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Attention control and process overlap theory: Searching for cognitive processes underpinning the positive manifold

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ABSTRACT

Process overlap theory provides a contemporary explanation for the positive correlations observed among cognitive ability measures, a phenomenon which intelligence researchers refer to as the positive manifold. According to process overlap theory, cognitive tasks tap domain-general executive processes as well as domain-specific processes, and correlations between measures reflect the degree of overlap in the cognitive processes that are engaged when performing the tasks. In this article, we discuss points of agreement and disagreement between the executive attention framework and process overlap theory, with a focus on attention control: the domain-general ability to maintain focus on task-relevant information and disengage from irrelevant and no-longer relevant information. After describing the steps our lab has taken to improve the measurement of attention control, we review evidence suggesting that attention control can explain many of the positive correlations between broad cognitive abilities, such as fluid intelligence, working memory capacity, and sensory discrimination ability. Furthermore, when these latent variables are modeled under a higher-order *g* factor, attention control has the highest loading on *g*, indicating a strong relationship between attention control and domain-general cognitive ability. In closing, we reflect on the challenge of directly measuring cognitive processes and provide suggestions for future research.

Over a century of research has established that measures of cognitive ability correlate positively with one another, a phenomenon which intelligence researchers refer to as the *positive manifold* (Spearman, 1904, 1927). Simply put, people who perform poorly on one cognitive ability test tend to perform below average on other tests, too (Carroll, 1993; Jensen, 1998). This maxim holds for tests measuring different broad cognitive abilities, such as knowledge (i.e., crystallized intelligence), reasoning (i.e., fluid intelligence), and memory (i.e., working memory capacity), as well as for tests tapping different content areas, such as math, verbal, or visuospatial skills. The critical question is not *whether* the positive manifold exists, but *why*.

From a statistical perspective, the positive correlations observed among broad cognitive abilities can be explained by a unitary, higher-order latent factor, known as *g* (Fig. 1). The *g*-factor represents general intelligence, and it is one of the best variables in the differential psychologist's toolkit for predicting real-world outcomes such as academic achievement, job performance, occupational attainment, income, and, to a lesser degree, relationship satisfaction, health behaviors, and mortality (e.g., Brown, Wai, & Chabris, 2021). Obviously, *g* is important, whatever it is. But by itself, the *g*-factor is merely a statistical description of the positive manifold—not a psychological explanation. A psychological explanation would require researchers and theorists to identify the cognitive processes that underlie *g*, describe why some cognitive abilities are more closely related to *g* than others, and explain why some cognitive ability measures "cluster" together, such that groups of tests correlate more strongly among themselves than with other measures.

In this article, we review two theoretical frameworks that provide explanations for the positive manifold: process overlap theory (Kovacs & Conway, 2016, 2019a, 2019b) and the executive attention framework (Burgoyne & Engle, 2020; Kane & Engle, 2002; Shipstead, Harrison, & Engle, 2016). In the following sections, we describe each theoretical account and identify points of agreement and disagreement between them. We also discuss challenges associated with testing each theory and conduct re-analyses of data showing that attention control and the *g*-factor are closely entwined. Finally, we provide directions for future research aimed at testing each theory.

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1. Process overlap theory

One hypothesis that has been suggested as an explanation for the positive manifold is that all cognitive ability tests tap a combination of domain-specific and domain-general cognitive processes. *Domain-specific processes* are cognitive operations which uniquely contribute to a particular ability or content area. At a conceptual level, one could imagine a set of cognitive processes that are specifically relevant to verbal test items, and another set of cognitive processes that are relevant to numerical reasoning items. *Domain-general processes*, on the other hand, are cognitive operations that can be brought to bear on a wide variety of tasks. Domain-general processes are not bound to a particular content area or broad cognitive ability; for example, they are important for solving verbal questions, numerical problems, and visuospatial items. Broadly speaking, these premises form the basis of a "sampling theory" of intelligence (Thomson, 1916), and are consistent with a modern sampling theory known as "process overlap theory" (Kovacs & Conway, 2016, 2019a, 2019b).

According to process overlap theory, all cognitive tests draw from the same pool of domain-general processes, leading to the positive correlations observed across different assessments of cognitive ability. However, only tests that measure the same cognitive ability or content area also tap the same domain-specific processes, which leads to the "clustering" or grouping of similar tests typically observed in factor-analytic work (see Fig. 1). In other words, the strength of the correlation between two measures of cognitive performance is determined—at least in part—by the degree of overlap in the domain-general and domain-specific cognitive processes that are engaged when performing the tasks. Beyond explaining the clustering of ability measures, this idea also provides a parsimonious explanation for why some broad cognitive abilities, notably fluid intelligence, are more strongly related to the *g*-factor than others; they draw more heavily on domain-general processes and less so on domain-specific ones, meaning that more of their variance is shared with other abilities. This would lead to larger loadings on a general factor.

