/crystallized (Gf/Gc) model of intelligence (Cattell, 1971; Horn, 1994) is warranted.[3] The main idea of the model is the distinction between the ability to solve problems in novel situations, regardless of previously acquired knowledge (fluid intelligence or Gf), and the ability to solve problems using already acquired skills or knowledge (crystallized intelligence or Gc). The model includes other group factors as well, the most important of which are Gv (visual-spatial), Gs (speed), and Gr (retrieval from memory). A more recent development is the Cattell–Horn–Carroll (CHC) model (McGrew, 2009), which merges the fluid/crystallized model with Carroll's three-stratum hierarchical model with one crucial difference: the original conception of Gf/Gc did not allow a general factor, whereas CHC does.

A particular appeal of the Gf/Gc model is that the group factors are relatively easy to interpret as within-individual abilities, which can account for correlations at lower levels of the hierarchy, that is, in primary abilities or the mental test scores themselves. Gf is interpreted as fluid reasoning, a thoroughly studied cognitive ability, the neural correlates of which are also identified. Gc, on the other hand, mostly translates to acquired knowledge and/or the amount of formal schooling one has been exposed to (Kan, Kievit, Dolan, & van der Maas, 2011).

Demonstrated first by Gustafsson (1984), and by numerous studies since, the higher order general factor, *g*, is statistically identical to the lower order fluid reasoning factor, Gf, that is, *g* and Gf correlate perfectly. Matzke, Dolan, and Molenaar (2010) reviewed 14 such studies, and even though they emphasized that most of them were underpowered and thus could not have refuted the *g*-Gf identity, the single study with necessary power, as well as two only slightly underpowered studies, equivocally found that the general factor is identical to the fluid reasoning factor. Moreover, in the remainder of the studies, the correlations between *g* and Gf were between $r = .93$ and $r = .99$ and the fluid reasoning factor had the strongest correlation with *g*, much higher than any other group factor in the CHC model. As well, a perfect correlation between Gf and the lower order factor "inductive reasoning," measured typically by matrix reasoning items and number series was found (Kan et al., 2011), which means that the correlation between *g* and inductive reasoning is perfect or almost perfect as well.

Feature 2: Factor Differentiation

A second important feature of the positive manifold is factor differentiation. Originally discovered by Spearman (1927) who called it the "Law of Diminishing Returns," factor differentiation means that *g* explains more variance at lower levels of mental ability than at higher levels of ability (e.g., Detterman & Daniel, 1989; Kane, Oakland, & Brand, 2006; Molenaar, Dolan, Wicherts, & van der Maas, 2010). Because *g* reflects the strength of the positive manifold, this result means that there are higher cross-domain correlations in samples with lower average ability.

The same phenomenon exists across populations as well; it was recently found that the higher a nation scores on international standardized tests, the less the general factor explains the variance of test scores in that nation (Coyle & Rindermann, 2013). The Flynn-effect is also related to the phenomenon of factor differentiation; the secular gains in IQ are accompanied by a decrease in the average correlation between scores on different intelligence tests and thus a decrease in the variance explained by *g* (Juan-Espinosa, Cuevas, Escorial, & García, 2006; Kane, 2000; Kane & Oakland, 2000; Lynn & Cooper, 1993, 1994; Must, Must, & Raudik, 2003). Even though it has been claimed that the *g* of intelligence is similar to the g (the gravitational constant) in physics (Miele, 2002), factor differentiation, both according to ability within a single cohort and between different cohorts with different levels of ability, demonstrates that *g* is far from being a constant. Instead, the average correlation between diverse tests and thus the domain-generality of the positive manifold varies across time and ability level, and *g* is only informative of the extent of domain-general variance in a given population at a given time.

Feature 3: Complex Tests Correlate Strongly With g

A third important feature is that more complex tests load higher on *g* than less complex tests (Jensen, 1981). This implies that *g* is related to the complexity of cognitive activity. An example is backward digit span, a test in which examinees have to recall digits in reversed order, which has a higher *g* loading than forward digit span, in which digits are recalled in the original order of presentation (Jensen, 1981, 1998).

However, "complexity" is not an explanatory construct that can help our understanding of *g*, nor is it consensual, as there is no necessary agreement between experts about how complex a test is and how complexity differs from difficulty (Mackintosh, 1998). Moreover, there are certainly different "complexities." For example, in a simple continuous performance test, reaction

[3] We are aware that there are several important models of intelligence other than the Gf/Gc model (e.g., Johnson & Bouchard, 2005). Yet in practically the entirety of research on working memory and intelligence, as well as on goal neglect and intelligence, Gf-Gc is the model that was applied, and this line of research lays the foundations of our theory. Hence our focus on Gf/Gc is motivated by its proliferation of recent cognitive research on intelligence through providing the comprehensive framework of "fluid reasoning," which is readily interpretable by cognitive psychologists. See, for instance, Blair (2006); Heitz et al. (2006); and Kovacs, Plaisted, and Mackintosh (2006).

time shows a moderate correlation with intelligence but making the continuous performance test more "complex" can enhance the magnitude of the correlation. Three different ways to achieve this enhancement are (a) using the odd-man-out paradigm, in which participants have to select a light that is farther apart from two other lights; (b) showing words instead of lights, and the word that is synonymous to a target word has to be selected; (c) having participants perform a dual task, that is, having them perform a simple reaction time test while information from another test has to be remembered. Although these versions are clearly more complex than the original, they probably invoke rather different cognitive processes.

To explain why "complexity" is related to *g*, we need to better understand the nature of the cognitive processes involved in more "complex" tests. That is, the nature of "complexity" (or complexities) has to be conceptualized, which we attempt in "Process Overlap Theory."

Feature 4: The Worst Performance Rule

The final *g*-related phenomenon we consider here is the "worst performance rule," a phrase coined by Larson and Alderton (1990) to describe the finding that worst performance predicts *g*-loaded measures better than best performance. Larson and Alderton found that the correlation between *g* and the slowest reaction times was almost twice as large as the correlation between *g* and the fastest reaction times in a reaction time task. Also, the same effect was found between reaction time and working memory, and the effect was also of the same magnitude. In practice, the worst performance rule means that the difference between the fastest reaction times between high- and low-ability groups is much smaller than the difference between the slowest reaction times. This is consistent with the finding that the correlation between the variability of reaction time and *g* is as high as the correlation between mean reaction time and *g*; moreover, the mean and variability of reaction time explain independent parts of the *g* variance (Jensen, 1992).

Larson and Alderton argued that the worst performance rule is the result of lapses in attention or working memory in people with low cognitive ability. The phenomenon that the difference between high- and low-ability groups is largest in the slowest reaction times and smallest in the fastest reaction times has been found in a number of other studies, some of which used different reaction time tests (e.g., choice vs. simple reaction time). The results demonstrated that the more complex a reaction time test, the stronger the worst performance rule, that is, the larger the slowest reaction times' correlation with intelligence—whereas the correlations between the fastest reaction times and intelligence remained relatively constant (Jensen, 1982; Kranzler, 1992).

Coyle (2001) studied the worst performance rule in a word recall test and found the same effect; the correlation between intelligence and worst performance was significantly larger than it was with best performance. This suggests that this phenomenon is not restricted to reaction time measures. Of importance, Coyle (2003a) repeated a study with an additional group from the top 1 percentile of the intelligence distribution and found no evidence of the worst performance rule in this high-ability group. Also, Coyle (2003b) reviewed studies of the worst performance rule and concluded that it is the function of the tests' *g* loading: The difference between the correlations with best and worst performance is larger on tests that are more *g* loaded.

Overall, these *g*-related phenomena point to four conclusions:

1. A theory of intelligence must account for the central role of fluid abilities in *g*.
2. Because the strength of *g*, and thus of the positive manifold, is population dependent, a new theory must account for why it is stronger in some populations and weaker in others. In particular, it must account for the increasing explanatory power of the general factor at lower levels of ability.
3. Complex tests reveal strong correlations with *g*. A new theory should, therefore, provide a framework that explains test complexity without falling prey to circular logic.
4. Indices of the worst performance on complex tests reveal strong correlations with *g*. A new theory should, therefore, focus on the limitations of cognitive processes that result in errors in complex cognitive activity.

Working Memory

Working memory is a construct developed by cognitive psychologists to refer to the processes that enable one to hold goal-relevant information in mind, even in the face of concurrent processing and/or distraction. The construct was introduced in a seminal chapter by Baddeley and Hitch (1974). Prior to their work, the dominant theoretical construct used to explain "immediate" memory performance was the short-term store (STS), epitomized by the so-called modal model of memory popular in the late 1960s (Atkinson & Shiffrin, 1968). According to these models, the STS plays a central role in cognitive behavior, essentially serving as a gateway to further information processing.

However, the concept of STS could not account for a number of within-individual phenomena, demonstrated by experimental and neuropsychological studies. Baddeley and Hitch therefore proposed the construct "working memory" that could maintain information in a readily accessible state, consistent with the STS, but could also engage in concurrent processing, as well as maintain access to more information than the limited capacity STS could purportedly maintain. According to this perspective, a small amount of information can be maintained via two domain-specific "slave" storage systems, verbal and spatial, but more information can be processed and accessed via a domain-general central executive (and according to later models, an episodic buffer; see Baddeley, 2000).

Even though the model of working memory was developed to account for intra-individual phenomena, interest soon arose in measuring individual differences in the capacity of this system and, as it happens, such research has greatly furthered our understanding of the limitations of human cognition. It is important to clarify the distinction between working memory and the capacity of working memory. Working memory refers to a complex cognitive system including mechanisms involved in stimulus representation, maintenance, manipulation, and retrieval, whereas the capacity of working memory refers to the maximum amount of information an individual can maintain in their working memory.

One of the first tests of the capacity of working memory was the reading span test (Daneman & Carpenter, 1980). The test requires subjects to read sentences aloud and remember the last word of each sentence for later recall, thus heavily taxing both the storage and the central executive component of working memory, contrary to memory tasks requiring only storage and retrieval. The number of sentences/words per list varies, typically from two to six or seven.

Another early example is the counting span test (Case, Kurland, & Goldberg, 1982), in which subjects are presented with an array of items, such as blue and red circles and squares, and instructed to count a particular class of items, such as blue squares. After counting aloud, subjects are required to remember the total and are then presented with another array. They again count the number of blue squares aloud and remember the total. After a series of arrays, they are required to recall all the totals in correct serial order. Thus, the storage and recall demands are the same as a simple digit span test, but there is the additional requirement of counting the arrays, which demands controlled attention and therefore disrupts active maintenance of the digits.

A large number of such "complex span tests" have now been developed to measure the capacity of working memory (for a review, see Conway et al., 2005). The crucial point here is that the construction of complex span tests is a theory-driven enterprise. Such tests require subjects to engage in some sort of simple processing task between the presentations of to-be-remembered items. After several items have been presented, the subject is prompted to recall all the to-be-remembered items in correct serial order. Such tests are thought to be valid measures of working memory as proposed by Baddeley and Hitch because they require access to information in the face of concurrent processing.

Simple memory span tests (e.g., digit span, word span, letter span), in contrast to complex memory span tests, do not include an interleaved processing task between the presentation of to-be-remembered items. For example, in digit span, one digit is presented at a time, and after a series of digits the subject is asked to recall the digits in correct serial order.

One of the most important findings from studies investigating complex and simple span tests is that, from an individual differences perspective, complex span is less domain specific than simple span (Turner & Engle, 1989). Kane et al. (2004) administered several verbal and several spatial complex span tests, and the range of correlations across domains was as high as the within-domain correlations among simple span tests, and about two thirds of the covariance among complex span tests was across domains. These results suggest that, although simple span tests appear to be more domain specific, the processes that complex span tests tap beyond the pure storage and retrieval of information appear to be largely domain general. Hence. general factor models fit better for working memory tasks than for simple span tasks (see the next section).

Individual difference studies of working memory reveal the same type of positive manifold common in the intelligence literature; as with batteries of intelligence tests, patterns of convergence and divergence are typically observed amidst the positive manifold. For example, complex span tests with verbal content tend to be more strongly correlated with other verbal tests than with tests with spatial content. Yet the positive manifold is still observed. Because the positive manifold in itself is always sufficient to extract a general factor (see "*g*: A Well-Aged Puzzle"), it comes as no surprise that a general factor of working memory could be extracted, which is generally referred to as "working memory capacity" (WMC; Conway, Cowan, Bunting, Therriault, & Minkoff, 2002; Conway, Kane, & Engle, 2003; Engle, Tuholski, Laughlin, & Conway, 1999).

In the working memory literature, there is considerable debate about the domain-generality of variation in WMC or, in other words, whether there is a unitary source of variation or multiple sources. The debate bears a striking resemblance to the debate between Spearman and Thurstone. On one side is the more general/unitary view, which assumes that variation is largely caused by domain-general factors, and on the other side is the specificity view, which assumes that variation is largely caused by more specific factors. In the end, the two sides acknowledge the existence of both domain-general and domain-specific sources of variation but they argue about their relative importance.

There are, however, crucial differences between the possible interpretation of the general factor of WMC and the general factor of intelligence. First, as opposed to tests of intelligence, positive correlations between complex span tests have never been a prerequisite of "validity," hence the positive manifold cannot be attributed to test design.[4] Second, working memory researchers cannot interpret this general factor as a unitary, within-individual, domain-general working memory process and/or mechanism that is employed in every working memory task, similarly to how *g* is often identified with general cognitive ability. Such an interpretation would contradict the very findings that complex span tests were built upon and that define the within-individual construct of working memory as a complex system of domain-general and domain-specific processes. The right question to ask, then, is, *Which component(s) of working memory cause(s) the general variation?*

The answer probably is that WMC reflects individual differences in the executive component of working memory, particularly executive attention and cognitive control (Engle & Kane, 2004; Engle et al., 1999; Kane, Bleckley, Conway, & Engle, 2001; Kane & Engle, 2002). Cognitive control is a construct, synonymous to executive function, used mostly in cognitive neuroscience to refer to the processes, and their neural substrates, that enables top-down, goal-oriented behavior and that describes different functions such as

> sustained activity that is robust to interference; multimodal convergence and integration of behaviorally relevant information; feedback pathways that can exert biasing influences on other structures throughout the brain; and ongoing plasticity that is adaptive to the demands of new tasks. (Miller & Cohen, 2001, p. 182)

This is a natural candidate to explain the cross-domain correlations among complex span tests, as opposed to the within-

[4] This is a typical (albeit incorrect; see Mackintosh, 2011b) line of criticism against the importance of the positive manifold.

domain correlations among simple span tests, because the theory of working memory is in fact an overlap-theory: The processes that bridge verbal and spatial tests are the ones that constitute the executive component.

According to this view, the reason for the domain-generality of WMC, as measured by complex span tests, is that complex span tests "reflect primarily general executive processes and secondarily, domain-specific rehearsal and storage processes," whereas simple span tests "reflect domain-specific storage and rehearsal skills and strategies primarily and executive attention processes only secondarily" (Kane, Conway, Hambrick et al., 2007, p. 24). WMC, then, reflects "the ability to engage controlled attention. That is, they reflect the ability to maintain activation to a representation in the face of interference or distraction. Therefore, working memory capacity is not 'capacity' per se, but rather the ability to control activation" (Conway et al., 1999). That is, individuals with greater WMC have better cognitive control processes, such as goal maintenance, selective attention, and interference resolution (inhibition).

There is a great deal of support for this theory. For example, individuals who perform better on complex span tests also perform better on tests of cognitive control, requiring goal maintenance and the inhibition of irrelevant stimuli (Conway, Cowan, & Bunting, 2001; Conway, Tuholski, Shisler, & Engle, 1999; Kane et al., 2001; Kane & Engle, 2003), and are better at resolving proactive interference from previous trials (Bunting, 2006; Kane & Engle, 2000; Unsworth & Engle, 2007). Similarly, individuals who perform better on complex span tests are also more accurate on lure trials in the n-back test (Burgess, Gray, Conway, & Braver, 2011; Gray, Chabris, & Braver, 2003; Kane, Conway, Miura, & Colflesh, 2007).

Research on WMC thus demonstrates that it is domain-general processes of cognitive control that are responsible for across-domain correlations in complex span tests. These processes can be operationally defined as what complex span tests measure beyond the storage and retrieval of information, or more precisely, for instance, in the case of the reading span test, the processes that *we do not engage* when we remember a simple list of words but we *do engage* when we remember a list of words presented as the last word of sentences we read aloud.

So the available evidence points to the role of the central executive component in the positive manifold of WMC. But how should one conceptualize this component? In the original working memory construct,

> the central executive was initially conceived in the vaguest possible terms as a limited capacity pool of general processing resources. … Implicitly, the central executive functioned as a homunculus, a little man who took the important decisions as to how the two slave systems should be used. (Baddeley, 2002, p. 89)

Thus, further research was required to investigate whether the executive component of working memory is "a single coordinated system that serves multiple functions, a true executive, or a cluster of largely autonomous control processes—an executive committee" (Baddeley, 1996, p. 26).

Further research indeed found that this "homunculus" can be fractionated to subcomponents and should not be conceptualized as a single, unitary executive. Many different tests purport to measure executive functioning directly, including random number generation, Stroop, Tower of Hanoi/London, Stop-signal, Wisconsin Card Sorting Test, and several others. The n-back test, and especially lure trial performance, is also thought to tap executive processes involved in updating and to reflect interference resolution. Research on these tests also indicates a multiplicity of executive processes rather than a unitary central executive. For instance, relatively low correlations have been found between (a) n-back lure trial performance and complex span (Kane, Conway, Miura et al., 2007); (b) complex span, Tower of Hanoi, and Wisconsin Card Sorting (Lehto, 1996); and (c) Tower of Hanoi and random number generation (Miyake, Friedman, Rettinger, Shah, & Hegarty, 2001). Neuroimaging and neuropsychological studies also support the fractionation of executive processes (Dreher & Berman, 2002; Kievit et al., 2014; Parkin, 1998; Robbins, 1996).

A latent variable study of executive functions (Miyake et al., 2000) identified three correlated processes: "(a) shifting between tests or mental sets, (b) updating and monitoring of working memory representations, and (c) inhibition of dominant or pre-potent responses" (p. 54). However, even though the result of some studies are in agreement with the three-component model of executive functions (e.g., Lehto, Juujärvi, Kooistra, & Pulkkinen, 2003), others are inconsistent with it (e.g., McCabe, Roediger, McDaniel, Balota, & Hambrick, 2010; Salthouse, Atkinson, & Berish, 2003; St Clair-Thompson & Gathercole, 2006).

Overall, the emerging view is that there are multiple executive processes involved in the performance of working memory tests and there are multiple and independent sources of variance contributing to variation in test performance. The general factor of WMC does not appear to be linked to a single psychological process. Instead, it reflects multiple domain-general, executive processes that are tapped in an overlapping fashion across a battery of working memory tests.

Working Memory Capacity and Fluid Reasoning (GF)

Because a positive manifold is observed among measures of WMC, as well as measures of intelligence, it is reasonable to ask how these general factors are related. The reading span test, one of the initial complex span tests, was in fact designed to study the extent to which individual differences in WMC predict reading comprehension and reasoning, and results demonstrated that reading span correlated more strongly with the verbal SAT than did a simple word span test (Daneman & Carpenter, 1980).

Subsequent work showed that other complex span tasks that do not involve reading, or even verbal memoranda, also correlate more strongly with verbal SAT and other reasoning tests than do simple memory span tests such as word span, digit span, and letter span, suggesting that the relationship between complex span performance and intelligence is largely domain-general (Kane et al., 2004; Turner & Engle, 1989). Thus, even though within-domain correlations between working memory tests and cognitive tests are generally stronger than cross-domain correlations, complex span tests have shown strong correlations with measures of reasoning in a domain-general fashion: verbal complex span tests predict spatial reasoning tests and vice versa.

A large number of cognitive tests have been correlated with diverse complex and simple span tests, and as expected, complex span tests have been shown to be more strongly correlated with measures of complex cognition, including intelligence tests, than simple span tests. Most of this research has focused on tests of fluid reasoning, such as Raven's Progressive Matrices or Cattell's Culture Fair tests. This should come as no surprise, because working memory is most important in situations that do not allow for the use of prior knowledge and less important in situations in which previously learned skills and strategies guide behavior (Ackerman, 1988; Engle et al., 1999). This largely echoes Cattell's original definition of fluid intelligence: "an expression of the level of complexity of relationships which an individual can perceive and act upon when he does not have recourse to answers to such complex issues already stored in memory" (Cattell, 1971, p. 115).

Two meta-analyses, conducted by different groups of researchers, estimate the correlation between WMC and the fluid intelligence factor (Gf) to be somewhere between $r = .72$ (Kane, Hambrick, & Conway, 2005) and $r = .85$ (Oberauer, Schulze, Wilhelm, & Süss, 2005). Moreover, a study suggests that it might be even higher for when imposing certain time contraints on the tests (Chuderski, 2015). This is substantially higher than the correlation between the general factor (*g*) and WMC ($r = .48$) found in another meta-analysis (Ackerman, Beier, & Boyle, 2005). Thus, according to these analyses, WMC accounts for at least half the variance in Gf but only about one fourth of the variance in *g*.

Therefore, despite being statistically (near)-identical when appearing in a latent variable model of cognitive tests, *g* and Gf are different constructs. Besides prefrontal damage (see "Overlapping Networks in the Brain") and the Flynn-effect, their different correlation with WMC is a further means toward dissociating *g* and Gf (see "Process Overlap Theory" and "Conclusion" for more elaborate discussions of this issue).

As well, complex span tests are a stronger predictor of Gf than simple span tests (Conway et al., 2002; Engle et al., 1999; Kane et al., 2004) and, of importance, what WMC involves beyond simple storage correlates to a smaller extent with tests of crystallized intelligence (Gc) or perceptual speed (Gs). Although Ackerman et al.'s meta-analysis of working memory and intelligence independently explored short-term memory's and working memory's correlation with various types of cognitive tests, it did not originally compare these results for each individual cognitive domain. Based on their results, Figure 6 shows in decreasing order the difference in correlations with working memory and short-term memory in different types of ability tests (from Conway & Kovacs, 2013).

It is clear that on one side, with the largest difference, is the Raven's Progressive Matrices (Gf), whereas on the other side, with negligible differences, are tests of general knowledge, as well as tests with verbal content (Gc) and the ones that measure perceptual speed (Gs). In the middle, with significant, but less substantial differences than in the case of Gf, are spatial tests (Gv) and ones that purport to measure "general ability" or *g*. Therefore, this result shows that the processes complex span tests tap beyond simple storage and retrieval are strongly associated with Gf, but to a much smaller extent with Gc and Gs.

There is also evidence showing that the relation between Gf and WMC is driven by executive processes. A study by Bunting (2006) demonstrated a correlation between Gf and complex span and, more important, found that the correlation is a function of the degree of proactive interference in the span test; the more proactive interference in the test, the stronger the correlation with Gf. Also, a detailed analysis of item performance on the Raven's Progressive Matrices (Carpenter, Just, & Shell, 1990), a trademark test of Gf, concluded that an important aspect of the test was the discovery and maintenance of rules that govern the variation among entries in a problem. More difficult matrix problems (as evidenced by more errors) typically involve more rules. Thus, to solve difficult matrix problems, one must discover a rule and then maintain that rule while searching to discover a second rule, and so on. Therefore, the ability to maintain goal-relevant information (i.e., rules) in the face of concurrent processing (i.e., searching for new rules) and distraction

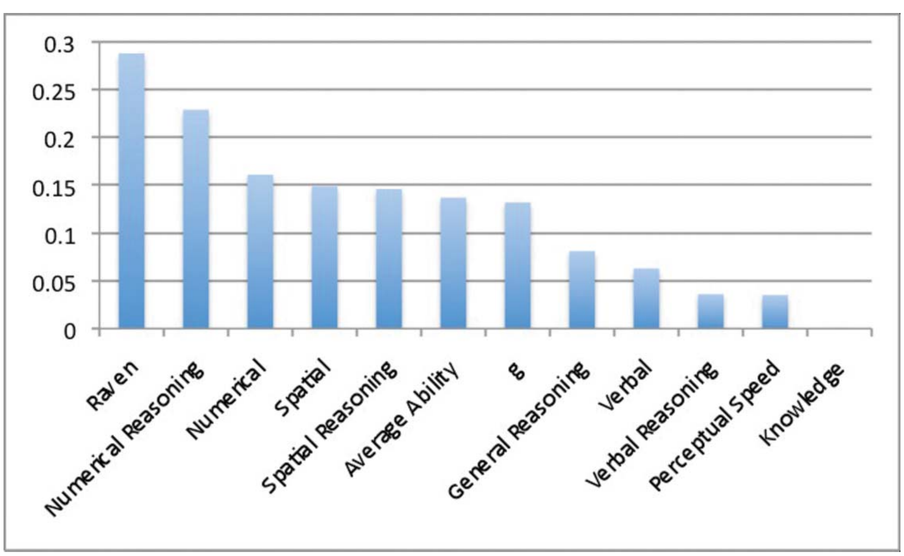

Figure 6. The difference between the correlation with working memory and short term memory for different types of mental tests (based on Kovacs, 2009, p. 94).

(i.e., filtering of irrelevant features) is essential for successful performance.

Another study, using the same rules Carpenter et al. identified, revealed that it is the application of new rules and switching from old ones that drives the correlation between complex span and Gf (Wiley & Jarosz, 2011). Finally, it has been demonstrated that as soon as performance on elementary cognitive tests becomes automatic and therefore does not require controlled attention, the correlation between such tests and Gf decreases (Ackerman, 1988; Rabbitt, 1997).

Although a large number of studies have relied on complex span tests to demonstrate the link between working memory and Gf, there are other tests that purport to measure individual differences in WMC but are based on slightly different operationalizations of the construct. One such method is the visual array comparison test (Luck & Vogel, 1997), in which an array of objects (e.g., colored squares) is briefly presented, followed by a delay interval, then followed by another array of objects that may be the same or different as the previous array. An example of a "different" array would be one in which the color of one square changed from the first array to the second. The examinee must determine whether the second array is the same or different from the first. Performance is nearly perfect when there are fewer than three items in the array but then declines as more items are added, reflecting the capacity of working memory. Such array comparison tests have been shown to correlate quite strongly with tests of fluid intelligence (Chow & Conway, 2015; Cowan et al., 2005; Fukuda, Vogel, Mayr, & Awh, 2010; Shipstead, Redick, Hicks, & Engle, 2012).

Another kind of working memory test requires coordination and transformation; subjects are presented with infor–mation and required to manipulate and/or transform that information to arrive at a correct response. An example is letter-number sequencing, a test originally developed for neuropsychological research, which also appears in the most recent versions of the Wechsler Intelligence Scales (Gold, Carpenter, Randolph, Goldberg, & Weinberger, 1997). In this task a series of alternating digits and letters are presented (e.g., K 6 D 3), and the subject is required to recall first the letters in alphabetical order and then the digits in ascending order.

Another widely used coordination and transformation test is alphabet recoding, which requires the subject to perform addition and subtraction using the alphabet, for example, (C − 2) = A. The subject is presented with a problem and required to generate the answer. Difficulty is manipulated by varying the number of letters presented, as (CD − 2) = AB. Very strong correlations have been found between reasoning ability and a variety of working memory tests that can all be considered in this "coordination and transformation" class (Kyllonen & Christal, 1990; Oberauer, 2004; Oberauer, Süß, Wilhelm, & Wittman, 2003; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002).

An n-back test constitutes yet another kind of working memory test. In an n-back test, the subject is presented with a series of stimuli, one at a time, and must determine if the current stimulus matches the one presented n-back. The stimuli may be verbal, such as letters or words, or visual objects, or spatial locations. Gray et al. (2003) showed that a verbal n-back test was a strong predictor of performance on the Raven's Advanced Progressive Matrices.

Modified versions of simple span tests that transcend simple storage also tap domain-general WM processes and correlate as well with measures of Gf as complex span tests. For instance, simple span tests with long lists correlate as strongly with measures of Gf as complex span tests (Unsworth & Engle, 2006, 2007). Correlations between simple span and Gf also increase if the presentation of stimuli is swift. In a running memory span test (Pollack, Johnson, & Knaff, 1959), subjects are rapidly presented with a very long list of to-be-remembered items, the length of which is unpredictable. At the end of the list, the subject is prompted to recall as many of the last few items as possible.

Cowan et al. (2005) found that running span correlates well with various measures of cognitive ability in children and adults (see also Mukunda & Hall, 1992). Cowan et al. argued that the rapid presentation in the running span task (e.g., four items per second as compared to one item per second in digit span) prevents verbal rehearsal and that any working memory test that prevents well-learned maintenance strategies, such as rehearsal and chunking, will serve as a good predictor of Gf. It is important to note that Cowan does not restrict this interpretation to the running span task: He argued that the critical feature of working memory tasks such as complex span as opposed to short term memory tasks such as digit span is that the former prevent rehearsal, hence they provide a more direct measure of the scope of attention.

In sum, results with working memory tests other than complex span indeed suggest that it is not the dual-task nature of complex span tests (i.e., processing and storage) per se that is necessary for a working memory test to be predictive of Gf; instead, *it is the involvement of executive processes*, achievable in different ways—including but not restricted to dual tasking—that is common to these tasks, and what drives their relation with fluid intelligence.

However, even though all these tests—array comparison, coordination and transformation, n-back, simple span with long lists, and running span—are able to predict Gf, multiple regression analyses indicate that the variance explained by these tests is not entirely the same as the variance explained by complex span tests (Conway, Macnamara, Getz, & Engel de Abreu, 2011; Kane, Conway, Miura et al., 2007). Hence they probably tap overlapping but different executive processes, each of which is differently related to Gf.

Overall, according to the available evidence, *the strong correlation between Gf and working memory is driven by the operation of multiple domain-general cognitive processes* that are required for the performance on tests designed to measure the capacity of working memory and for the performance on test batteries designed to assess fluid intelligence.

Goal Neglect

Further evidence for the association between Gf, WMC, and executive processes comes from studies on goal neglect (Duncan, Emslie, Williams, Johnson, & Freer, 1996; Duncan et al., 2008). In a standard goal-neglect experiment, subjects are presented with two streams of stimuli on a computer screen and are instructed to monitor the appearance of targets in one stream but not in the other. For instance, they might watch two streams of digits and letters, and they have to read aloud the letters but ignore the digits in one stream and completely ignore the other stream. The task starts with an instruction "watch left" or "watch right," indicating which stream the subjects must watch. Near the end of each trial, subjects see another cue, a + or a – sign, meaning that for the remainder of the task the subject has to watch the right or left stream, respectively. That is, if they are already watching the right stream, a + sign indicates they have to keep watching to the right, whereas a – sign indicates they have to change to the left.

Some subjects regularly fail to follow the goal instructions. Duncan and colleagues (Duncan, 1995; Duncan et al., 1996) termed these errors *goal-neglect*. They found that the correlation between the subjects' ability to effectively switch attention according to the cue strongly correlated with Gf as measured by the Cattell's Culture Fair. Moreover, the relationship was not linear: "Neglect is hardly ever seen among people whose Culture Fair scores are above the population mean but is almost universal at more than one standard deviation below the mean" (Duncan, 1995, p. 725). That is, neglect is almost universal below a fluid IQ of 85 but practically nonexistent above 100.

Also, Duncan concluded that people in the lowest segment of the IQ distribution show symptoms of perseveration similar to those of frontal patients. People with fluid IQ scores under 1 standard deviation below the mean could recall the task requirements after the instruction phase, and just like frontal lobe patients, they were able to correctly recall the instruction at the end of the experiment; they simply failed to maintain the goal throughout the course of the test. Neglect was also sensitive to external prompts, such that when subjects were given trial-by-trial error feedback so that their attention was drawn to the neglected task requirement, those who previously demonstrated goal neglect were able to perform at a normal level. These results demonstrate that goal neglect is due not to people with lower IQ being unable to understand instructions but to their inability to follow them during the task.

Subsequent experiments (Duncan et al., 2008) revealed a few important characteristics of goal neglect. One of these is that goal neglect is unaffected if, instead of + and – signs, more spatially orienting cues, such as arrows pointing to the left or right, are used. Moreover, neglect is determined neither by the attentional demand during task execution nor by readiness to multiple task components. Various experimental modifications of the original goal neglect task, such as increasing the processing demand of the task by increasing the number of letters or numbers to be monitored, or having different instructions simultaneously prepared for different components of the task, had no influence on the extent of goal neglect.

However, a manipulation of the complexity of task instruction, without a corresponding change in the actual real-time demands of the task to be executed, has a strong effect on goal neglect (Duncan et al., 2008). That is, goal neglect reflects a limit in WMC that manifests itself in maintaining representations of task-relevant rules and requirements rather than limits in the actual attentional processing required for the task. This conclusion is further supported by a study (Duncan, Schramm, Thompson, & Dumontheil, 2012) examining a "rule working memory" task. In this new task, participants had to remember a list of complex rules and apply them to stimuli. Duncan et al. (2012) found that performance on this task correlated more strongly with Gf than operation span.

Overall, studies on goal neglect and rule maintenance demonstrate that as task requirements become more complex, and more facts, rules, and instructions have to be stored in working memory while actually performing the task, the more often lapses in goal-related control processes will occur in people with low fluid intelligence.

Process Overlap Theory

We offer a new explanation of the positive manifold, which we refer to as process overlap theory. The briefest possible summary of its central assumption is that any test item or cognitive task requires a number of domain-specific as well as domain-general cognitive processes. The domain-general processes that are central to performance on cognitive tests are primarily the ones that are identified as executive processes in cognitive psychology in general and the working memory literature in particular. Such processes are recruited by a large number of test items, alongside domain-specific processes, which are tapped by items appearing in specific types of tests only. In turn, domain-general executive processes overlap with domain-specific processes more than the domain-specific processes overlap with one another. Such a pattern of overlap of executive and specific processes explains the positive manifold as well as the hierarchical structure of cognitive abilities. In this section we elaborate on this idea as well as its implications.