Process overlap theory posits that domain-general cognitive processes play a critical role in overall cognitive functioning. In fact, they are described as creating a "bottleneck" for information processing (Kovacs & Conway, 2019b, p. 190). In other words, someone with low domain-general abilities will likely perform poorly on all kinds of cognitive tests, regardless of whether they have sufficient domain-specific abilities for a particular test item. For example, an individual with strong verbal skills (i.e., a domain-specific ability) may struggle on a reading comprehension test if they lack the domain-general ability to control their attention when confronted with a long passage of text. By contrast, individuals with sufficiently high domain-general abilities are more likely to get a test item wrong because they lack the domain-specific ability relevant to the problem at hand. For instance, they may have no trouble focusing while reading a long passage, but instead struggle because they lack the requisite vocabulary to understand its content. Essentially, domain-specific strengths and weaknesses are revealed when individuals have sufficient domain-general ability for domain-specific factors to matter. Process overlap theory therefore provides an explanation for Spearman's (1927) "Law of Diminishing Returns," the observation that *g* explains more variance in the positive manifold in lower-ability samples than in higher-ability samples (Blum & Holling, 2017; Kovacs, Molenaar, & Conway, 2019). Performance on a test battery is more multiply-determined in samples with higher domain-general ability than in lower-ability samples, meaning that the *g*-factor is comparatively less "important" in samples with higher domain-general ability.

But what *are* the domain-general processes that give rise to the positive manifold? According to process overlap theory, "cognitive tests tap domain-general *executive processes, identified primarily in research on working memory*," and these executive processes are brought to bear in an overlapping fashion across a variety of cognitive tasks, explaining their positive correlations (Kovacs & Conway, 2016, p. 151, italics added). Kovacs and Conway (2016) name some of the cognitive processes that appear to play a role in working memory capacity tasks, including "goal maintenance, selective attention, and interference resolution (inhibition)," a point we return to below (p. 158). However, it is worth noting that this line of reasoning raises a distinction across levels of analysis: *g* is unitary from a psychometric or statistical perspective—that is, a single latent factor explains (or emerges as a result of) the positive manifold; but *g* is not unitary at the level of the brain—according to process overlap theory, *g* is the result of a number of independent domain-general processes, a distinction which Gottfredson (2016) notes can be traced back to Spearman (1927).

Because process overlap theory suggests that the positive manifold is the result of many domain-general processes, Kovacs and Conway (2016) state that the *g*-factor should not be "interpreted as a psychological construct of any kind" (p. 171). This is not a novel concept in intelligence research (Gottfredson, 2016). What contrasts process overlap theory with many other established theories of intelligence,

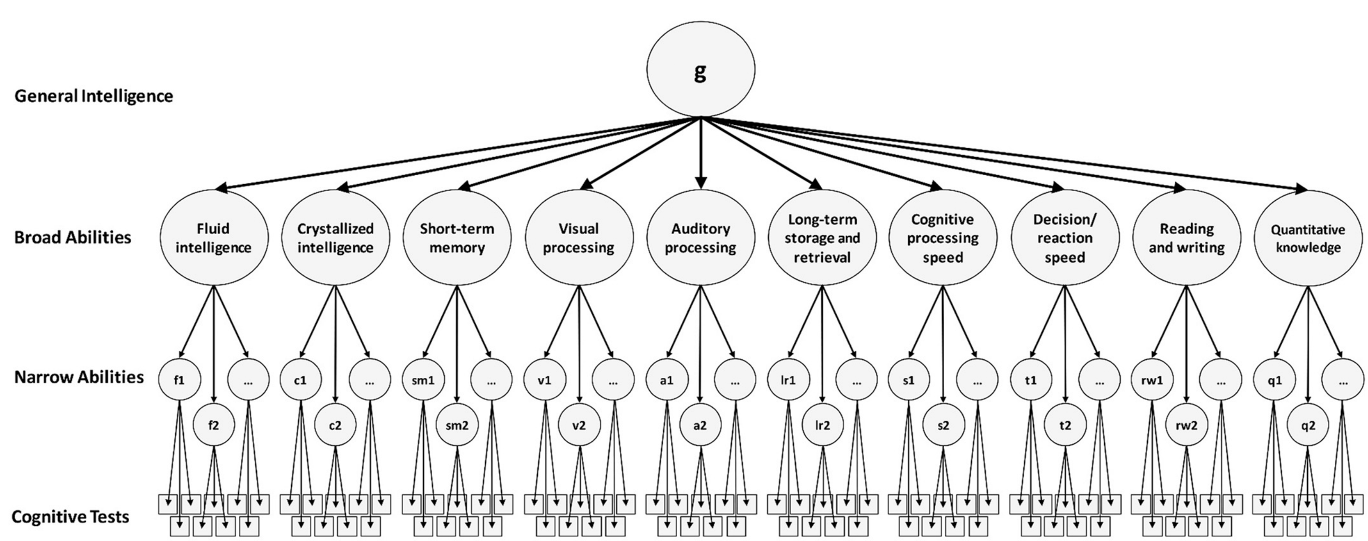

Fig. 1. Hierarchical factor structure of intelligence based on the Cattell-Horn-Carroll (CHC) framework (for a review and discussion of differences between the Carroll and Cattell-Horn models, see McGrew, 2009). Ovals represent latent factors; rectangles represent observed measures (i.e., measures of performance on cognitive tests). Ellipses (…) indicate that there are more narrow abilities than could be depicted.

however, is that the *g*-factor is re-envisioned as a "formative" variable, rather than a reflective latent factor. Stated differently, whereas many models of intelligence depict a higher-order *g*-factor with arrows leading from it to broad cognitive abilities (as in Fig. 1), thereby tacitly assuming a causal role for *g* in the generation of the positive manifold, the model proposed by process overlap theory draws the arrows in the opposite direction, originating from broad cognitive abilities and pointing towards *g* (see Fig. 2). In short, *g* is not hypothesized to cause the positive manifold, but rather, emerges as a necessary algebraic consequence of it.