Process overlap theory is clearly not the first account of the positive manifold that proposes an overlap of psychological processes. In particular, it is in many ways similar to Thomson's sampling theory. However, it is also different in crucial aspects, as becomes apparent from this section and further highlighted in "Comparison with Other Theories." Process overlap theory is also not the first cognitive approach to human intelligence. Yet it is the first cognitive theory that also provides a latent variable model and an item response model (discussed next), as well as an account of the neural mechanisms underlying the proposed overlap of psychological processes (see "Overlapping Networks in the Brain").

Crucially for the theory, the general factor of intelligence seems not to reflect a single, unitary process but instead emerges from a limited number of independent sources. Detterman (1994) demonstrated mathematically, by calculating limits of correlations in different scenarios, that *g* is the result of a limited number of independent processes, rather than of a single, unitary process or an almost infinitely large number of processes. As well, a large number of studies looked at the correlation between so-called elementary cognitive tasks and intelligence. Summarizing the result of such studies, Detterman (2000) concluded that these elementary tasks do not correlate with one another, yet each task independently correlates with *g*, and it is only together that they explain a substantial part of the *g* variance. Similar conclusions were reached by Kranzler and Jensen (1991, 1993).

In fact, in the intelligence literature the expression "0.30 barrier" refers to the fact that although virtually any cognitive task correlates with IQ (in this case, as a proxy for *g*), the correlation

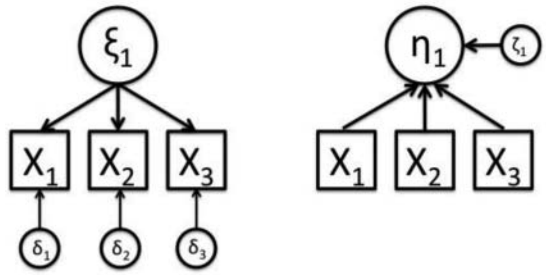

Figure 7. A reflective (left) and a formative (right) model.

is always smaller than 0.30 (see Mackintosh, 2011a). Of importance, this barrier is exceeded by tasks measuring WMC with correlations as high as 0.80. However, WMC arguably reflects executive processes and is therefore hardly elementary. Moreover, as we have seen, WMC itself is the result of a number of independent processes. In fact, according to process overlap theory, WMC correlates with fluid intelligence exactly because it is a multicomponent construct with overlapping processes. Results with tasks that are indeed elementary, and supposedly tap a small number of cognitive processes, show that *g* reflects a number of independent sources.

Process overlap theory can be translated to a structural model, similar to the ones depicted in Figures 1 to 5. However, it is different from all those models in a crucial aspect; it challenges the idea that the across-domain correlations between diverse mental tests are caused by an underlying factor. Instead, it proposes that the positive manifold is an emergent property and, consequently, it translates to a formative model with regard to the general factor.

The difference between reflective and formative models is illustrated in Figure 7. The model on the left is a *reflective* model, in which the measurements *reflect* the latent variable. Such a model requires a stance of entity realism with respect to the latent variable, in this case the general factor. For reflective measurement to make sense, one must assume that there is something out there, represented by the construct, and the measures are (imperfect) indicators of this something (Borsboom et al., 2003). In the case of *g*, it is proposed that *g* causes the measures as well as the covariance of the measures. According to the theory of general intelligence, *g* causes the measures because a person's score on the measure, that is, the IQ-test, is determined by his score on the latent variable, that is, *g*. Consequently, variance in the latent variable determines variance in the manifest variable; hence, the manifest variables' covariance is caused by the latent variable.

In formative models the chain of causation is the opposite. The latent variable emerges *because* of the indicators and not the other way around. In a formative model of *g*, *g* is the result, rather than the cause, of the correlations between group factors. Similar formative latent variables are socioeconomic status and general health, which each tap common variance between measures but do not explain it; according to process overlap theory, *g* is no different (see also van der Maas, Kan, & Borsboom, 2014).[5]

However, at the level of specific abilities, process overlap theory translates into a reflective model. That is, tests indeed reflect specific abilities, which do have ontological reality. Therefore, for the stratum (or strata) below *g*, process overlap theory is compatible with a standard oblique model, depicted in Figure 5. The only addition is that the specific abilities are not perfectly independent, in the sense that they tap overlapping psychological processes. Consequently, there is no possible categorization of abilities in which the abilities will not be correlated.

Thus, overall, process overlap theory translates to a hybrid structural model: part formative, part reflective. As a reflective causal model it corresponds to the oblique model, but it can also accommodate *g* as a formative latent variable—the common consequence, rather than the common cause, of the correlation between group factors. This is illustrated in Figure 8 on a simplified model, consisting only of a verbal, a spatial, and a fluid ability factor, and corresponding verbal, visuospatial, and executive processes.

Because process overlap is probably not the only source of the all-positive correlations, this model also accommodates other sources of the general factor, which can range from white matter tract integrity to mutualism, and so on. In the model, this is represented as ζ, the unique variance of *g*.

The most important difference, then, from *g*-oriented accounts of the positive manifold is that, whereas reflective general factor theories propose a causal influence of a latent variable, *g*, on the positive manifold, according to process overlap theory *the positive manifold is an emergent property*, the result of the specific patterns in which item response processes overlap. A crucial aspect of the theory is that it emphasizes the processes responsible for errors in performance on cognitive test items. The processes that are responsible for various aspects of executive attention (goal-monitoring, updating, inhibition of irrelevant stimuli, etc.), and that are incorporated in the more global concept of WMC, reflect limits in domain-general processes that affect performance on a wide range of items.

Therefore, according to process overlap theory, *the processes sampled by different mental test items are not additive*. Each process has its own limitations, and each process has to be functioning at an appropriate level to arrive at a correct answer to a mental test item. Thus, executive processes act as a bottleneck, and they mask individual differences in specific abilities. Even if someone were, in theory, capable of successful performance on the domain-specific aspect of a mental test item, he or she might be unable to arrive at a correct answer because of failing to meet its executive attention demands.

The aforementioned aspects of process overlap theory are formalized in an item response model (Equation 1), which provides the probability of a person (p) arriving at a correct answer on a test item (i) that taps component processes (C) from a number of different domains (D). Item response theory is a paradigm of psychometrics for the study of the mathematical relationship between latent traits (abilities, in this case) and test scores. Even though item response theory is primarily used for the construction and scoring of psychometric instruments, including mental ability tests, it also has explanatory applications.

According to process overlap theory, there are distinct within-individual processes (C) tapped by different test items,

[5] Formative and reflective measurement is drastically different, but this issue cannot be dealt with in this article. The interested reader is referred to Bagozzi (2007); Edwards (2011); and Howell, Breivik, and Wilcox (2007).

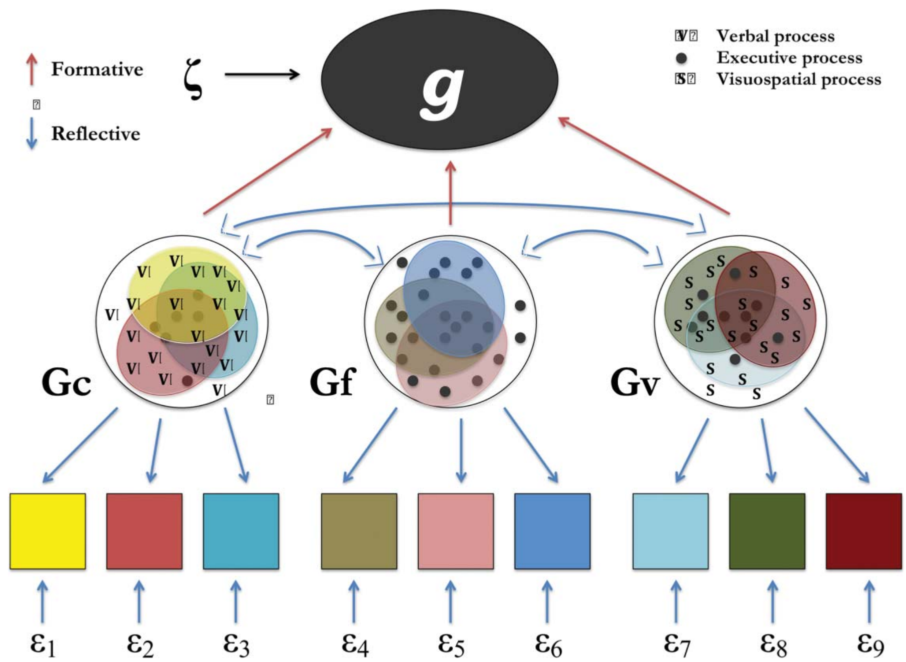

Figure 8. Process overlap theory as a latent variable model.

and these might belong to different cognitive domains (D). Therefore, process overlap theory translates into a *multidimensional* item response theory (MIRT). There are two general kinds of multidimensional models: compensatory and noncompensatory models (for an introduction to MIRT, see Reckase, 2009). In compensatory models, the different dimensions (processes) are combined in a linear, additive manner to produce the probability of solving the item correctly. Therefore a high score on one of the dimensions can *compensate* for a weakness in another.

In noncompensatory models, each dimension is treated separately, and the final probability of solving the item is the product of all of the individual probabilities, as if a single item consisted of a set of independent, unidimensional "subitems," each of which has to be solved correctly in order to arrive at a correct answer. Therefore the probability of solving the item is a nonadditive and nonlinear function of the score on each individual dimension. In such a model, because each dimension has to be passed individually, a low score on any of the dimensions will not be compensated by a high score on another one. Mathematically, the main difference is that in compensatory models it is the *sum* of ability scores that determine the overall probability of success, whereas in noncompensatory models it is their *product*.

$$P(U_{pi}=1 \mid \Theta_{plm}, a_{il}, b_{il}) = \prod_{l=1}^{D} \frac{e^{\sum_{m=1}^{C} a_{il}(\Theta_{plm}-b_{il})}}{1+e^{\sum_{m=1}^{C} a_{il}(\Theta_{plm}-b_{il})}}$$

where:

Θ_{plm} = the process score for the p$^{\text{th}}$ person on the m$^{\text{th}}$ process of the l$^{\text{th}}$ domain

a_{il} = the discrimination parameter for the l$^{\text{th}}$ domain on the i$^{\text{th}}$ item

b_{il} = the difficulty parameter for the l$^{\text{th}}$ domain on the i$^{\text{th}}$ item

D = number of domains tapped by the item

C = number of processes in the given domain tapped by the item

Again, process overlap theory translates into a hybrid between the two general families of MIRT models. *Within* each cognitive domain (D) the processes are additive, which is reflected by a compensatory model. *Across domains*, however, the model is noncompensatory. The probability of passing each individual dimension (i.e., executive, spatial, verbal, etc.) is calculated, and their overall *product* determines the probability of solving the item. Therefore, if there is a single one of the dimensions involved that the person cannot pass, they will not provide a correct answer—in practice, the model behaves as if the individual cognitive domains are individual and independent obstacles to overcome within the same item.

For example, a person with low-executive "ability" scores will have a low probability of getting an item right, even if the person has high scores on the specific processes that are also tapped by the items. That is, with lower executive functioning, *errors are more likely to be the result of not being able to cope with the executive demands of the task*, regardless of the additional domain-specific components. This nonlinearity is responsible for the bottleneck nature of the overlapping executive processes, which in turn explains why the strength of the positive manifold differs between populations.

For instance, let us assume that the processes that are tapped by the tasks developed by Duncan and colleagues, outlined in the previous section, and that are involved in maintaining task goals in working memory, are tapped along with domain-specific abilities by different tests. Populations that differ in their average level of goal maintenance processes will show marked differences in the extent of domain-general versus domain-specific variance. The greater the probability of failing on the goal maintenance component, the less individual differences in specific processes matter in arriving at a correct answer in different tests. Therefore, different tests will correlate more strongly, and a general factor will explain more variance. Process overlap theory proposes that this is the cause of factor differentiation.

Yet, according to process overlap theory, the strength of the positive manifold is not the sole function of the population's level of executive functioning; it is also of the extent to which the tests tap executive processes. The more they do, the more probable it is that a person's error will be the result of a failure on the executive dimension(s) of the task, regardless of its burden on other processes, and the person's possible high level on those processes.

Take working memory as a theoretically unambigous example.[6] As we have seen, working memory tasks, such as complex span, require executive processes to a much larger extent than short-term memory tasks, such as simple span. According to process overlap theory, this is exactly why WMC is much more domain-general than short-term memory capacity, that is, why the patterns of variation are more domain-general in complex span than in simple span. In complex span, relative to simple span, errors are more likely to occur as the result of domain-general executive processes, regardless of whether the task is spatial or verbal.

The example of short-term versus working memory also highlights how *complexity* is defined in the context of process overlap theory: It refers to the extent to which a test taps executive/attentional processes. Hence, the reason why tests of fluid reasoning have the highest *g*-loading is the same reason why complex tasks have higher *g*-loadings than less complex tasks; they all tap central executive processes that are involved in a wide variety of mental test performance across domains. This also explains why working memory is strongly related to intelligence in general, and in particular why what working memory tasks measure above and beyond pure storage is most strongly related to fluid reasoning.

Through its emphasis on errors due to ineffective executive processes as well as executive task demands, the theory also accounts for the worst performance rule, because worst performance is often indicative of failures in executive attention processes (Larson & Alderton, 1990). In particular, in the vast majority of studies, the worst performance rule has been identified in reaction time tasks, in which the slowest reaction times are hypothesized to be the result of posterror slowing, which, in turn, reflects response-monitoring and cognitive control (Dutilh et al., 2012).

Overall, the most important aspect of the MIRT model previously proposed is that it formalizes the interplay between a tests' load on the executive system *and* a given population's level of executive functioning in determining the strength of the positive manifold and therefore the amount of variance accounted for by the general factor. This is because the probability of not arriving at a correct solution to a mental test item due to failures on domain-general rather than domain-specific processes will be a function of both the extent to which a test item taps domain-general executive processes *and* the level of functioning of these domain-general processes in the population studied.

Process overlap theory therefore explains the strength of the positive manifold *in a given population*. This also means that a complete understanding of the within-individual processes that are required to solve an item is not needed in order to explain patterns of individual differences. Figure 9 illustrates this point. The figure shows a matrix-reasoning item, the kind that is typically found in tests of inductive, nonverbal, fluid reasoning that load highly on fluid intelligence (Gf). To solve the item, one has to apply the rule that Carpenter et al. (1990) defined as "distribution of three": The triangles come in three different colors, and the reversed S-s in the middle of the triangles come in three different sizes. Applying this rule to both dimensions gives the correct answer: 1.

Let us imagine that we have a test that comprises dozens of similar items, all of which require the discrimination and interpretation of color in order to map the relation between the figures. If one analyzes the latent dimensions of performance on this test, one is unlikely to find that individual differences in the accuracy of color discrimination, measured by a standard psychophysical task, contribute to variation in the total score.

However, this changes dramatically once the test is administered to a population of completely color-blind people when contrast is equated. If one is not able to discriminate red, green, and yellow, his chances of arriving at a correct answer on this example item is reduced to 33%, because the best response is a guess between Answers 1, 4, and 6—provided, of course, that the person already successfully applied the "distribution of three" rule on the other dimension. In a population where color vision is impaired but still exists, individual differences in color discrimination ability may become important and explain a large portion of the variance in test performance. The point is that, even though color vision is clearly required to solve the task, in normal healthy populations it will not contribute to variation in performance.

Similarly, if one modifies the item so that, instead of three different colors, three blue figures are of slightly different shades, with hardly noticeable differences, variation in the ability to notice such differences will also contribute to individual differences in the performance on the task. In fact, it is such subtle details of test content that determine what a test actually measures:

> Virtually any test can be made into a measure of Gf by raising the requirements for exercising reasoning. Similarly, almost any test can be made into a measure of Gc by increasing the extent to which individual differences in knowledge are assessed. And, by increasing the requirements for speeded performance, almost any test can be made to measure Gs, at least in part. (Horn, 1989)

At the same time, it is important to emphasize that the overlap of cognitive processes tapped by various mental tests is not simply a measurement problem. Of course, the characteristics of the task determine the nature of the processes involved at arriving at a correct solution. For instance, one can design a

[6] Working memory serves only as a comprehensible illustration here: Scores on working memory tasks are nondichotomous, and the actual IRT model, described by the preceding equation, is applicable only to dichotomous test scores.

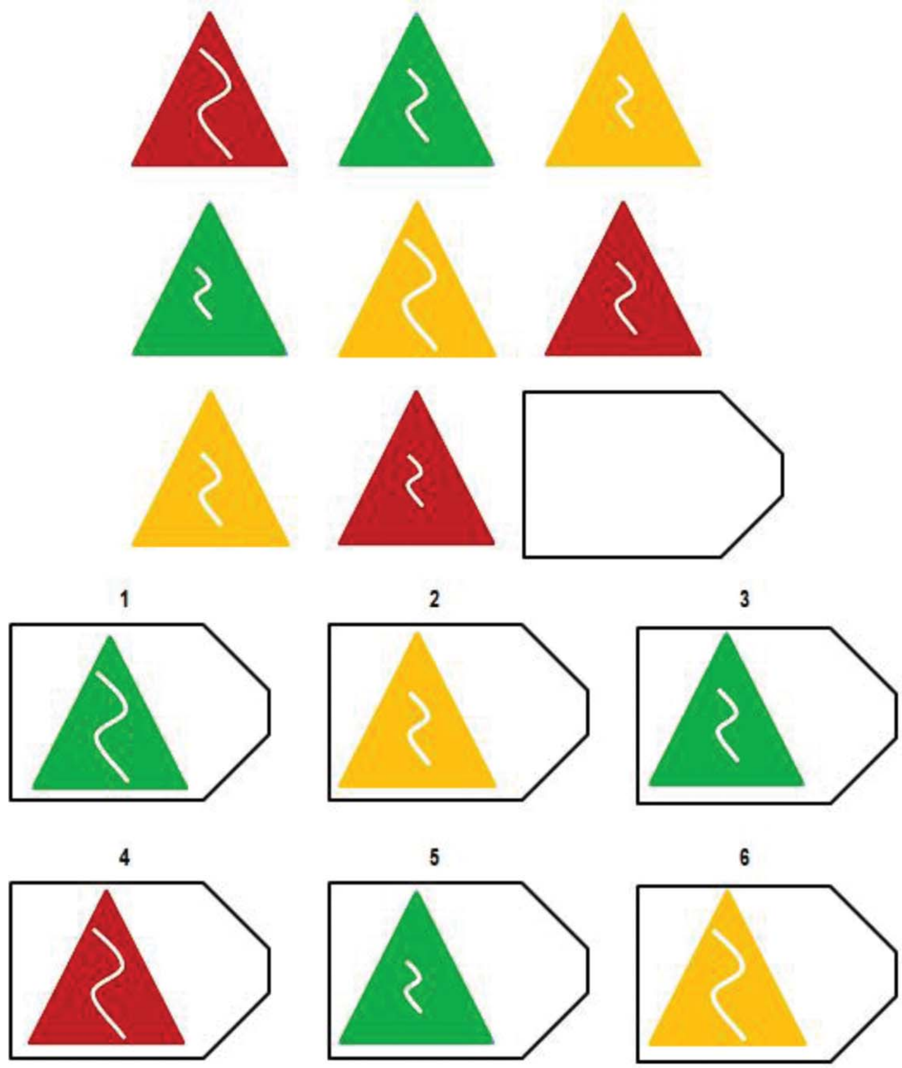

Figure 9. Example item to demonstrate process overlap theory.

spelling test, in which examinees have to decide whether a list of English words appearing on a screen, such as "baccalaureate" or "reconnaissance," are written correctly. Such a task purportedly measures crystallized skills, acquired through formal schooling. Now imagine that each item is mirrored to an axis above the given word. As a result of that, the test would start invoking visual skills. Finally, by adding a strict time constraint to make the correct-incorrect decision, variation in processing speed would start to have a strong role.

However, in practice, the exact opposite is the case. Test developers devote a lot of time and effort to constructing unidimensional measures, tests that purportedly tap a single ability only. That there is still an overlap in executive/attentional processes is more revealing of the psychological nature of such processes than of psychometric test construction.

Crucially, process overlap theory predicts that the psychological processes that determine whether individual differences will be primarily domain-general are not necessarily determined by the cognitive domain the test *purports* to measure. Consider, for instance, the following *number series* item, which is typically categorized as *numerical reasoning* (e.g., in Ackerman et al., 2005). To find the next element in the series, one has to find the simplest rule according to which the last number(s) can be calculated from the previous one(s).

2, 4, 8, ??

A) 9 B) 12 C) 14 D) 20

When eyeballing the three numbers in the preceding series, the first thing to occur is that they are 2 on the power of 1, 2, and 3. In other words, the subsequent number is always twice the number before, which instinctively provides 16 as the natural continuation of this series. The number 16, however, is not among the possible answers. One must, therefore, find another rule. The correct answer is in fact C, which one can figure out in two ways: (a) the difference between two subsequent numbers increases by two after each element (i.e., $4 - 2 = 2$, $8 - 4 = 4$, $X - 8 = 6$?) or (b) the subsequent number equals the sum of the last two elements plus 2. Both rules lead to 14 as the next element (albeit the one following the next differs in the two solutions: 22 and 24, respectively).

What kind of psychological processes contribute to arriving at a correct answer on this item? On a global level, this task requires the ability to find general rules from specific instances, which qualifies as inductive reasoning. Yet on a more refined scale, there are a number of processes at play. Naturally, one needs to be aware of numbers, as well as basic arithmetic operations. But more important, it also requires *cognitive inhibition*. One has to suppress a dominant response (16) and discard a superficially obvious rule in order to find another one.

Number series items correlate strongly with matrix tests, consisting of items like the one presented in Figure 9. The reason, according to process overlap theory, is the overlap of the psychological processes tapped by the two kinds of tests: Both require inductive reasoning and thus cognitive inhibition. Nevertheless, these two kinds of items are regularly categorized as numerical and figural, respectively, in accordance with the content of the items.[7] In a similar vein, verbal analogies, which also probably tap processes that overlap with the ones required for number series and matrix reasoning, are often categorized as tests of verbal ability.

Naturally, both test makers and test takers need to categorize tests, and at a practical level it does indeed make perfect sense to categorize number series, matrix reasoning, and verbal analogies as numerical, figural, and verbal, respectively. Yet, according to process overlap theory, categorization of tasks according to the kind of material, by domain or content, is not necessarily instrumental in understanding the determinants of individual differences.

The reason why tests of fluid intelligence are particularly successful at measuring the processes responsible for the across-domain correlations between mental tests is that they are more or less free from particular domains. Therefore they are able to reflect "pure" complexity, that is, executive/attentional requirements, which are also present in tests of verbal or spatial reasoning, but in those cases they are tapped alongside with the corresponding domain-specific processes.

This, according to process overlap theory, explains the relation between *g* and Gf. They are conceptually different, as Gf represents individual differences in fluid reasoning, whereas *g* does not represent any psychological process. Yet, according to confirmatory factor analysis, they correlate perfectly or almost perfectly. This is because, provided that the general factor was extracted from a large-enough test battery measuring diverse cognitive abilities, which is a key point in obtaining a "good" *g* (Major, Johnson, & Bouchard, 2011), variation in the specific abilities will be mostly cancelled out, and the variation reflected by *g* will mostly be the result of individual differences in domain-general processes. Process overlap theory proposes that such processes could mostly, although probably not exclusively, be labeled as executive processes, involved in cognitive control, goal monitoring, inhibition of irrelevant stimuli, and the like.

To sum up this section: Process overlap theory interprets *g* as a formative construct while accepting a reflective and therefore realist interpretation of specific abilities. It proposes that mental test items tap a number of items in different cognitive domains, and whereas a weakness in a process can be compensated by a strength in another process within the same domain, such compensation is not possible across domains.

Overlapping Networks in the Brain

A comprehensive review of neuroimaging studies, which reviewed imaging studies not only of a wide range of intelligence tests but also of mind games such as chess, found that intelligence is distributed throughout the entire brain (Jung & Haier, 2007). One of the main findings of the publication was that multiple discrete brain regions are associated with intelligence, with no single area activated in all of the studies surveyed. However, the article also demonstrated that the areas active in most studies are typically found in the frontal as well as the parietal lobes.

Another study, focusing on the subscales of the Wechsler Intelligence Scales, demonstrated that the neural correlates of *g* were to be found in several brain areas, with the strongest relationship in the frontal lobes (Colom, Jung, & Haier, 2006a). Yet another study, which applied the method of correlated vectors (cf. Jensen, 1998) in order to focus specifically on *g*, reinforced the conclusion that neural correlates of *g* are distributed across the entire brain, but the majority of them are found in the frontal lobe (Colom, Jung, & Haier, 2006b).

Besides neuroimaging, lesion studies have arrived at a similar conclusion, highlighting distributed brain regions for *g* but also the importance of prefrontal cortex as well as the white matter tracts connecting it with other areas (Barbey, Colom, & Grafman, 2013; Gläscher et al., 2010). However, as we see, different components of *g* can be dissociated through frontal damage, because performance on some tests is sensitive to such damage while performance on other kinds of tests remains intact.

Because of a lack of corroborating results, the search for a "*neuro-g*" has met with minimal success. As discussed earlier, the *g* factors extracted from different batteries are virtually equivalent from a statistical perspective, provided that the batteries are diverse enough. In the light of this, it is remarkable that the search to find the common neural underpinnings of different *g* factors has failed:

> If two test batteries, for example, are weighted differently with tests of memory, spatial reasoning, verbal ability and the like, different brain correlates of the respective *g*-factors may emerge, gray matter (GM) correlates of *g* depend in part on the tests used to derive *g*. (Haier et al., 2009, p. 137)

A confirmatory modeling approach to the brain correlates of *g* (Kievit et al., 2012) also found that "neuro *g* should not be taken to refer to a unidimensional constellation of neural properties identical to *g*" (p. 7); on the contrary, "neuro-*g*" is a formative latent property determined by, rather than the cause of or reflected by, neural measures. It indeed appears that "intelligence is a moving target" (Colom et al., 2011). Overall, studies that have focused on *g* to identify the neural correlates of intelligence have found little consistency, but of equal importance, especially for process overlap theory, is the result that also emerged from such studies, that the prefrontal cortex seems to play an important role.

Instead of *g*, other studies have focused on specific ability factors, and indeed identified different brain correlates for each factor. For instance, scores on the Wechsler Intelligence Scales have weaker neural correlates in the prefrontal cortex than scores on the Raven's Progressive Matrices, suggesting that the

[7] With notable exceptions: Horn (1989), for instance, in his categorization of ability tests according to the Gf-Gc model, put "inductive reasoning, measured using letter series, number series and/or figure series" as the first example of indicators of Gf, "matrices reasoning with visual patterns" comes only second (p. 79).

prefrontal cortex is more strongly related to Gf than to Gc. On the other hand, the temporal lobes were strongly related to Gc but not Gf (Choi et al., 2008). Another study also found that Gc is uniquely correlated with activity in the temporal lobes, whereas Gv, the spatial factor, had nonoverlapping correlates in the frontal and occipital lobes (Colom, Haier, & Head, 2009).

Again, the results of lesion studies corroborate with imaging studies: They also imply different neural substrates for different specific abilities. In classic neuropsychology, the received view was that frontal lobe damage does not impair IQ (e.g., Hebb, 1940; Weinstein & Teuber, 1957) exactly because the clinical tests used in such patients were strongly biased toward crystallized intelligence, Gc. Once the distinction between Gf and Gc is made, it becomes clear that frontal lobe damage severely impairs the former, whereas the latter indeed often remains intact (Duncan, 1995; Duncan et al., 1996).

In the light of such results, it should come as no surprise that the "intelligence" measured by different test batteries gravitating to different specific abilities cannot be universally localized, and the *g* factors derived from such batteries, despite being statistically indistinguishable, do not have identical neural correlates.

Instead of *g*, then, let us focus on fluid reasoning (Gf). Again, even though it is statistically identical to *g*, imaging studies demonstrate their dissociability; whereas *g* cannot be localized, Gf is linked to the prefrontal (primarlily dorsolateral) and partly to the (primarily posterior) parietal cortex with remarkable consistency. That is, diverse tests tapping fluid reasoning, including matrix items, letter series, or verbal syllogisms, all have similar patterns of activation in the prefronal, and partly in the parietal cortex (for a review, see Kane, 2005). In particular, reasoning problems identical or similar to the ones found in Raven's Progressive Matrices, probably the most typical test of Gf, consistently activate certain areas in the prefrontal cortex (Christoff et al., 2001; Prabhakaran, Smith, Desmond, Glover, & Gabrieli, 1997; Wharton et al., 2000), and this conclusion is further supported by lesion studies (e.g., Waltz et al., 1999). Similar activation was found in other, mostly verbal analogical reasoning tasks (Green, Fugelsang, Kraemer, Shamosh, & Dunbar, 2006; Luo et al., 2003; Volle, Gilbert, Benoit, & Burgess, 2010; Wendelken, Nakhabenko, Donohue, Carter, & Bunge, 2008), pointing to an indifference of content in fluid tasks (see also Duncan et al., 2000).

A lesion study provides further evidence that is in agreement with imaging studies by pointing to the importance of specified areas within the prefrontal and parietal cortex (Woolgar et al., 2010). The study compared different areas of the brain to explore the extent to which, statistically, brain damage in a given area is associated with loss of fluid intelligence on average. Using multiple regression, it found that the same amount of tissue damage that predicts a 1-point loss of fluid IQ, if it occurred elsewhere in the brain, corresponds to a 6.5-point impairment if found in particular prefrontal and parietal regions. Of importance, partial correlations showed that each of the regions studied made an independent contribution to the impairment in fluid intelligence, pointing to the involvement of independent neural mechanisms.

Imaging studies of working memory have identified similar patterns of prefrontal and parietal activation for the central executive as the ones identified for Gf (see Henson, 2001; Wager & Smith, 2003). A large-scale review concludes that "the central executive maps to mid-lateral prefrontal regions, particularly left and right dorsal lateral prefrontal cortex" (Henson, 2001, p. 166).

Looking at various actual cognitive functions that any mechanism called the "central executive" could be reasonably expected to perform, it has indeed been found that one of the chief functions of the prefrontal cortex is cognitive control (Badre & Wagner, 2004; Botvinick, Braver, Barch, Carter, & Cohen, 2001; Cole & Schneider, 2007; E. K. Miller, 2000; E. K. Miller & Cohen, 2001; Vincent, Kahn, Snyder, Raichle, & Buckner, 2008) or, synonymously, the top-down monitoring of goal-directed behavior (Asplund, Todd, Snyder, & Marois, 2010; Braver & Bongiolatti, 2002; Corbetta & Shulman, 2002; Farooqui, Mitchell, Thompson, & Duncan, 2012; B. T. Miller & D'Esposito, 2005). On a less global scale, the prefrontal cortex is involved in such cognitive operations as task switching (e.g., Derrfuss, Brass, Neumann, & von Cramon, 2005; Sohn, Ursu, Anderson, Stenger, & Carter, 2000) and response inhibition (e.g., Aron, Robbins, & Poldrack, 2004; Chambers et al., 2006), among others.

Once again: In agreement with neuroimaging studies of healthy participants, lesion studies also point to a large commonality between the neural substrate of executive functions and fluid intelligence, and locate this substrate in the prefrontal and posterior parietal areas (Barbey et al., 2012). Yet it is crucial to note that the prefrontal cortex comprises a large portion of the entire cortex and contains a number of distinct subsystems, both cyto-architectonically and functionally. Accordingly, different executive functions probably map on different parts of the prefrontal cortex (e.g., MacDonald, 2000; Stuss & Alexander, 2000).

In particular, some of the studies surveyed earlier in this article have found more medial activation, whereas others registered the activation of lateral areas; some processes seem to induce bilateral activation, whereas the neural substrate of others appears to be unilateral; finally, some studies found the coactivation of the anterior cingulate and/or parietal areas, whereas others have not. However, a recent meta-analysis of 193 imaging studies of different executive processes tapped by various executive tasks was able to identify common activation in what they call a "cognitive control network," comprising the dorsolateral prefrontal cortex, the frontopolar and orbitofrontal cortices, and the anterior cingulate (Niendam, Laird, & Ray, 2012).

To sum up the argument so far: fluid intelligence (Gf), the central executive component of working memory, and various cognitive processes that serve the top-down control of goal-directed behavior have strongly overlapping neural substrates in the prefrontal cortex (for a summary of related evidence, cf. Kane & Engle, 2002).

It is at least as important from the perspective of process overlap theory that the activation of these brain areas is independent of content: These same brain areas of the prefrontal and parietal cortex are involved in different domains of cognition. For instance, Duncan and Owen (2000) reviewed 20 studies that explored brain activation in different types of tasks, the content domain of which included both spatial and verbal tasks. They concluded that the recruitment of frontal areas "is extremely similar from one cognitive demand to another, suggesting a specific network of prefrontal regions recruited to solve diverse cognitive problems" (Duncan & Owen, 2000, p. 476). The same areas that compose the "cognitive control network" have also been labeled the "multiple demand system" in order to directly refer to the fact that they are involved in diverse cognitive activities (Duncan, 2010).

However, there is a danger of such analysis revealing overlapping activation at the group level even when it does not exist within individuals. This methodological problem was addressed by Fedorenko, Duncan, and Kanwisher (2013), who undertook a study looking at activation overlap within individual subjects. They used seven tasks, including a spatial and a verbal working memory task, a mental arithmetic task, and the Stroop task, and found domain-general activation in the expected frontal and parietal areas at the indivdiual level, too, confirming the results of previous studies that employed group analysis.

A study by Duncan et al. (2000), which purportedy attempted to identify a neural system associated with *g* but in fact employed tests of fluid reasoning (Gf), found that when high *g*-(Gf)-loading was contrasted with low *g*-(Gf)-loading, a pattern of activation in the lateral frontal cortex emerged, and this was the only area commonly activated by spatial and verbal tasks. Another study investigated neuroanatomic overlap of different cognitive abilities and identified specific regions in the frontal lobes that are frequently shared (Colom et al., 2013).