Statistical modeling cannot adjudicate whether *g* is better specified as a reflective latent factor (i.e., Fig. 1) or a formative variable (i.e., Fig. 2). Despite process overlap theory's argument that *g* should be considered formative, our position is that the theory's tenets are readily interpretable within a reflective framework. Specifically, process overlap theory argues that 1) there are domain-general executive processes that play a role in all sorts of cognitive tasks, and 2) these domain-general executive processes *cause* performance on cognitive tasks to correlate positively with one another. Given the hypothesized direction of causality implied by the preceding statements, it seems reasonable to model the *g* factor as a reflective latent factor, with paths leading from *g* to broad cognitive abilities.

As counterpoint, process overlap theory argues that the distinction between whether a factor should be considered reflective or formative should be based on different grounds: the *reality* of the ability being represented. Kovacs and Conway (2016) argue that only the *g*-factor should be considered formative, and that broad abilities should be thought of as reflective. Specifically, they state: "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*" (p. 162, italics added). It is not clear how fluid intelligence, which is depicted in Fig. 2 as exclusively sampling domain-general executive processes, is more *real* than *g*, which also exclusively comprises domain-general executive processes in their model. Further complicating matters, fluid intelligence and the *g*-factor often correlate nearly perfectly with one another (Kovacs & Conway, 2016). Greater elaboration may be warranted on the distinction between fluid intelligence and the *g*-factor according to process overlap theory, as well as the rationale for why *g* is considered a formative variable while fluid intelligence is considered reflective.

2. Attention control

With a few notable exceptions, such as the preceding comment about whether *g* should be thought of as a reflective or formative variable, process overlap theory broadly aligns with our perspective on intelligence. Our laboratory has argued that the domain-general ability to control one's attention plays a role in a variety of cognitive functions, from learning and reasoning to memory and multitasking (Burgoyne & Engle, 2020; Burgoyne, Mashburn, Tsukahara, Hambrick, & Engle, 2021). We define *attention control* as the ability to focus on task-relevant information while resisting interference and distraction by task-irrelevant thoughts and events. Borne out of research on working memory, attention control has also been referred to as *executive attention*, *cognitive control*, and more generally, *executive functioning* (Kane & Engle, 2002). Attention control supports goal-directed behavior, and is particularly important in circumstances in which one's objective runs 'upstream' against a current of automatic impulses, sensory overload, or a maelstrom of divergent thought. For example, individual differences in the ability to control attention have been shown to predict self-control (Broadway, Redick, & Engle, 2010), emotional regulation (Schmeichel & Demaree, 2010), and task engagement (Miller & Cohen, 2001), revealing far-reaching effects of attention control on everyday functioning and performance. In general, the control of attention is thought to be effortful, and therefore constitutes mental work (Burgoyne, Tsukahara, Draheim, & Engle, 2020).

We have argued that the ability to control attention supports two

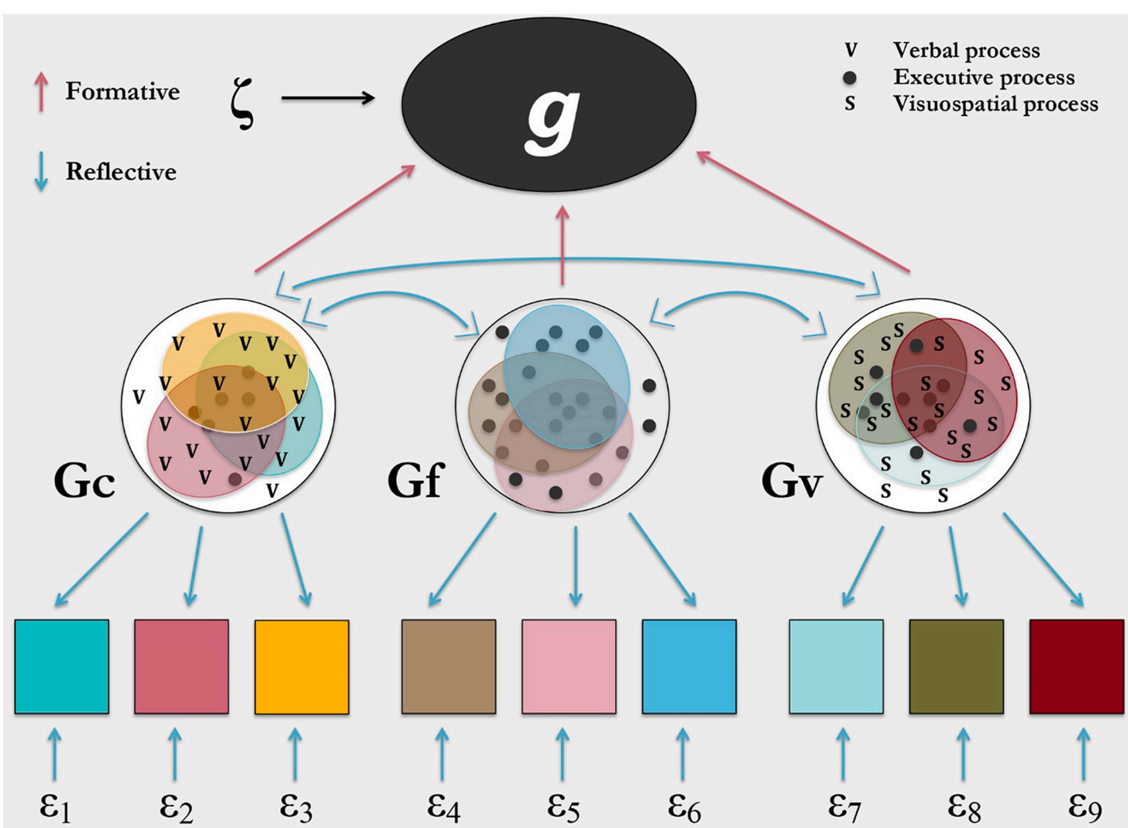

Fig. 2. Process overlap theory's formative model of the *g*-factor. Adapted from Kovacs and Conway (2016) with permission.

distinct but complementary domain-general functions (or processes) that underpin performance in many cognitive tasks: maintenance and disengagement (Burgoyne & Engle, 2020; Burgoyne et al., 2020; Shipstead et al., 2016; Fig. 3). *Maintenance* refers to the cognitive operations that support keeping information in an active, highly retrievable and usable state. For example, maintenance is required when attempting to understand a passage of text amid distractions and interruptions, such as when reading a novel in a public park. Sources of interference could include thoughts about lunch or the sounds of passersby in conversation—in other words, internal thoughts and external events. *Disengagement*, by contrast, refers to removing no-longer relevant information from active processing and flagging it for non-retrieval. For instance, one must disengage from the conversation the passersby were having in order to refocus on one's reading material. Our perspective is that most tasks require both information maintenance and disengagement to varying degrees, and that these functions are supported more broadly by attention control. As such, maintenance and disengagement appear to be viable candidates for a few of the domain-general cognitive processes proposed by Kovacs and Conway (2016, 2019a, 2019b).

Returning to the example of reading amidst distraction and interference, the ability to maintain focus partially explains why attention control predicts individual differences in reading comprehension. In a study of over 200 participants, McVay and Kane (2012) found a strong correlation between latent factors representing attention control and reading comprehension. Furthermore, attention control was negatively related to the number of task-unrelated thoughts participants reported during the study. In other words, participants with greater attention control reported less mind wandering; they were better able to stay on task and overcome potential distractions. In turn, less mind wandering was associated with better reading comprehension. Taken together, task-unrelated thoughts partially mediated the relationship between attention control and reading comprehension, suggesting that goal maintenance and task engagement are specific mechanisms by which attention control and reading performance are linked.

More recently, Martin et al. (2020) estimated the specific contributions of maintenance and disengagement to reading comprehension. First, they administered tests of working memory capacity, memory updating, and fluid intelligence to 567 young adults. Next, they used structural equation modeling to partition variance in task performance into distinct maintenance and disengagement reflective latent factors. Although maintenance and disengagement are subsumed under the broader construct of attention control, Martin et al.'s (2020) work showed that they can also be separated at the latent level, depending on the tasks that are administered to participants. Finally, Martin et al. (2020) found that maintenance and disengagement each made substantial and significant contributions to reading comprehension above and beyond one another (βs = .54 and .28, respectively), together accounting for 58% of the variance. This pattern of results indicated that both maintenance and disengagement contribute to reading comprehension.

As another example, consider the hypothetical contribution of information maintenance and disengagement to performance on working memory tests. In a typical complex span test such as Symmetry Span (Redick et al., 2012), the participant is presented a series of spatial locations they must memorize in alternation with a distractor task, in which the participant must determine whether abstract grid designs are