A recent study conducted by Román et al. (2014) took a different perspective: They looked at brain correlates of latent variables at different levels of the "hierarchy of intelligence," that is, in the higher order latent variable model (see "*g*: A Well-Aged Puzzle"). They found that as one moves upward in the hierarchy from specific factors through group factors to *g*, the gray matter correlates are smaller and more frontal. The study concluded that "factors capturing the variance common to both specific measures and group factors partial out the specificity present at the measurement level. Interestingly, removing specific variance reveals that frontal regions in the brain are crucial for supporting human intelligence" (p. 3816).

Process overlap theory proposes that as one moves up the hierarchy of abilities, specific component processes gradually disappear, and by the time one gets to the processes directly reflecting *g*, executive ones are of great importance. Because specific processes have diverse brain correlates, whereas it is mostly frontal regions that are involved in executive processes, the results of Román et al. can be interpreted as the neural equivalent of the psychological explanation proposed by process overlap theory.

Having discussed the domain-general involvement of frontoparietal areas in reasoning tasks, it is important to point out that imaging studies of working memory have also registered the domain-generality of neural activation in the frontal cortex. A meta-analysis of 60 neuroimaging studies (Wager & Smith, 2003) found that the fractionation of working memory according to content was limited to the posterior areas: No fractionation was found in the frontal cortex according to content domains. More precisely: They found that the central executive could be further fractionated as well, but according to processes rather than the type of material.

Because the significance of complex span tasks has been emphasized throughout this article, an imaging study of complex span tasks is particularly interesting, especially because it directly looked for the common neural underpinnings of spatial and verbal complex span, applying a novel methodology that uses both within-domain and across-domain conditions, as well as contrasting complex span with both pure storage and pure processing (Chein, Moore, & Conway, 2011). The study indeed demonstrated the domain-general activation of the prefrontal cortex, the posterior parietal cortex, and the anterior cingulate in complex span tasks.

More recent studies employing a network perspective have also concluded that the prefrontal cortex is often coactivated with brain areas involved in domain-specific cognition. The network approach to brain functioning is an emerging paradigm in cognitive neuroscience, based on the recognition that neural computations involved in cognition are not performed by isolated brain areas but rather are the result of networks of interconnected areas (Bressler & Menon, 2010; He & Evans, 2010; Heuvel & Pol, 2010; Sporns, 2002). Therefore, the study and graph theoretical modeling of the structural and functional connectivity of the human brain—*the human connectome* (Toga, Clark, & Thompson, 2012)—is the central aim of research in the network approach.

Network analysis of the human brain has revealed that it can be characterized as a "*small world network*," that is, a network consisting of local clusters of strongly interconnected nodes but also of short paths that link the individual clusters (Achard, Salvador, Whitcher, Suckling, & Bullmore, 2006; Bassett & Bullmore, 2006). This architecture, which is both modular and strongly interconnected, makes brain wiring economical and highly efficient at the same time. The specialized modules are connected with the aid of *connector hubs*: sets of highly connected and central nodes with diverse and long-range connections that function as global interlinks or bridges between the individual modules or clusters, ensuring short overall path length and thus high efficiency (Sporns, Honey, & Kötter, 2007).

Of importance, "most studies identified hubs among parietal and prefrontal regions, providing a potential explanation for their well-documented activation by many cognitive functions" (Bullmore & Sporns, 2009, p. 190), and "studies on the network of areas of the primate and human cerebral cortex showed that the PFC, especially the dorsolateral part (PFC DL) is an important hub region where information from different functional brain systems are integrated" (Négyessy, Bányai, Nepusz, & Bazsó, 2012, p. 39). Négyessy et al. (2012) also documented that in the imaging literature the single area identified most often is the prefrontal cortex, and they performed network analysis to demonstrate that this is not the result of the selectivity of eresearchers but an inevitable consequence of cortical processing.

Apparently, the same regions that were identified in traditional studies as the overlapping neural substrate of executive processes, working memory, and fluid reasoning are referred to as the "frontoparietal control system" in network neursocience as well (Spreng, Sepulcre, Turner, Stevens, & Schacter, 2013; Vincent et al., 2008). Being one of the most connected networks of the brain (Cole, Pathak, & Schneider, 2010), this system is attributed with functions of regulating other subnetworks.

It is remarkable from an individual differences perspective that of all brain networks the frontoparietal network has the largest variability in functional connectivity, larger than any other network in the brain (Mueller et al., 2013). Moreover, several studies have demonstrated that variation in the global connectivity of these regions correlates with intelligence as well as cognitive control (Cole & Yarkoni, 2012; Heuvel & Stam, 2009; Santarnecchi & Galli, 2014; Song et al., 2008).

There are two further results in cognitive neuroscience that are highly relevant with regard to process overlap theory. First, a number of studies found that the same frontal areas that function as hubs are capable of serial processing only, and therefore they severely limit the capacity of different domain-specific cognitive systems: "The prefrontal and dorsal medial frontal cortex [function] as a frontal lobe network recruited to meet a wide variety of cognitive demands, making this system well suited to act as a central, amodal bottleneck of information processing" (Dux, Ivanoff, Asplund, & Marois, 2006). These areas are therefore primary candidates for being the neural substrate of capacity limits (Dux et al., 2006; Koechlin & Hyafil, 2007; Marois & Ivanoff, 2005; Tombu et al., 2011), probably strongly affecting working memory and intelligence. Because process overlap theory focuses on the limitations of executive processes as the cause of both the positive manifold and factor differentiation, this provides a direct link from the theory's psychological hypothesis to its possibly underlying neural mechanism.

Second, process overlap theory proposes that the interaction between the level of executive processes and the executive demands of the task is of critical importance with regard to the strength of the positive manifold. Hence it is of great significance that activation in relevant regions appears to be a function of both the level of ability and the executive demands of a given task. The vast majority of the studies just cited, documenting prefrontal and parietal activation for executive processes, working memory, and fluid intelligence, demonstrated increased activation as a function of the demand for the construct in question. As well, several studies found an increase in activation that is inversely related to the participants' level on the construct. Kane's (2005) review of prefrontal involvement in fluid reasoning concludes that "PFC is recruited to solve inductive reasoning problems under worst-case conditions, such as when problems are most difficult or when one has reduced fluid abilities" (p. 156).

Unfortunately, simultaneous tests for brain activity as the function of performance within a task and as the function of differences between tasks are largely missing from the literature. That is, activation differences due to task complexity and activation differences due to variation in individuals' ability are not clearly differentiated. Therefore a current study, which addresses exactly this question, is particularly interesting. Kievit et al. (2016) employed a modern psychometric approach to neuroimaging to test for overlapping brain correlates of difficulty and ability parameters in fluid reasoning tasks. Using a conjunction analysis, they found three regions the activation of which depended on difficulty and ability: bilateral angular gyri, bilateral precuneus, and the left superior frontal gyrus. This demonstrates that the regions that are registered in between-subject designs (of differing fluid intelligence) are the same ones that are registered in within-subject designs (of increasing difficulty in fluid tasks); again, this seems to point to the neural underpinning of the interaction proposed by process overlap theory.

To summarize this section: According to process overlap theory, the positive manifold is caused by the overlap of executive processes that are involved in both working memory and intelligence. The present state of research in neuroscience demonstrates that the neural correlates of such processes are (a) indeed involved in working memory and intelligence, and (b) indeed activated in an overlapping fashion that is in agreement with the tenets of the theory, and finally: (c) the frontal lobe is strongly connected to other, more specialized parts of the brain. In other words, the overlap the theory proposes appears to actually take place in the human brain.

Comparison With Other Theories

There have been enormous theoretical endeavors in the field of human intelligence, mostly focusing on the nature, structure, or interpretation of the concept itself. Even a simple elaboration of these accounts is beyond the possibilities or aims of this article. We have provided an explanation of the positive manifold and a number or strongly related phenomena. In this section, therefore, we compare only process overlap theory to accounts of the same empirical phenomena and not to theories of intelligence in the broad sense. Similarly, because process overlap theory is not a taxonomy of the structure of variation in human abilities, no comparison to such taxonomies (like the CHC, McGrew, 2009; or the VPR, Johnson & Bouchard, 2005, model) is provided.

The first theory to consider is, of course, *g*-theory, the idea that different IQ-tests correlate because they all measure the same latent variable, which can be interpreted as either general intelligence or a parameter affecting all cognitive operations. Because this idea is thoroughly criticized in the first part of the article, we find it unnecessary to further elaborate on why process overlap theory is more plausible than this account.

The second is Thomson's sampling theory, which proposes that the correlation between any two mental tests is the function of the number of shared "bonds" the tests sample. Thomson demonstrated that this principle is sufficient to produce the positive manifold, without postulating a general factor. This account has a lot in common with process overlap theory, especially with regard to higher order, more general processes versus lower order, more specific processes:

> The mind, in carrying out any activity such as a mental test, has two levels at which it can operate. The elements of activity at the lower level are entirely specific, but those at the higher level are such that they may come into play in different activities. Any activity is a sample of these elements. (Thomson, 1916, p. 341)

In fact, from a broad perspective, process overlap theory can be considered a modern sampling theory.

The continuation of the preceding paragraph, however, already highlights a crucial difference: "The elements are assumed to be additive like dice, and each to act on the 'all or none' principle, not being in fact further divisible"[8] (Thomson, 1916, p. 341). Contrary to this assumption, process overlap theory proposes a nonadditive overlap of psychological processes. In particular, the executive/attentional processes that typically overlap with domain-specific ones function as a bottleneck: Failure to pass the executive demands of a test renders individual differences in specific processes unimportant for overall performance. As a consequence, the correlation between tests is not simply the function of the sheer number of overlapping processes in relation to the total number of activated processes, as in Thomson's account.

The two accounts also differ markedly in their view of brain functioning. The bonds theory subscribed to a version of contemporary views on "equipotentiality," denying the localization of brain function. In fact, Thomson argued that the human brain consists of a myriad of bonds and assumed that the sampling process is completely random, with tests differing only in the number of bonds they sample. Process overlap theory, on the other hand, draws heavily on results from neuroscience that have been obtained since Thomson's time, and which demonstrate that executive processes are primarily seated in the prefrontal cortex and that this area of the brain is the one most heavily interconnected with other areas.

This is an important difference, as it directly addresses two valid criticisms of the sampling model (summarized in Eysenck, 1987, and van der Maas et al., 2006). First, it logically follows from the sampling model that the more bonds a test samples, the higher its average correlation with all other tests, because it is more likely to randomly share bonds sampled by other tests. This means that a test's *g* loading is the sole function of the number of bonds sampled by the test. However, a number of tests, which supposedly measure a narrow range of "bonds," load highly on *g*. Yet, according to process overlap theory, *g* loadings depend on the involvement of executive processes seated primarily in the prefrontal cortex rather than on the number of processes measured.

The second criticism is even more directly related to the brain: It has been cited as falsifying evidence against the sampling model that brain damage can lead to specific impairments, whereas its conception on brain functioning determines the bonds theory to predict general impairments. Again, according to process overlap theory it is damage to the neural substrate of overlapping executive process that is relevant in predicting the generality of the impairment rather than the total amount of damage.

There is a third criticism against the sampling model, which is particularly informative in highlighting the difference between Thomson's account and process overlap theory: "Some seemingly completely unrelated tests, such as visual and memory scan tasks, are consistently highly correlated, whereas related tests, such as forward and backward digit span, are only modestly correlated" (van der Maas et al., 2006, p. 843.)

Because process overlap theory, as opposed to sampling, does not propose additive processes, it does not predict a linear relationship between the size of the correlation and the extent of the overlap relative to the total number of activated processes. Instead, it predicts that the size of the correlation will be a function of the overlap of domain-general executive processes. Therefore the third criticism is not relevant for process overlap theory. In particular, whereas forward digit span measures only the storage and retrieval of digits, backward digit span also taps executive processes involved in fluid reasoning (Kovacs et al., 2016). With regard to visual and memory scan tasks: They correlate strongly exactly because both are good measures of the executive component of working memory.

Anderson (2001) provided an account of the general factor similar to the one provided by Thomson, but here the overlap of elements takes place at the level of genes. He argued that any cognitive task requires the coordinated functioning of distributed neurons, and because the development of these neurons depends on a large number of genes, "any two cognitive tasks of the type used for IQ tests will share some fraction of their genetic determinants" (p. 368).

Assuming that each locus has an independent and equal effect on behavioral variance, Anderson (2001) claimed that the overlapping genetic components cause the positive manifold: "Any two traits with shared components will have a positive correlation" (p. 369). Indeed, this account is very similar to the one proposed by Thomson, even to the equation predicting the size of the correlation based on the number of shared genes.[9] Therefore, the reasons why process overlap theory is more empirically plausible than the sampling model are also relevant to Anderson's account. Moreover, we disagree about the optimal level of explanation. It is not genes but psychological processes that are involved in cognitive behavior, hence we need an understanding of the nature of psychological processes as a proximate cause for the positive manifold.

The third theoretical account of the positive manifold that we wish to discuss is the mutualism model, a developmental account of the positive manifold that proposes positive reciprocal interactions between cognitive processes during development (van der Maas et al., 2006). The model describes the development of intelligence as the emergence of a complex dynamical network through the mutually beneficial interaction of modules or processes. According to this model, individual differences in cognitive abilities are uncorrelated at the beginning of development and start to correlate only because of such interactions.

The mutualism model bears many similarities to process overlap theory. It also explains *g* without postulating a single, general ability; it also rejects the reflective interpretation of *g*; and the explanation also relies on the interaction of separate processes. At the same time, van der Maas and colleagues proposed the functional independence of cognitive processes in mental test performance in their model while arguing that the positive manifold is the result of mutual interactions between cognitive processes only during development. That is, whereas in the mutualism model the interaction between processes takes place during development only, process overlap theory claims

[8] This assumption by Thomson (1916) was, in fact, more practical than substantive: "Note that I do not for one moment suggest that psychological 'factors,' if they exist, can be added together like dice: I merely intend to apply Professor Spearman's formulae to dice throwing" (p. 275).

[9] Even though the article does not refer to Thomson or to the concept of sampling.

that such interaction takes place when people solve mental tests.

The central assumption of the mutualism model is that learning in one cognitive domain positively affects development in other domains. In our opinion, even though the mathematical scaffolding of the mutualism model is greatly sophisticated and appealing, this assumption may need further empirical grounding. In particular, the strong cognitive transfer across domains that it proposes seems somewhat implausible. Furthermore, mutualism predicts that in adults, elementary cognitive tasks will be correlated, and as we have seen, this is not the case. Finally, combining evidence from psychometrics, experimental cognitive psychology, and neuroscience, process overlap theory is arguably based on more converging evidence.

On the other hand, because cognitive transfer probably occurs more easily within than across domains, mutualism appears as a very plausible explanation of how specific psychological processes get organized into clusters of abilities, represented by broad group factors—more so than of the correlations between the group factors themselves or between tests tapping different domains. Therefore, it might be possible to reconcile the two accounts, as it is quite likely that some processes indeed interact during development but not later in life, whereas others interact during actual problem solving.

The final theoretical account of the positive manifold to discuss is Detterman's (1987) system theory of intelligence. It argues that human intelligence functions as a complex system composed of smaller parts, and a global rating of cognitive functioning, such as IQ, does not reflect its constituents. In his conception of intelligence, Detterman borrowed two central concepts from system theory: *wholeness* and *centrality*. Wholeness refers to the interrelatedness of different parts of the system, and centrality means the extent to which a single part of the system influences the operation of the entire system.

Detterman (1987) argued that "the amount of variance accounted for by the first principal component is considered to be a measure of system wholeness for the variables measured" (p. 6). Therefore, the identification of individual components of the system results in processes that do not correlate. Moreover, according to Detterman, "a measure of wholeness, which I regard the first principal component to be, says nothing about centrality" (p. 7).

We completely subscribe to Detterman's basic theoretical approach and his conception of intelligence as a complex system with many independent components. In fact, it is quite easy to integrate the two theories. Employing his system terminology, process overlap theory emphasizes the centrality of executive processes rather than system wholeness as the main reason for the emergence of the positive manifold. The empirical evidence points to such executive processes overlapping with domain-specific ones in cognitive activity rather than to every process being related to every other process, as would be the case if intelligence were a system with very high wholeness.

Conclusion

Process overlap theory builds on available knowledge from psychometrics, cognitive psychology, and neuroscience to explain patterns of variation in mental abilities. As such, it is not a taxonomy of human cognitive abilities and more than a latent variable model: It is a theoretical account that specifies the within-individual item response processes that are responsible for the positive manifold in intelligence. Besides the positive manifold, the theory explains a number of related phenomena: factor differentiation, the decrease of across-domain variance as a result of the Flynn effect, the identity or near-identity of Gf and *g* from an individual differences perspective, and the worst performance rule.

The theory proposes that the positive manifold, and thus *g*, will emerge from a battery of tasks that tap various important domain-general processes in an overlapping fashion. In particular, executive processes, seated primarily in the prefrontal and partly in the parietal cortex, overlap more with domain-specific processes in mental test performance than such specific processes overlap with one another. To arrive at a correct answer on a mental test item, one has to pass each tapped "dimension"; therefore, individual differences in executive processes function as a bottleneck for variation in specific processes. As a consequence, complex tasks requiring substantial executive processing, as well as errors in tasks requiring attention, are the most indicative of the domain-generality of the positive manifold.