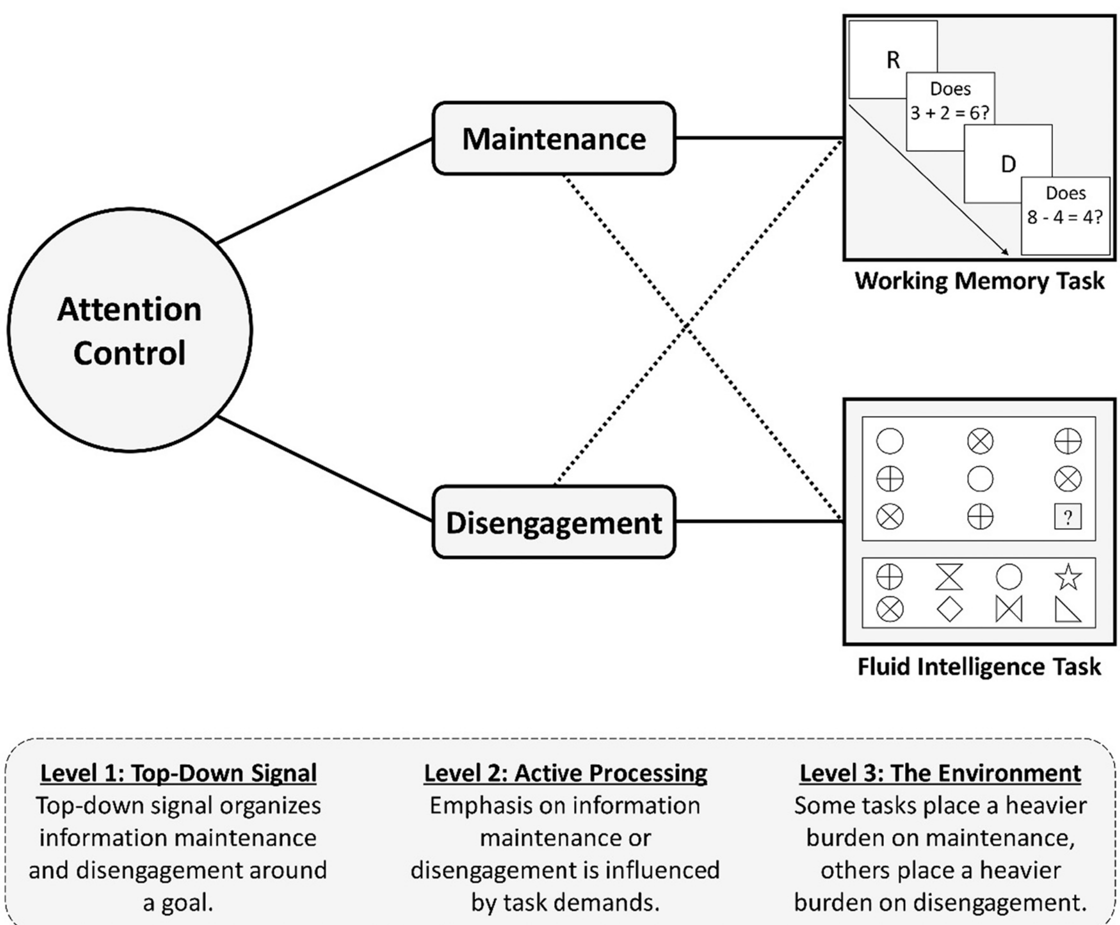

Fig. 3. Attention control supports maintenance and disengagement, two cognitive functions important to a wide range of tasks, including working memory and fluid intelligence tests. Adapted from Burgoyne and Engle (2020).

symmetrical or not. Information maintenance appears critical to working memory tests, because participants are challenged to remember items while actively processing distractors. Disengagement appears to play less of a role, although memoranda from previous trials must be forgotten to avoid a build-up of proactive interference. Furthermore, the distractor task (i.e., the symmetry judgments), once completed, must be rapidly removed from active processing so that attention can be focused on the next spatial location to be memorized.

With respect to fluid intelligence tasks, maintenance and disengagement both play a role, although disengagement may be particularly important. For example, in Raven's Matrices (Raven & Court, 1938), the performer is shown a pattern consisting of a 3 × 3 grid of symbols with the symbol in the bottom right corner missing. The performer's task is to figure out the pattern characterizing the 3 × 3 grid of shapes and select the response option that best completes the pattern. Information maintenance plays a role because performers must keep track of the rules governing the relations between the symbols to work out the solution to each item. Disengagement is crucial, however, because once a rule or hypothesis has been tested and ruled out, it must be abandoned; the performer should not waste time perseverating on previously rejected and failed solution attempts. Strategies can differ for solving matrix reasoning items—for example, some people choose to eliminate obviously wrong response options before selecting from those that remain (see, e.g., Bethell-Fox, Lohman, & Snow, 1984)—regardless, being able to control attention to maintain relevant information and disengage from no-longer-relevant information appears critical to solving matrix reasoning problems.

To our knowledge, no study has experimentally tested this hypothesis, but there is supporting evidence to suggest that working memory capacity correlates with performance on Raven's Matrices not simply due to storage demands, but likely due to attention control as well. For instance, Burgoyne, Hambrick, and Altmann (2019) found that the relationship between working memory capacity and reasoning performance did not increase as the capacity demands of the items increased, and Domnick, Zimmer, Becker, and Spinath (2017) similarly found that the working memory capacity-performance relationship was not driven by the storage demands of partial solutions. Turning the focus of the investigation to attention, Krieger, Zimmer, Greiff, Spinath, and Becker (2019) found that the ability to filter relevant information was positively related to performance on matrix reasoning items with selective encoding demands, indicating an important role for attentional filtering. Finally, Carpenter, Just, and Shell (1990) showed using computer simulations that better matrix reasoning performance could be explained by increasing the problem solver's ability to manage a larger set of goals in working memory *and* induce more abstract relations. In summary, attention control appears to be a common thread linking performance on working memory capacity and fluid intelligence tests, and indeed, it explains part of the positive correlation between these two broad cognitive abilities.

Early evidence for this hypothesis was provided by Engle, Tuholski, Laughlin, and Conway (1999), who used latent variable analyses to show that working memory capacity was dissociable from short-term memory, and that working memory capacity predicted fluid intelligence after accounting for individual differences in short-term memory. By contrast, short-term memory did not predict fluid intelligence after accounting for individual differences in working memory capacity. This suggested that it was the controlled attention component of the working memory system, and not the short-term storage component, that drove working memory capacity's relationship to fluid intelligence.

Following Engle et al. (1999), McCabe et al. (2010) used a battery of four executive function tasks to measure attention control directly and examine its relationship to working memory capacity, processing speed, and episodic memory at the latent level. They found a near-perfect correlation between working memory capacity and executive functioning (r = .97), suggesting that the two sets of tasks measured a common underlying construct. While they referred to this common construct as executive attention, we would refer to it as attention control. In turn, they showed that the common executive attention factor was empirically dissociable from processing speed; the correlation (r = .79) fell well short of unity. Finally, McCabe et al. (2010) found that executive attention predicted individual differences in episodic memory even after partialling out variance attributable to age and processing speed. They concluded that tests of working memory capacity and executive functioning share a common attentional substrate that is highly predictive of higher-level cognition.

More recently, Unsworth, Fukuda, Awh, and Vogel (2014) suggested that the relationship between working memory capacity and fluid intelligence was more multifaceted than previously thought. Specifically, they measured working memory capacity and fluid intelligence, as well as three facets of working memory capacity that they hypothesized could mediate the relationship: attention control, short-term storage capacity, and retrieval from secondary memory. Their analyses suggested that these three components fully mediated the relationship between working memory capacity and fluid intelligence, with each component accounting for unique variance above and beyond the other components. This more nuanced view suggests that while attention control is an important aspect of working memory capacity that helps explain its relations with other constructs, memory abilities (short-term capacity and retrieval from secondary memory) also play a role.

3. Measuring attention control

Although the preceding results suggest an important relationship between attention control and cognitive functioning, historically, the study of individual differences in attention control has been stymied by experimental tasks with poor psychometric properties, such as severe unreliability. Part of the problem is that the typical outcome measure for classic experimental tasks such as the Stroop (Stroop, 1935) and Flanker (Eriksen & Eriksen, 1974) is a *response time difference score*, in which performance in one condition is subtracted from performance in another. As a case in point, consider the arrow Flanker task. Participants must determine the direction that a central arrow is pointing while ignoring the arrows surrounding it (i.e., the flanking arrows). There are two types of trials, or conditions. On congruent trials (←←←←←), the central arrow points in the same direction as the flanking arrows. As a result, the flanking arrows do not create interference or bias the participant towards making an incorrect response. Congruent trials are subjectively easy, and it is thought they can be performed largely automatically—that is, without requiring attention to suppress or ignore the flanking arrows. Indeed, whether or not the participant restricts their attention to the central arrow, they should arrive at the correct answer in a matter of moments. On incongruent trials (←←→←←), the central arrow points in the opposite direction as the flanking arrows. The flanking arrows create interference, biasing the participant towards the wrong response. The participant must restrict their attention to the central arrow to reduce this interference and provide the correct response (see Heitz & Engle, 2007). Incongruent trials are subjectively difficult, and decades of experimental research have shown that participants are slower to respond accurately on them (Heitz & Engle, 2007).

Attention control tasks like the Flanker and Stroop produce reliable experimental effects at the group level—that is, people respond slower and often less accurately on incongruent trials than on congruent trials. Crucially, however, at the level of the individual, the difference score created by subtracting performance on congruent trials from performance on incongruent trials is notoriously unreliable. As explained by Draheim, Mashburn, Martin, and Engle (2019) and Hedge, Powell, and Sumner (2018), as the correlation between performance on congruent and incongruent trials increases, the reliability of the resulting difference score decreases, and this is exacerbated by the extent to which the measures are less than perfectly reliable (see Fig. 4). In our own work (e.g., Draheim, Tsukahara, Martin, Mashburn, & Engle, 2021), we have

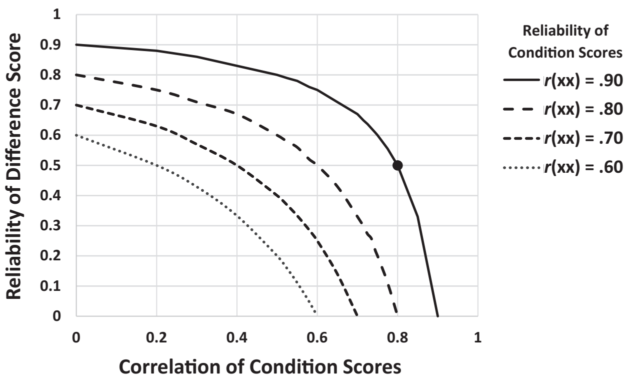

Fig. 4. The reliability of a difference score (Y-axis) decreases as the correlation between the condition scores increases (X-axis). Each line represents the reliability of the difference score when the reliability of the condition scores is set to r(xx) = .60, .70, .80, or .90. For a typical attention control task, one might find correlations between conditions to be around .80, and the reliability of each condition to be around .90, leading to a difference score reliability of .50, depicted by a black circle in the figure. Note that if the reliability of each condition score simply decreased from .90 to .80 while the correlation between them remained .80, the resulting difference score would have a reliability of zero. Adapted from Draheim et al. (2019).

found that measures of performance on congruent and incongruent trials are typically strongly correlated (e.g., $r = .80$) and have good reliability (e.g., $\alpha = .90$). And yet, given these values, the reliability of the resulting difference score is only $\alpha = .50$, meaning that only 25% of the variance in the measure (i.e., $.50^2$) reflects the construct of interest—the rest is error variance(!). Because unreliability limits validity, measures of attention control that use difference scores rarely correlate strongly with each other, or with other cognitive tasks that require controlled attention (Draheim et al., 2019; Hedge et al., 2018; Paap & Sawi, 2016). For example, in an influential study of 220 undergraduates, Friedman and Miyake (2004) administered nine tasks designed to measure attention control; the average internal consistency was less than .60, and the task intercorrelations were generally weak (most were below $r = .20$).