It is important to note that the prefrontal cortex is not the seat of a unitary central executive, nor is executive function unitary from a psychological point of view. Hence *there need not be a single psychological process tapped by all intelligence tests* to obtain the positive manifold. Instead, a set of executive processes function as a "bridge" connecting more specialized networks of cognitive processes. Accordingly, process overlap theory's interpretation of double dissociation results in the light of the positive manifold is that cognition is not characterized by independent encapsulated processes or "modules" but instead by multiple sets of processes that are engaged in an overlapping fashion by cognitive operations.

Process overlap theory does not question the existence of psychometric *g*. In fact, it is not even logically possible to admit the existence of the positive manifold but not of a general factor, because the latter is a necessary algebraic consequence of the former. What is discarded is "*psychological g*": the interpretation of psychometric *g* as a psychological construct. There is no psychological process that corresponds to psychometric *g*. Instead, *g* is conceptualized as a formative variable: It emerges *because* of the positive manifold rather than *explaining* it.

Thus, it is imperative not to interpret process overlap theory as if it identified *g* with executive functions—with a few possible mediators like fluid reasoning and working memory. The theory indeed says that working memory and fluid intelligence are hugely overlapping constructs and that the overlap is caused by executive functions but *g* is not interpreted as a psychological construct of any kind. Instead, it is characterized as an emergent property, a result of how processes overlap to produce cognitive activity required by mental tests.

Also, even though our reading of the evidence is that such a functional overlap can account for the bulk of the domain-general variance that can be described with psychometric *g*, we are ready to acknowledge that there might be other sources contributing to the positive manifold. Mutualism is a likely candidate (see "Comparison with Other Theories"), and so is associative learning (e.g., Kaufman, DeYoung, Gray, Brown, & Mackintosh, 2009).

Besides explaining a large number of empirical phenomena, process overlap theory also makes a number of unique predictions. First, if the theory is correct, differentiation should occur in working memory as it occurs in intelligence. That is, correlations between verbal and spatial working memory tasks should be stronger below the population mean than above, and such differentiation should be more characteristic of working memory than of short-term memory. Second, there is a controversy surrounding age-differentiation, the assumption that the positive manifold is stronger in younger children. The available results are inconclusive, largely because the batteries and age groups are created in an arbitrary manner. Process overlap theory predicts that age patterns of the maturation, as well as aging of the prefrontal cortex and thus of executive processes, should determine the domain-generality of the positive manifold. However, this prediction might be difficult to test because different executive processes show different developmental and aging patterns, and there is large individual variation in the maturation and aging process itself.

Finally, process overlap theory and sampling provide different predictions for neuroscience. Thomson postulated a large number of domain-general bonds that are randomly sampled by different cognitive demands, and the more bonds sampled the higher they correlate with the general factor. Therefore, according to original sampling models, *g* loadings should correlate with the number of activated clusters in the brain, regardless of their location. Process overlap theory, on the other hand, predicts that *g* loading should be a function of the involvement of particular areas of the brain rather than total activation. We hope that the theory will inspire substantial empirical research and data-driven development in the fascinating field of human intelligence.

Acknowledgments

This article is dedicated to the loving memory of our friend and mentor, Nicholas J. Mackintosh (1935–2015). We are grateful to Rogier Kievit and Nick Mackintosh for providing valuable feedback on earlier drafts of the manuscript.

Funding

The first author's research was funded by a Marie Curie Intra-European Fellowship of the European Commission.

References

Achard, S., Salvador, R., Whitcher, B., Suckling, J., & Bullmore, E. (2006). A resilient, low-frequency, small-world human brain functional network with highly connected association cortical hubs. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *26*(1), 63–72. doi:10.1523/JNEUROSCI.3874-05.2006

Ackerman, P. L. (1988). Determinants of individual differences during skill acquisition: Cognitive abilities and information processing. *Journal of Experimental Psychology: General*, *117*, 288–318. doi:10.1037/0096-3445.117.3.288

Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2005). Working memory and intelligence: The same or different constructs? *Psychological Bulletin*, *131*, 30–60. doi:10.1037/0033-2909.131.1.30

Anderson, B. (2001). g as a consequence of shared genes. *Intelligence*, *29* (5), 367–371. doi:10.1016/S0160-2896(01)00069-1

Aron, A. R., Robbins, T. W., & Poldrack, R. A. (2004). Inhibition and the right inferior frontal cortex. *Trends in Cognitive Sciences*, *8*(4), 170–177. doi:10.1016/j.tics.2004.02.010

Asplund, C. L., Todd, J. J., Snyder, A. P., & Marois, R. (2010). A central role for the lateral prefrontal cortex in goal-directed and stimulus-driven attention. *Nature Neuroscience*, *13*(4), 507–512. doi:10.1038/nn.2509

Atkinson, R. C., & Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. *Psychology of Learning and Motivation*, *2*, 89–105. doi:10.1016/S0079-7421(08)60422-3

Baddeley, A. D. (1996). Exploring the central executive. *The Quarterly Journal of Experimental Psychology Section A*, *49*(1), 5–28. doi:10.1080/713755608

Baddeley, A. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, *4*(11), 417–423. doi:10.1016/S1364-6613(00)01538-2

Baddeley, A. D. (2002). Is working memory still working? *European Psychologist*, *7*(2), 85–97. doi:10.1027/1016-9040.7.2.85

Baddeley, A. D., & Hitch, G. (1974). Working memory. *Psychology of Learning and Motivation*, *8*, 47–89. doi:10.1016/S0079-7421(08)60452-1

Badre, D., & Wagner, A. D. (2004). Selection, integration, and conflict monitoring; assessing the nature and generality of prefrontal cognitive control mechanisms. *Neuron*, *41*(3), 473–487.

Bagozzi, R. P. (2007). On the meaning of formative measurement and how it differs from reflective measurement: Comment on Howell, Breivik, and Wilcox (2007). *Psychological Methods*, *12*(2), 229–237; discussion 238–245. doi:10.1037/1082-989X.12.2.229

Barbey, A. K., Colom, R., & Grafman, J. (2013). Dorsolateral prefrontal contributions to human intelligence. *Neuropsychologia*, *51*(7), 1361–1369. doi:10.1016/j.neuropsychologia.2012.05.017

Barbey, A. K., Colom, R., Solomon, J., Krueger, F., Forbes, C., & Grafman, J. (2012). An integrative architecture for general intelligence and executive function revealed by lesion mapping. *Brain: A Journal of Neurology*, *135*(Pt. 4), 1154–1164. doi:10.1093/brain/aws021

Bartholomew, D. J., Allerhand, M., & Deary, I. J. (2013). Measuring mental capacity: Thomson's Bonds model and Spearman's g-model compared. *Intelligence*, *41*(4), 222–233. doi:10.1016/j.intell.2013.03.007

Bartholomew, D. J., Deary, I. J., & Lawn, M. (2009). A new lease of life for Thomson's bonds model of intelligence. *Psychological Review*, *116*(3), 567–579. doi:10.1037/a0016262

Bassett, D. S., & Bullmore, E. (2006). Small-world brain networks. *The Neuroscientist : A Review Journal Bringing Neurobiology, Neurology and Psychiatry*, *12*(6), 512–523. doi:10.1177/1073858406293182

Blair, C. (2006). How similar are fluid cognition and general intelligence? A developmental neuroscience perspective on fluid cognition as an aspect of human cognitive ability. *The Behavioral and Brain Sciences*, *29*(2), 109–125; discussion 125–160. doi:10.1017/S0140525×06009034

Borsboom, D., Mellenbergh, G. J., & van Heerden, J. (2003). The theoretical status of latent variables. *Psychological Review*, *110*(2), 203–219.

Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, *108*(3), 624–652.

Braver, T. S., & Bongiolatti, S. R. (2002). The role of frontopolar cortex in subgoal processing during working memory. *NeuroImage*, *15*(3), 523–536. doi:10.1006/nimg.2001.1019

Bressler, S., & Menon, V. (2010). Large-scale brain networks in cognition: Emerging methods and principles. *Trends in Cognitive Sciences*, *14*, 277–290. doi:10.1016/j.tics.2010.04.004

Bullmore, E., & Sporns, O. (2009). Complex brain networks: Graph theoretical analysis of structural and functional systems. *Nature Reviews. Neuroscience*, *10*(3), 186–198. doi:10.1038/nrn2575

Bunting, M. (2006). Proactive interference and item similarity in working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*(2), 183–196. doi:10.1037/0278-7393.32.2.183

Burgess, G. C., Gray, J. R., Conway, A. R. A., & Braver, T. S. (2011). Neural mechanisms of interference control underlie the relationship between

fluid intelligence and working memory span. *Journal of Experimental Psychology. General*, *140*(4), 674–692. doi:10.1037/a0024695
Carpenter, P. A., Just, M. A., & Shell, P. (1990). What one intelligence test measures: A theoretical account of the processing in the Raven Progressive Matrices Test. *Psychological Review*, *97*(3), 404–431.
Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. Cambridge, UK: Cambridge University Press.
Case, R., Kurland, D. M., & Goldberg, J. (1982). Operational efficiency and the growth of short-term memory span. *Journal of Experimental Child Psychology*, *33*(3), 386–404. doi:10.1016/0022-0965(82)90054-6
Cattell, R. B. (1971). *Abilities: Their structure, growth, and action*. Boston, MA: Houghton Mifflin.
Chambers, C. D., Bellgrove, M. A., Stokes, M. G., Henderson, T. R., Garavan, H., Robertson, I. H., … Mattingley J. B. (2006). Executive "brake failure" following deactivation of human frontal lobe. *Journal of Cognitive Neuroscience*, *18*(3), 444–455. doi:10.1162/089892906775990606
Chein, J. M., Moore, A. B., & Conway, A. R. A. (2011). Domain-general mechanisms of complex working memory span. *NeuroImage*, *54*(1), 550–559. doi:10.1016/j.neuroimage.2010.07.067
Choi, Y. Y., Shamosh, N. A., Cho, S. H., DeYoung, C. G., Lee, M. J., Lee, J.-M., … Lee, K. H. (2008). Multiple bases of human intelligence revealed by cortical thickness and neural activation. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *28*(41), 10323–10329. doi:10.1523/JNEUROSCI.3259-08.2008
Chow, M., & Conway, A. R. A. (2015). The scope and control of attention: Sources of variance in working memory capacity. *Memory & Cognition*, *43*(3), 325–339. doi:10.3758/s13421-014-0496-9
Christoff, K., Prabhakaran, V., Dorfman, J., Zhao, Z., Kroger, J. K., Holyoak, K. J., & Gabrieli, J. D. (2001). Rostrolateral prefrontal cortex involvement in relational integration during reasoning. *NeuroImage*, *14*(5), 1136–1149. doi:10.1006/nimg.2001.0922
Chuderski, A. (2015). The broad factor of working memory is virtually isomorphic to fluid intelligence tested under time pressure. *Personality and Individual Differences*, *85*, 98–104. doi:10.1016/j.paid.2015.04.046
Cole, M. W., Pathak, S., & Schneider, W. (2010). Identifying the brain's most globally connected regions. *NeuroImage*, *49*(4), 3132–3148. doi:10.1016/j.neuroimage.2009.11.001
Cole, M. W., & Schneider, W. (2007). The cognitive control network: Integrated cortical regions with dissociable functions. *NeuroImage*, *37*(1), 343–360. doi:10.1016/j.neuroimage.2007.03.071
Cole, M., & Yarkoni, T. (2012). Global connectivity of prefrontal cortex predicts cognitive control and intelligence. *The Journal of Neuroscience*, *32*(26), 8988–8999. doi:10.1523/JNEUROSCI.0536-12.2012
Colom, R., Burgaleta, M., Martínez, K., Román, F. J., Álvarez-Linera, J., Quiroga, M. Á., … Privado, J. (2011). Consistency of intelligence in the brain. In *International Society for the Study of Individual Differences (ISSID) 2011 meeting*.
Colom, R., Burgaleta, M., Román, F. J., Karama, S., Álvarez-linera, J., Abad, F. J., … Haier R. J. (2013). Neuroanatomic overlap between intelligence and cognitive factors: Morphometry methods provide support for the key role of the frontal lobes. Paper presented at International Society for the Study of Individual Differences (ISSID), Barcelona, Spain, July 22–25. doi:10.1016/j.neuroimage.2013.01.032
Colom, R., Haier, R., & Head, K. (2009). Intelligence Gray matter correlates of fluid, crystallized, and spatial intelligence: Testing the P-FIT model. *Intelligence*, *37*(2), 124–135. doi:10.1016/j.intell.2008.07.007
Colom, R., Jung, R. E., & Haier, R. J. (2006a). Distributed brain sites for the g-factor of intelligence. *NeuroImage*, *31*(3), 1359–65. doi:10.1016/j.neuroimage.2006.01.006
Colom, R., Jung, R. E., & Haier, R. J. (2006b). Finding the g-factor in brain structure using the method of correlated vectors. *Intelligence*, *34*(6), 561–570. doi:10.1016/j.intell.2006.03.006
Conway, A. R. A., Cowan, N., & Bunting, M. F. (2001). The cocktail party phenomenon revisited: The importance of working memory capacity. *Psychonomic Bulletin & Review*, *8*(2), 331–335. doi:10.3758/BF03196169
Conway, A. R. A., Cowan, N., Bunting, M. F., Therriault, D. J., & Minkoff, S. R. (2002). A latent variable analysis of working memory capacity, short-term memory capacity, processing speed, and general fluid intelligence. *Intelligence*, *30*(2), 163–183. doi:10.1016/S0160-2896(01)00096-4
Conway, A. R. A., Kane, M. J., Bunting, M. F., Hambrick, D. Z., Wilhelm, O., & Engle, R. W. (2005). Working memory span tasks: A methodological review and user's guide. *Psychonomic Bulletin & Review*, *12*(5), 769–786. doi:10.3758/BF03196772
Conway, A. R. A., Kane, M. J., & Engle, R. W. (1999). Is Spearman's g determined by speed or working memory capacity? Book review of Jensen on Intelligence-g-Factor. *PSYCOLOQUY*, *10*(074).
Conway, A. R. A., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. *Trends in Cognitive Sciences*, *7*(12), 547–552. doi:10.1016/j.tics.2003.10.005
Conway, A. R. A., & Kovacs, K. (2013). Individual differences in intelligence and working memory. *Psychology of Learning and Motivation*, *58*, 233–270. doi:10.1016/B978-0-12-407237-4.00007-4
Conway, A. R. A., Macnamara, B., Getz, S., & Engel de Abreu, P. (2011). Working memory and fluid intelligence: A multi-mechanism view. In R. Sternberg & S. Kaufman (Eds.), *Cambridge handbook of intelligence* (pp. 394–418). New York, NY: Cambridge University Press.
Conway, A. R. A., Tuholski, S. W., Shisler, R. J., & Engle, R. W. (1999). The effect of memory load on negative priming: An individual differences investigation. *Memory & Cognition*, *27*(6), 1042–1050. doi:10.3758/BF03201233
Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews. Neuroscience*, *3*(3), 201–215. doi:10.1038/nrn755
Cowan, N., Elliott, E. M., Saults, S. J., Morey, C. C., Mattox, S., Hismjatullina, A., & Conway, A. R. A. (2005). On the capacity of attention: Its estimation and its role in working memory and cognitive aptitudes. *Cognitive Psychology*, *51*, 42–100. doi:10.1016/j.cogpsych.2004.12.001
Coyle, T. R. (2001). IQ is related to the worst performance rule in a memory task involving children. *Intelligence*, *29*(2), 117–129. doi:10.1016/S0160-2896(00)00044-1
Coyle, T. R. (2003a). IQ, the worst performance rule, and Spearman's law: A reanalysis and extension. *Intelligence*, *31*(5), 473–489. doi:10.1016/S0160-2896(02)00175-7
Coyle, T. R. (2003b). A review of the worst performance rule: Evidence, theory, and alternative hypotheses. *Intelligence*, *31*(6), 567–587. doi:10.1016/S0160-2896(03)00054-0
Coyle, T. R., & Rindermann, H. (2013). Spearman's Law of Diminishing Returns and national ability. *Personality and Individual Differences*, *55*(4), 406–410. doi:10.1016/j.paid.2013.03.023
Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. *Journal of Verbal Learning and Verbal Behavior*, *19*(4), 450–466. doi:10.1016/S0022-5371(80)90312-6
Deary, I. J., Penke, L., & Johnson, W. (2010). The neuroscience of human intelligence differences. *Nature Reviews. Neuroscience*, *11*(3), 201–211. doi:10.1038/nrn2793
Derrfuss, J., Brass, M., Neumann, J., & von Cramon, D. Y. (2005). Involvement of the inferior frontal junction in cognitive control: Meta-analyses of switching and Stroop studies. *Human Brain Mapping*, *25*(1), 22–34. doi:10.1002/hbm.20127
Detterman, D. K. (1987). Theoretical notions of intelligence and mental fretardation. *American Journal of Mental Deficiency*, *92*, 2–11.
Detterman, D. K. (1994). Theoretical possibilities: The relation of human intelligence to basic cognitive abilities. In D. K. Detterman (Ed.), *Current topics in human intelligence volume 4: Theories of intelligence* (pp. 85–115). Norwood, NJ: Ablex.
Detterman, D. K. (2000). General intelligence and the definition of phenotypes. In G. R. Bock, J. A. Goode, & K. Webb (Eds.), *The nature of intelligence* (pp. 136–143). New York, NY: Wiley & Sons.
Detterman, D. K., & Daniel, M. H. (1989). Correlations of mental tests with each other and with cognitive variables are highest for low IQ groups. *Intelligence*, *13*(4), 349–359. doi:10.1016/S0160-2896(89)80007-8
Dreher, J.-C., & Berman, K. F. (2002). Fractionating the neural substrate of cognitive control processes. *Proceedings of the National Academy of Sciences of the United States of America*, *99*, 14595–14600. doi:10.1073/pnas.222193299
Duncan, J. (1995). Attention, intelligence, and the frontal lobes. In M. S. Gazzaniga (Ed.), *The cognitive neurosciences* (pp. 721–733). Cambridge, MA: MIT Press.

Duncan, J. (2010, February). The multiple-demand (MD) system of the primate brain: Mental programs for intelligent behaviour. *Trends in Cognitive Sciences*, pp. 172–179. doi:10.1016/j.tics.2010.01.004

Duncan, J., Burgess, P., & Emslie, H. (1995). Fluid intelligence after frontal lobe lesions. *Neuropsychologia*, *33*(3), 261–268. doi:10.1016/0028-3932(94)00124-8

Duncan, J., Emslie, H., Williams, P., Johnson, R., & Freer, C. (1996). Intelligence and the frontal lobe: The organization of goal-directed behavior. *Cognitive Psychology*, *30*(3), 257–303. doi:10.1006/cogp.1996.0008

Duncan, J., & Owen, A. M. (2000). Common regions of the human frontal lobe recruited by diverse cognitive demands. *Trends in Neurosciences*, *23*(10), 475–483. doi:10.1016/S0166-2236(00)01633-7

Duncan, J., Parr, A., Woolgar, A., Thompson, R., Bright, P., Cox, S., … Nimmo-Smith, I. (2008). Goal neglect and Spearman's g: Competing parts of a complex task. *Journal of Experimental Psychology. General*, *137*, 131–148. doi:10.1037/0096-3445.137.1.131

Duncan, J., Schramm, M., Thompson, R., & Dumontheil, I. (2012). Task rules, working memory, and fluid intelligence. *Psychonomic Bulletin & Review*, *19*(5), 864–870. doi:10.3758/s13423-012-0225-y

Duncan, J., Seitz, J., Kolodny, J., Bor, D., Herzog, H., Ahmed, A., … Emslie, H. (2000, July). A neural basis for general intelligence. *Science*, *289*, 457–460.

Dutilh, G., Vandekerckhove, J., Forstmann, B. U., Keuleers, E., Brysbaert, M., & Wagenmakers, E.-J. (2012). Testing theories of post-error slowing. *Attention, Perception, & Psychophysics*, *74*, 454–465. doi:10.3758/s13414-011-0243-2

Dux, P. E., Ivanoff, J., Asplund, C. L., & Marois, R. (2006). Isolation of a central bottleneck of information processing with time-resolved FMRI. *Neuron*, *52*(6), 1109–1120. doi:10.1016/j.neuron.2006.11.009

Edwards, J. R. (2011). The Fallacy of Formative Measurement. *Organizational Research Methods*, *14*(2), 370–388. doi:10.1177/1094428110378369

Engle, R. W., & Kane, M. J. (2004). Executive attention, working memory capacity, and a two-factor theory of cognitive control. *The Psychology of Learning and Motivation*, *44*, 145–199.

Engle, R. W., Tuholski, S. W., Laughlin, J. E., & Conway, A. R. A. (1999). Working memory, short-term memory, and general fluid intelligence: A latent-variable approach. *Journal of Experimental Psychology. General*, *128*(3), 309–331.

Eysenck, H. J. (1987). Thomson's "bonds" or Spearman's "energy": Sixty years on. *Mankind Quarterly*, *27*, 259–274.

Eysenck, H. J. (1998). *Intelligence: A new look*. New Brunswick, NJ: Transaction.

Farooqui, A., Mitchell, D., Thompson, R., & Duncan, J. (2012). Hierarchical organization of cognition reflected in distributed frontoparietal activity. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *32*(48), 17373–17381. doi:10.1523/JNEUROSCI.0598-12.2012

Fedorenko, E., Duncan, J. & Kanwisher, N. (2013). Broad domain generality in focal regions of frontal and parietal cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *110*, 16616–16621. doi:10.1073/pnas.1315235110/-/DCSupplemental.www.pnas.org/cgi/doi/10.1073/pnas.1315235110

Flynn, J. R. (1998). Reply to Rushton: A gang of gs overpowers factor analysis. *Personality and Individual Differences*, *26*, 391–393.

Flynn, J. R. (2007). *What Is intelligence?: Beyond the Flynn Effect*. Cambridge, UK: Cambridge University Press.

Fukuda, K., Vogel, E., Mayr, U., & Awh, E. (2010). Quantity, not quality: The relationship between fluid intelligence and working memory capacity. *Psychonomic Bulletin & Review*, *17*, 673–679. doi:10.3758/17.5.673

Gläscher, J., Rudrauf, D., Colom, R., Paul, L. K., Tranel, D., Damasio, H., & Adolphs, R. (2010). Distributed neural system for general intelligence revealed by lesion mapping. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(10), 4705–4709. doi:10.1073/pnas.0910397107

Gold, J. M., Carpenter, C., Randolph, C., Goldberg, T. E., & Weinberger, D. R. (1997). Auditory Working Memory and Wisconsin Card Sorting Test performance in schizophrenia. *Archives of General Psychiatry*, *54*, 159–165. doi:10.1001/archpsyc.1997.01830140071013

Gray, J. R., Chabris, C. F., & Braver, T. S. (2003). Neural mechanisms of general fluid intelligence. *Nature Neuroscience*, *6*(3), 316–322. doi:10.1038/nn1014

Green, A. E., Fugelsang, J. a, Kraemer, D. J. M., Shamosh, N. A., & Dunbar, K. N. (2006). Frontopolar cortex mediates abstract integration in analogy. *Brain Research*, *1096*(1), 125–137. doi:10.1016/j.brainres.2006.04.024

Gustafsson, J.-E. (1984). A unifying model for the structure of intellectual abilities. *Intelligence*, *8*(3), 179–203. doi:10.1016/0160-2896(84)90008-4

Haier, R. J., Colom, R., Schroeder, D. H., Condon, C. A., Tang, C., Eaves, E., & Head, K. (2009). Intelligence Gray matter and intelligence factors: Is there a neuro-g? *Intelligence*, *37*(2), 136–144. doi:10.1016/j.intell.2008.10.011

Hampshire, A., Highfield, R. R., Parkin, B. L., & Owen, A. M. (2012). Fractionating human intelligence. *Neuron*, *76*(6), 1225–1237. doi:10.1016/j.neuron.2012.06.022

He, Y., & Evans, A. (2010). Graph theoretical modeling of brain connectivity. *Current Opinion in Neurology*, *23*(4), 341–350. doi:10.1097/WCO.0b013e32833aa567

Hebb, D. O. (1940). Human behavior after extensive bilateral removal from the frontal lobes. *Archives of Neurology And Psychiatry*, *44*(2), 421. doi:10.1001/archneurpsyc.1940.02280080181011

Heitz, R. P., Redick, T. S., Hambrick, D. Z., Kane, M. J., Conway, A. R. A., & Engle, R. W. (2006). Working memory, executive function, and general fluid intelligence are not the same. *Behavioral and Brain Sciences*, *29*(02), 135–136. doi:10.1017/S0140525×06319036

Henson, R. N. A. (2001). Neural working memory. In J. Andrade (Ed.), *Working memory in perspective* (pp. 151–173). New York: Psychology Press.

Heuvel, M. P. Van Den, & Pol, H. E. H. (2010). Exploring the brain network: A review on resting-state fMRI functional connectivity. *European Neuropsychopharmacology*, *20*(8), 519–534. doi:10.1016/j.euroneuro.2010.03.008

Heuvel, M. van den, & Stam, C. (2009). Efficiency of functional brain networks and intellectual performance. *The Journal of Neuroscience*, *29*, 7619–7624. doi:10.1523/JNEUROSCI.1443-09.2009

Horn, J. L. (1989). Cognitive diversity: A framework of learning. In P. L. Ackerman, R. J. Sternberg, & R. Glaser (Eds.), *Learning and individual differences* (pp. 61–116). New York, NY: W.H. Freeman.

Horn, J. L. (1994). Theory of fluid and crystallized intelligence. In R. Sternberg (Ed.), *Encyclopedia of Human Intelligence* (pp. 443–451). New York: MacMillan Reference Library.

Howell, R. D., Breivik, E., & Wilcox, J. B. (2007). Reconsidering formative measurement. *Psychological Methods*, *12*(2), 205–218. doi:10.1037/1082-989X.12.2.205

Jensen, A. R. (1981). Reaction time and intelligence. In M. Friedman, J. P. Das, & N. O'Connor (Eds.), *Intelligence and learning*. (pp. 39–50). New York: Plenum.

Jensen, A. R. (1982). Reaction time and psychometric g. In H. J., Eysenck (Ed.), *A model for intelligence* (pp. 93–132). New York: Springer Verlag.

Jensen, A. R. (1992). The importance of intraindividual variation in reaction time. *Personality and Individual Differences*, *13*(8), 869–881. doi:10.1016/0191-8869(92)90004-9

Jensen, A. R. (1998). *The g factor: The science of mental ability. East* (Vol. 17). Westport, CT: Praeger.

Jensen, A. R. (2000). "The g factor" is about variance in mental abilities, not a cognitive theory of mental structure. Reply to Anderson on Jensen on Intelligence-g-Factor. *PSYCOLOQUY*, *11*(041).

Johnson, W., & Bouchard, T. J. (2005). The structure of human intelligence: It is verbal, perceptual, and image rotation (VPR), not fluid and crystallized. *Intelligence*, *33*(4), 393–416. doi:10.1016/j.intell.2004.12.002

Jonides, J., Reuter-Lorenz, P. A., Smith, E. E., Awh, E., Barnes, L. L., Drain, M., & Al, E. (1996). Verbal and spatial working memory in humans. *Psychology of Learning and Motivation*, *35*, 43–88.

Juan-Espinosa, M., Cuevas, L., Escorial, S., & García, L. F. (2006). The differentiation hypothesis and the Flynn effect. *Psicothema*, *18*(2), 284–287.

Jung, R. E., & Haier, R. J. (2007). The Parieto-Frontal Integration Theory (P-FIT) of intelligence: Converging neuroimaging evidence. *The Behavioral and Brain Sciences*, *30*(2), 135–154; discussion 154–187. doi:10.1017/S0140525×07001185

Kan, K.-J., Kievit, R. A., Dolan, C., & van der Maas, H. L. J. (2011). On the interpretation of the CHC factor Gc. *Intelligence*, *39*(5), 292–302. doi:10.1016/j.intell.2011.05.003

Kane, H. (2000). A secular decline in Spearman's g: Evidence from the WAIS, WAIS-R and WAIS-III. *Personality and Individual Differences*, *29*, 561–566.

Kane, H. D., Oakland, T. D., & Brand, C. R. (2006). Differentiation at higher levels of cognitive ability: Evidence from the United States. *The Journal of Genetic Psychology*, *167*(3), 327–341. doi:10.3200/GNTP.167.3.327-341

Kane, H., & Oakland, T. D. (2000). Secular declines in Spearman's g: Some evidence from the United States. *The Journal of Genetic Psychology*, *161* (3), 337–345. doi:10.1080/00221320009596716

Kane, M., & Engle, R. (2000). Working-memory capacity, proactive interference, and divided attention: Limits on long-term memory retrieval. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(2), 336–358. doi:10.10371/0278-7393.26.2.336

Kane, M. J. (2005). Full frontal fluidity. In O. Wilhelm & R. Engle (Eds.), *Handbook of understanding and measuring intelligence* (pp. 141–165). Thousand Oaks, CA: Sage.

Kane, M. J., Bleckley, M. K., Conway, A. R. A., & Engle, R. W. (2001). A controlled-attention view of working-memory capacity. *Journal of Experimental Psychology: General*, *130*(2), 169–183. doi:10.1037/0096-3445.130.2.169

Kane, M. J., Conway, A. R. A., Miura, T. K., & Colflesh, G. J. H. (2007). Working memory, attention control, and the N-back task: A question of construct validity. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *33*(3), 615–622. doi:10.1037/0278-7393.33.3.615

Kane, M. J., Conway, A. R. A., Hambrick, D. Z., & Engle, R. W. (2007). Variation in working memory as variation in executive attention and control. In A. R. A. Conway, C. Jarrold, M. J. Kane, A. Miyake & J. N. Towse (Eds.),*Variation in working memory*. New York: Oxford University Press.

Kane, M. J., & Engle, R. W. (2002). The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective. *Psychonomic Bulletin & Review*, *9*(4), 637–671.

Kane, M. J., & Engle, R. W. (2003). Working-memory capacity and the control of attention: The contributions of goal neglect, response competition, and task set to Stroop interference. *Journal of Experimental Psychology: General*, *132*(1), 47–70. doi:10.1037/0096-3445.132.1.47

Kane, M. J., Hambrick, D. Z., & Conway, A. R. A. (2005). Working memory capacity and fluid intelligence are strongly related constructs: Comment on Ackerman, Beier, and Boyle (2005). *Psychological Bulletin*, *131*, 66–71; author reply 72–75. doi:10.1037/0033-2909.131.1.66

Kane, M. J., Hambrick, D. Z., Tuholski, S. W., Wilhelm, O., Payne, T. W., & Engle, R. W. (2004). The generality of working memory capacity: A latent-variable approach to verbal and visuospatial memory span and reasoning. *Journal of Experimental Psychology. General*, *133*(2), 189–217. doi:10.1037/0096-3445.133.2.189

Kaufman, S. B., DeYoung, C. G., Gray, J. R., Brown, J., & Mackintosh, N. (2009). Associative learning predicts intelligence above and beyond working memory and processing speed. *Intelligence*, *37*(4), 374–382. doi:10.1016/j.intell.2009.03.004

Kievit, R. A., Davis, S. W., Mitchell, D. J., Taylor, J. R., Duncan, J., & Henson, R. N. A. (2014). Distinct aspects of frontal lobe structure mediate age-related differences in fluid intelligence and multitasking. *Nature Communications*, *5*, 56–58. doi:10.1038/ncomms6658

Kievit, R. A., Rooijen, H. van, Wicherts, J. M., Waldorp, L. J., Kan, K.-J., Scholte, H. S., & Borsboom, D. (2012). Intelligence and the brain: A model-based approach. *Cognitive Neuroscience*, *3*(2), 89–97. doi:10.1080/17588928.2011.628383

Kievit, R. A., Scholte, H. S., Waldorp, L. J. & Borsboom, D. (2016). Inter- and intra-individual differences in fluid reasoning show distinct cortical responses. *bioRxiv*, preprint. doi:10.1101/039412

Koechlin, E., & Hyafil, A. (2007). Anterior Prefrontal Function and the Limits of Human Decision-Making. *Science*, *318*(5850), 594–598.

Kovacs, K. (2009). A component process account of the general factor of intelligence. Unpublished PhD thesis. University of Cambridge.

Kovacs, K., Plaisted, K. C., & Mackintosh, N. J. (2006). Difficulties differentiating dissociations. *Behavioral and Brain Sciences*, *29*(02), 138–139. doi:10.1017/S0140525×06349035

Kovacs, K., Rozsa, S., Ko, N., Meszaros, A., Mlinko, R., Kuncz, E., Nagyne Rez, I., Lanyine Engelmayer, A. (2016). Forward and backward digit span measure different cognitive abilities. Manuscript submitted for publication.

Kranzler, J. H. (1992). A test of Larson and Alderton's (1990) worst performance rule of reaction time variability. *Personality and Individual Differences*, *13*(3), 255–261. doi:10.1016/0191-8869(92)90099-B

Kranzler, J. H., & Jensen, A. R. (1991). The nature of psychometric g: Unitary process or a number of independent processes? *Intelligence*, *15*(4), 397–422. doi:10.1016/0160-2896(91)90003-V

Kranzler, J. H., & Jensen, A. R. (1993). Psychometric g is still not unitary after eliminating supposed "impurities": Further comment on Carroll. *Intelligence*, *17*(1), 11–14. doi:10.1016/0160-2896(93)90033-2

Krijnen, W. P. (2004). Positive loadings and factor correlations from positive covariance matrices. *Psychometrika*, *69*(4), 655–660. doi:10.1007/BF02289861

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

Larson, G. E., & Alderton, D. L. (1990). Reaction time variability and intelligence: A "worst performance" analysis of individual differences. *Intelligence*, *14*(3), 309–325. doi:10.1016/0160-2896(90)90021-K

Lehto, J. (1996). Are executive function tests dependent on working memory capacity? *The Quarterly Journal of Experimental Psychology A*, *49*, 29–50. doi:10.1080/027249896392793

Lehto, J. E., Juujärvi, P., Kooistra, L., & Pulkkinen, L. (2003). Dimensions of executive functioning: Evidence from children. *British Journal of Developmental Psychology*, *21*(1), 59–80. doi:10.1348/026151003321164627

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*, 279–281. doi:10.1038/36846

Luo, Q., Perry, C., Peng, D., Jin, Z., Xu, D., Ding, G., & Xu, S. (2003). The neural substrate of analogical reasoning: An fMRI study. *Brain Research. Cognitive Brain Research*, *17*(3), 527–534.