Before the study of individual differences in attention control could advance, measures of the construct needed to improve. To this end, our laboratory recently developed new attention control tasks that avoided the use of response time difference scores. We took classic paradigms such as the Stroop and Flanker and made them adaptive in difficulty (i.e., the tasks became easier or more difficult depending on how well the participant performed). In particular, participants were instructed to respond before a deadline on each trial (e.g., they might have 1 s to respond to a Flanker or Stroop item). The deadline became shorter, requiring quicker responses, when the participant performed accurately within the time limit, and became longer, allowing slower responses, when the participant made mistakes or did not respond in time. These adaptive tasks were programmed to converge on the same accuracy rate across all participants, and the outcome measure was the level of task difficulty (i.e., the response deadline duration) at which the participant could maintain the critical accuracy rate. We also tested accuracy-based tasks which did not rely on reaction time. These accuracy-based tasks each had components which were designed to require participants to control their attention, for example, to overcome interference from distractors or to filter out irrelevant items to reduce cognitive load. Broadly speaking, these new attention control tasks performed much better than the old versions, demonstrating greater reliability and construct validity (Draheim et al., 2021).

4. Accounting for the positive manifold

Having remedied some of the measurement limitations of classic attention control tasks, we discovered that attention control could explain many of the positive correlations observed among broad cognitive abilities. To reiterate, we have argued that the primary reason working memory capacity correlates with other cognitive abilities such as fluid intelligence is because they tap attention control (see, e.g., Burgoyne & Engle, 2020). Draheim et al. (2021) corroborated this hypothesis by showing that a latent factor representing attention control fully accounted for the relationship between working memory capacity and fluid intelligence, depending on which tasks were used to define the attention control factor. In particular, the newly developed attention control tasks appeared to account for more of the variance in the working memory capacity-fluid intelligence relationship than the old versions of the attention control tasks, likely due to their improved psychometric properties. Furthermore, Draheim et al. (2021) found that processing speed did not account for the relationships between attention control and working memory capacity and fluid intelligence.

As another example, attention control appears to explain the relationship between some broad cognitive abilities and sensory discrimination ability, operationally defined as an individual's ability to make perceptual distinctions between pairs of stimuli in the visual or auditory domain. For example, in an auditory task, a participant might be played two tones one after another and asked to indicate which was a higher pitch; in a visual task, they might be shown two lines and asked to indicate which line is longer. The relationship between sensory discrimination ability and general intelligence has been a long-standing area of interest for psychologists (Galton, 1883). For instance, Spearman (1904) uncovered a near-perfect correlation between sensory discrimination ability and general intelligence in some of the first factor analytic work ever reported. Over one hundred years later, Tsukahara, Harrison, Draheim, Martin, and Engle (2020) used latent variable analyses to show that attention control fully mediated the relationship between fluid intelligence and sensory discrimination ability, as well as the relationship between working memory capacity and sensory discrimination ability. In other words, the reason sensory discrimination ability correlates positively and significantly with these broad cognitive abilities appears to be because they mutually depend on the ability to control attention.

Thus far, we have described how individual differences in the domain-general ability to control attention can explain the positive correlations observed among some broad cognitive abilities. We have identified two mechanisms in particular, maintenance and disengagement, which are supported by attention control, appear to play a role in a variety of cognitive tasks, and are consistent with the "domain-general processes" that explain the positive manifold according to process overlap theory. From this line of reasoning, it seems plausible that attention control might account for a piece of the *g*-factor.

To test the relationship between attention control and *g*, we conducted secondary analyses on data from Tsukahara et al. (2020) and Draheim et al. (2021). These two studies draw from the same sample of participants because they were supported by one large-scale data collection effort conducted at the Georgia Institute of Technology from August 2017 to November 2018. The dataset comprises 10 measures of attention control (the best performing four from Draheim et al., 2021 are chosen for this analysis: Antisaccade, Flanker Adaptive Deadline, Sustained Attention to Cue, and Selective Visual Arrays; all tasks avoid the use of response time difference scores), three measures of working memory capacity (Operation Span, Symmetry Span, and Rotation Span), three measures of fluid intelligence (Raven's Advanced Progressive Matrices, Letter Sets, and Number Series), and three auditory measures of sensory discrimination ability (Pitch, Loudness, and Duration). The sample size for these variables is $N = 399$, which exceeds the minimum sample size needed for latent variable analyses to converge on stable parameter estimates (Kline, 2015). The participants were recruited from Georgia Tech as well as the greater Atlanta community, with considerable effort invested in recruiting a sample representing a broad range of ability and socioeconomic status. The sample ranged in age from 18 to 35. Further details about the study procedures, sample, exclusions, task descriptions, and measures can be found in Draheim et al. (2021) and

Tsukahara et al. (2020), and a list of all publications based on this data collection effort can be found at https://osf.io/be34k/.

The purpose of the following analyses is to investigate a common argument made by process overlap theory and the executive attention framework: attention control should be highly related to *g*, and as a result, largely explain the covariation between broad cognitive ability factors. To test whether attention control explains the positive correlations observed among broad cognitive abilities, we ran three latent factor models using maximum likelihood estimation. In the first model, we specified latent factors representing attention control, working memory capacity, fluid intelligence, and sensory discrimination ability, and allowed them to correlate (i.e., a correlated-factors model; Fig. 5). Based on prior research (e.g., Draheim et al., 2021), we expected these latent factors to correlate positively and significantly. In the second model, we specified a higher-order *g*-factor predicting all cognitive abilities, to determine which cognitive ability factor had the highest *g*-loading (Fig. 6). In the third model, we replaced the *g*-factor with a latent factor representing attention control. This attention control factor was specified to predict individual differences in the lower-order cognitive ability factors (a common-cause model; Fig. 7). The residuals of the lower-order cognitive ability factors (R_1 through R_3 in Fig. 7) represent the variance in each cognitive ability not explained by attention control; these residuals were allowed to correlate in order to quantify their magnitude.