Lynn, R., & Cooper, C. (1993). A secular decline in Spearman's g in France. *Learning and Individual Differences*, *5*(1), 43–48.

Lynn, R., & Cooper, C. (1994). A secular decline in the strength of Spearman'sg in Japan. *Current Psychology*, *13*(1), 3–9.

MacDonald, A. W. (2000). Dissociating the role of the dorsolateral prefrontal and anterior cingulate cortex in cognitive control. *Science*, *288* (5472), 1835–1838. doi:10.1126/science.288.5472.1835

Mackintosh, N., & Bennett, E. (2002). IT, IQ and perceptual speed. *Personality and Individual Differences*, *32*(4), 685–693. doi:10.1016/S0191-8869(01)00069-1

Mackintosh, N. J. (1998). *IQ and human intelligence (first edition)*. Oxford, UK: Oxford University Press.

Mackintosh, N. J. (2008). Sex differences and IQ. *Journal of Biosocial Science*, *28*(04), 558–571. doi:10.1017/S0021932000022586

Mackintosh, N. J. (2011a). History of theories and measurement of intelligence. In R. Sternberg & S. Kaufman (Eds.), *Cambridge handbook of intelligence* (pp. 3–19). New York, NY: Cambridge University Press.

Mackintosh, N. J. (2011b). *IQ and human intelligence*. Oxford, UK: Oxford University Press.

Major, J. T., Johnson, W., & Bouchard, T. J. (2011). The dependability of the general factor of intelligence: Why small, single-factor models do not adequately represent g. *Intelligence*, *39*(5), 418–433. doi:10.1016/j.intell.2011.07.002

Marois, R., & Ivanoff, J. (2005). Capacity limits of information processing in the brain. *Trends in Cognitive Sciences*, *9*(6), 296–305. doi:10.1016/j.tics.2005.04.010

Matzke, D., Dolan, C. V., & Molenaar, D. (2010). The issue of power in the identification of "g" with lower-order factors. *Intelligence*, *38*(3), 336–344. doi:10.1016/j.intell.2010.02.001

Maxwell, A. E. (1972). Factor analysis: Thomson's sampling theory recalled. *British Journal of Mathematical and Statistical Psychology*, *25* (1), 1–21. doi:10.1111/j.2044-8317.1972.tb00474.x

McCabe, D. P., Roediger, H. L., McDaniel, M. A., Balota, D. A., & Hambrick, D. Z. (2010). The relationship between working memory capacity and executive functioning: Evidence for a common executive attention construct. *Neuropsychology*, *24*(2), 222–243. doi:10.1037/a0017619

McFarland, D. J. (2012). A single g factor is not necessary to simulate positive correlations between cognitive tests. *Journal of Clinical* *and Experimental Neuropsychology*, *34*(4), 378–384. doi:10.1080/13803395.2011.645018

McGrew, K. S. (2009). CHC theory and the human cognitive abilities project: Standing on the shoulders of the giants of psychometric intelligence research. *Intelligence*, *37*(1), 1–10. doi:10.1016/j.intell.2008.08.004

Miele, F. (2002). *Intelligence, race, and genetics. Conversations with Arthur R. Jensen.* Boulder, CO: Westview Press.

Miller, B. T., & D'Esposito, M. (2005). Searching for "the top" in top-down control. *Neuron*, *48*(4), 535–538. doi:10.1016/j.neuron.2005.11.002

Miller, E. K. (2000). The prefrontal cortex and cognitive control. *Nature Reviews. Neuroscience*, *1*(1), 59–65. doi:10.1038/35036228

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, *24*, 167–202. doi:10.1146/annurev.neuro.24.1.167

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "Frontal Lobe" tasks: A latent variable analysis. *Cognitive Psychology*, *41*, 49–100. doi:10.1006/cogp.1999.0734

Miyake, A., Friedman, N. P., Rettinger, D. A., Shah, P., & Hegarty, M. (2001). How are visuospatial working memory, executive functioning, and spatial abilities related? A latent-variable analysis. *Journal of Experimental Psychology: General*, *130*, 621–640. doi:10.1037/0096-3445.130.4.621

Molenaar, D., Dolan, C. V., Wicherts, J. M., & van der Maas, H. L. J. (2010). Modeling differentiation of cognitive abilities within the higher-order factor model using moderated factor analysis. *Intelligence*, *38*(6), 611–624. doi:10.1016/j.intell.2010.09.002

Molenaar, P. C. M., & Campbell, C. G. (2009). The New Person-Specific Paradigm in Psychology. *Current Directions in Psychological Science*, *18* (2), 112–117. doi:10.1111/j.1467-8721.2009.01619.x

Mueller, S., Wang, D., Fox, M. D., Yeo, B. T. T., Sepulcre, J., Sabuncu, M. R., … Liu, H. (2013). Individual variability in functional connectivity architecture of the human brain. *Neuron*, *77*(3), 586–595. doi:10.1016/j.neuron.2012.12.028

Mukunda, K. V., & Hall, V. C. (1992). Does performance on memory for order correlate with performance on standardized measures of ability? A meta-analysis. *Intelligence*, *16*(1), 81–97. doi:10.1016/0160-2896(92)90026-N

Must, O., Must, A., & Raudik, V. (2003). The secular rise in IQs: In Estonia, the Flynn effect is not a Jensen effect. *Intelligence*, *31*(5), 461–471. doi:10.1016/S0160-2896(03)00013-8

Négyessy, L., Bányai, M., Nepusz, T., & Bazsó, F. (2012). What makes the prefrontal cortex so appealing in the era of brain imaging? A network analytical perspective. *Acta Biologica Hungarica*, *63*, 38–53. doi:10.1556/ABiol.63.2012.Suppl.1.5

Niendam, T., Laird, A., & Ray, K. (2012). Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. *Cognitive, Affective, & Behavioral Neuroscience*, *12*(2), 241–268. doi:10.3758/s13415-011-0083-5.Meta-analytic

Oberauer, K. (2004). The measurement of working memory capacity. In O. Wilhelm & R. W. Engle (Eds.), *Handbook of understanding and measuring intelligence* (pp. 393–408). London, UK: Sage.

Oberauer, K., Schulze, R., Wilhelm, O., & Süss, H.-M. (2005). Working memory and intelligence—Their correlation and their relation: Comment on Ackerman, Beier, and Boyle (2005). *Psychological Bulletin*, *131*, 61–65; author reply 72–75. doi:10.1037/0033-2909.131.1.61

Oberauer, K., Süß, H.-M., Wilhelm, O., & Wittman, W. W. (2003). The multiple faces of working memory: Storage, processing, supervision, and coordination. *Intelligence*, *60*, 167–193. doi:10.1016/S0160-2896(02)00115-0

Parkin, A. (1998). The central executive does not exist. *Journal of the International Neuropsychological Society*, *4*, 518–22. doi:10.1017/s1355617798005128

Penke, L., Maniega, S. M., Bastin, M. E., Valdés Hernández M. C., Murray, C., Royle, N. A., … Deary, I. J. (2012). Brain white matter tract integrity as a neural foundation for general intelligence. *Molecular Psychiatry*, *17* (10), 1026–1030. doi:10.1038/mp.2012.66

Pollack, I., Johnson, L. B., & Knaff, P. R. (1959). Running memory span. *Journal of Experimental Psychology*, *57*, 137–146. doi:10.1037/h0046137

Prabhakaran, V., Smith, J. A, Desmond, J. E., Glover, G. H., & Gabrieli, J. D. (1997). Neural substrates of fluid reasoning: An fMRI study of neocortical activation during performance of the Raven's Progressive Matrices Test. *Cognitive Psychology*, *33*(1), 43–63. doi:10.1006/cogp.1997.0659

Rabaglia, C., Marcus, G., & Lane, S. (2011). What can individual differences tell us about the specialization of function? *Cognitive Neuropsychology*, *28*, 37–41.

Rabbitt, P. M. A. (1997). Introduction: Methodologies and models in the study of executive function. In P. M. A. Rabbitt (Ed.), *Methodology of frontal and executive function* (pp. 1–38). East Sussex, UK: Psychology Press.

Reckase, M. D. (2009). *Multidimensional item response theory*. New York, NY: Springer-Verlag.

Robbins, T. W. (1996). Dissociating executive functions of the prefrontal cortex. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *351*, 1463–1470; discussion 1470–1471. doi:10.1098/rstb.1996.013

Román, F. J., Abad, F. J., Escorial, S., Burgaleta, M., Martínez, K., Alvarez-Linera, J., … Colom, R. (2014). Reversed hierarchy in the brain for general and specific cognitive abilities: A morphometric analysis. *Human Brain Mapping*, *35*, 3805–3818. doi:10.1002/hbm.22438

Rushton, J. (1999). Secular gains in IQ not related to the g factor and inbreeding depression Ð unlike Black-White differences: A reply to Flynn. *Personality and Individual Differences*, *26*, 381–389.

Salthouse, T. A., Atkinson, T. M., & Berish, D. E. (2003). Executive functioning as a potential mediator of age-related cognitive decline in normal adults. *Journal of Experimental Psychology. General*, *132*(4), 566–594. doi:10.1037/0096-3445.132.4.566

Santarnecchi, E., & Galli, G. (2014). Efficiency of weak brain connections support general cognitive functioning. *Human Brain*, *35*, 4566–4582. doi:10.1002/hbm.22495

Shipstead, Z., Redick, T. S., Hicks, K. L., & Engle, R. W. (2012). The scope and control of attention as separate aspects of working memory. *Memory*, *20*, 608–662. doi:10.1080/09658211.2012.691519

Sohn, M. H., Ursu, S., Anderson, J. R., Stenger, V. A., & Carter, C. S. (2000). The role of prefrontal cortex and posterior parietal cortex in task switching. *Proceedings of the National Academy of Sciences of the United States of America*, *97*(24), 13448–13453. doi:10.1073/pnas.240460497

Song, M., Zhou, Y., Li, J., Liu, Y., Tian, L., Yu, C., & Jiang, T. (2008). Brain spontaneous functional connectivity and intelligence. *Neuroimage*, *41*, 1168–1176. doi:10.1016/j.neuroimage.2008.02.036

Spearman, C. (1904). "General intelligence," Objectively determined and measured. *The American Journal of Psychology*, *15*(2), 201–292. doi:10.2307/1412107

Spearman, C. (1927). *The abilities of Man: Their nature and measurement*. New York: Macmillan.

Sporns, O. (2002). Network analysis, complexity, and brain function. *Complexity*, *8*(1), 56–60.

Sporns, O., Honey, C., & Kötter, R. (2007). Identification and classification of hubs in brain networks. *PloS One*, *10*. doi:10.1371/Citation

Spreng, R. N., Sepulcre, J., Turner, G. R., Stevens, W. D., & Schacter, D. L. (2013). Intrinsic architecture underlying the relations among the default, dorsal attention, and frontoparietal control networks of the human brain. *Journal of Cognitive Neuroscience*, *25*(1), 74–86. doi:10.1162/jocn_a_00281

St Clair-Thompson, H. L., & Gathercole, S. E. (2006). Executive functions and achievements in school: Shifting, updating, inhibition, and working memory. *Quarterly Journal of Experimental Psychology*, *59*(4), 745–759. doi:10.1080/17470210500162854

Stuss, D. T., & Alexander, M. P. (2000). Executive functions and the frontal lobes: A conceptual view. *Psychological Research*, *63*(3–4), 289–298.

Süß, H. M., Oberauer, K., Wittmann, W. W., Wilhelm, O., & Schulze, R. (2002). Working-memory capacity explains reasoning ability—And a little bit more. *Intelligence*, *30*, 261–288. doi:10.1016/S0160-2896(01)00100-3

Thomson, G. H. (1916). A hierarchy without a general factor. *British Journal of Psychology, 1904-1920*, *8*, 271–281. doi:10.1111/j.2044-8295.1916.tb00133.x

Thurstone, L. L. (1938). *Primary mental abilities*. Chicago, IL: University of Chicago Press.

Toga, A., Clark, K., & Thompson, P. (2012). Mapping the human connectome. *Neurosurgery*, *71*(1), 1–5.

Tombu, M. N., Asplund, C. L., Dux, P. E., Godwin, D., Martin, J. W., & Marois, R. (2011). A unified attentional bottleneck in the human brain. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(33), 13426–13431. doi:10.1073/pnas.1103583108

Turner, M. L., & Engle, R. W. (1989). Is working memory capacity task dependent? *Journal of Memory and Language*, *28*(2), 127–154. doi:10.1016/0749-596X(89)90040-5

Unsworth, N., & Engle, R. W. (2006). Simple and complex memory spans and their relation to fluid abilities: Evidence from list-length effects. *Journal of Memory and Language*, *54*, 68–80. doi:10.1016/j.jml.2005.06.003

Unsworth, N., & Engle, R. W. (2007). The nature of individual differences in working memory capacity: Active maintenance in primary memory and controlled search from secondary memory. *Psychological Review*, *114*(1), 104–132. doi:10.1037/0033-295X.114.1.104

van der Maas, H. L. J., Dolan, C. V., Grasman, R. P. P. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. J. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, *113*(4), 842–861. doi:10.1037/0033-295X.113.4.842

van der Maas, H. L. J., Kan, K.-J., & Borsboom, D. (2014). intelligence is what the intelligence test measures. Seriously. *Journal of Intelligence*, *2* (1), 12–15. doi:10.3390/jintelligence2010012

Vicari, S., Bellucci, S., & Carlesimo, G. A. (2007). Visual and spatial working memory dissociation: Evidence from Williams syndrome. *Developmental Medicine & Child Neurology*, *45*(4), 269–273. doi:10.1111/j.1469-8749.2003.tb00342.x

Vincent, J. L., Kahn, I., Snyder, A. Z., Raichle, M. E., & Buckner, R. L. (2008). Evidence for a frontoparietal control system revealed by intrinsic functional connectivity. *Journal of Neurophysiology*, *100*(6), 3328–3342. doi:10.1152/jn.90355.2008

Voelkle, M. C., Brose, A., Schmiedek, F., & Lindenberger, U. (2014). Toward a unified framework for the study of between-person and within-person structures: Building a bridge between two research paradigms. *Multivariate Behavioral Research*, *49*(3), 193–213. doi:10.1080/00273171.2014.889593

Volle, E., Gilbert, S. J., Benoit, R. G., & Burgess, P. W. (2010). Specialization of the rostral prefrontal cortex for distinct analogy processes. *Cerebral Cortex (New York, N.Y. : 1991)*, *20*(11), 2647–2659. doi:10.1093/cercor/bhq012

Wager, T. O. R. D., & Smith, E. E. (2003). Neuroimaging studies of working memory: A meta-analysis. *Cognitive, Affective, & Behavioral Neuroscience*, *3*(4), 255–274.

Waltz, J. A., Knowlton, B. J., Holyoak, K. J., Boone, K. B., Mishkin, F. S., de Menezes Santos, M., … Miller, B. L. (1999). A System for Relational Reasoning in Human Prefrontal Cortex. *Psychological Science*, *10*(2), 119–125. doi:10.1111/1467-9280.00118

Wang, P. P., & Bellugi, U. (1994). Evidence from two genetic syndromes for a dissociation between verbal and visual-spatial short-term memory. *Journal of Clinical and Experimental Neuropsychology*, *16*(2), 317–322. doi:10.1080/01688639408402641

Weinstein, S., & Teuber, H.-L. (1957). Effects of penetrating brain injury on intelligence test scores. *Science*, *125*, 1036–1037. doi:10.1126/science.125.3256.1036

Wendelken, C., Nakhabenko, D., Donohue, S. E., Carter, C. S., & Bunge, S. A. (2008). "Brain is to thought as stomach is to ??": Investigating the role of rostrolateral prefrontal cortex in relational reasoning. *Journal of Cognitive Neuroscience*, *20*(4), 682–693. doi:10.1162/jocn.2008.20055

Wharton, C. M., Grafman, J., Flitman, S. S., Hansen, E. K., Brauner, J., Marks, A., & Honda, M. (2000). Toward neuroanatomical models of analogy: A positron emission tomography study of analogical mapping. *Cognitive Psychology*, *40*(3), 173–197. doi:10.1006/cogp.1999.0726

Wiley, J., & Jarosz, A. (2011). New rule use drives the relation between working memory capacity and Raven's Advanced Progressive Matrices. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *37*(1), 256–263. doi:10.1037/a0021613

Woolgar, A., Parr, A., Cusack, R., Thompson, R., Nimmo-Smith, I., Torralva, T., … Duncan, J. (2010). Fluid intelligence loss linked to restricted regions of damage within frontal and parietal cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(33), 14899–14902. doi:10.1073/pnas.1007928107