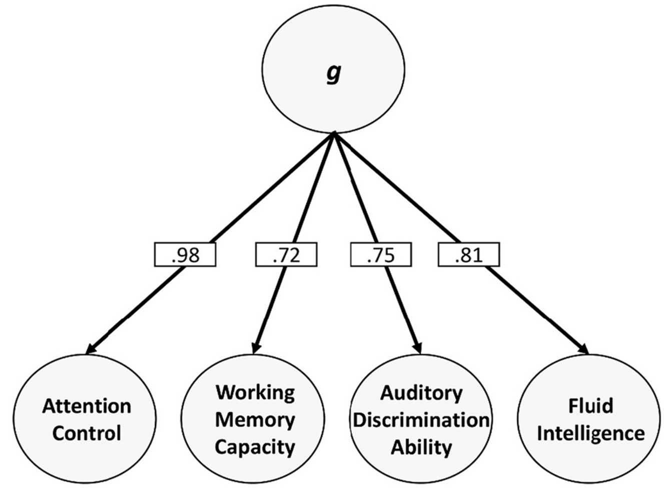

Fig. 6. A structural equation model with a higher-order *g*-factor (N = 399). $\chi^2(60) = 172.60$, $p < .001$, CFI = .93, RMSEA = .07 [.06, .08]. Lower-order factor indicators are identical to those depicted in Fig. 5 but are not shown for visual clarity.

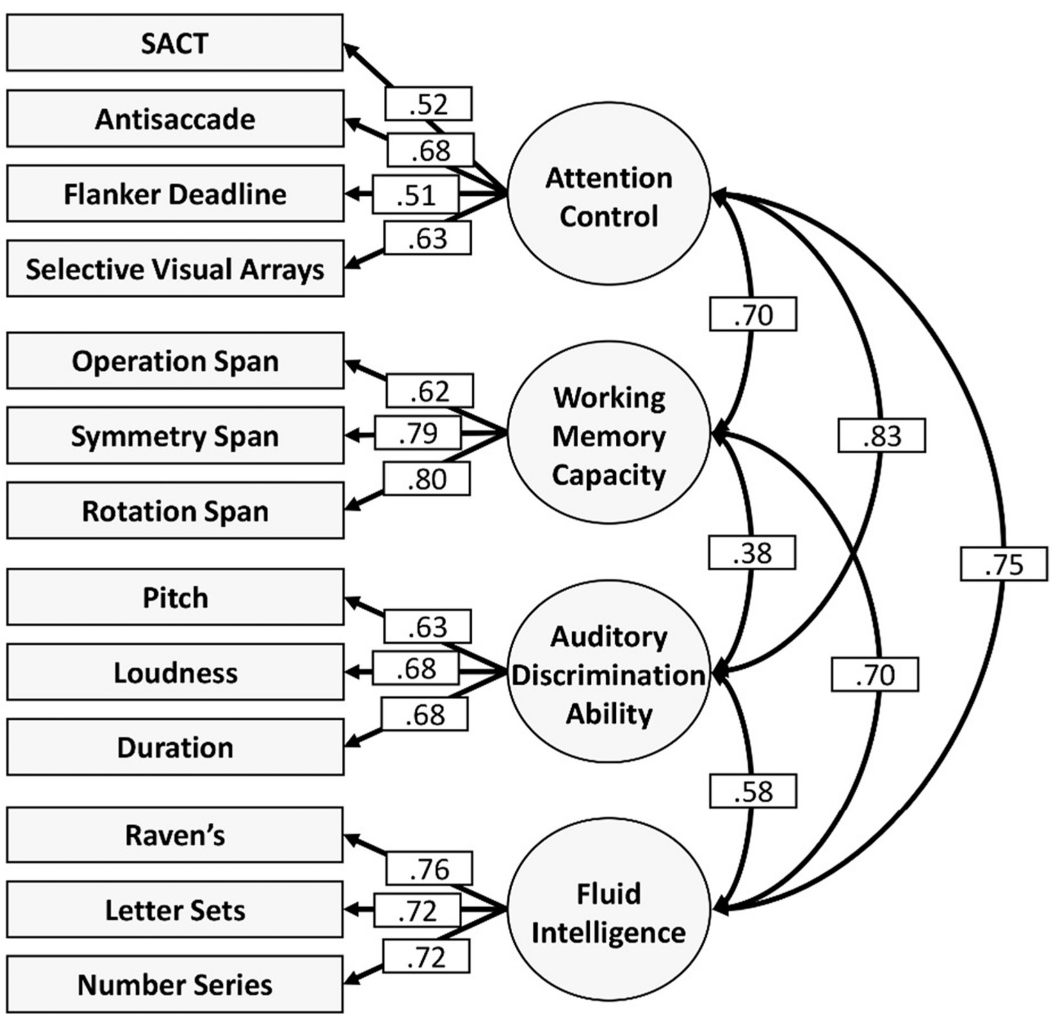

Fig. 5. Correlated-factors model (N = 399). $\chi^2(59) = 137.85$, $p < .001$, CFI = .95, RMSEA = .06 [.05, .07]. SACT = Sustained Attention to Cue Task. For the Flanker Deadline task and Auditory Discrimination Ability factor, high ability participants should have smaller deadline and threshold values, leading to negative relationships. To avoid confusion, these paths are sign-reversed to make them consistent with the "all positive correlations" heuristic for the positive manifold.

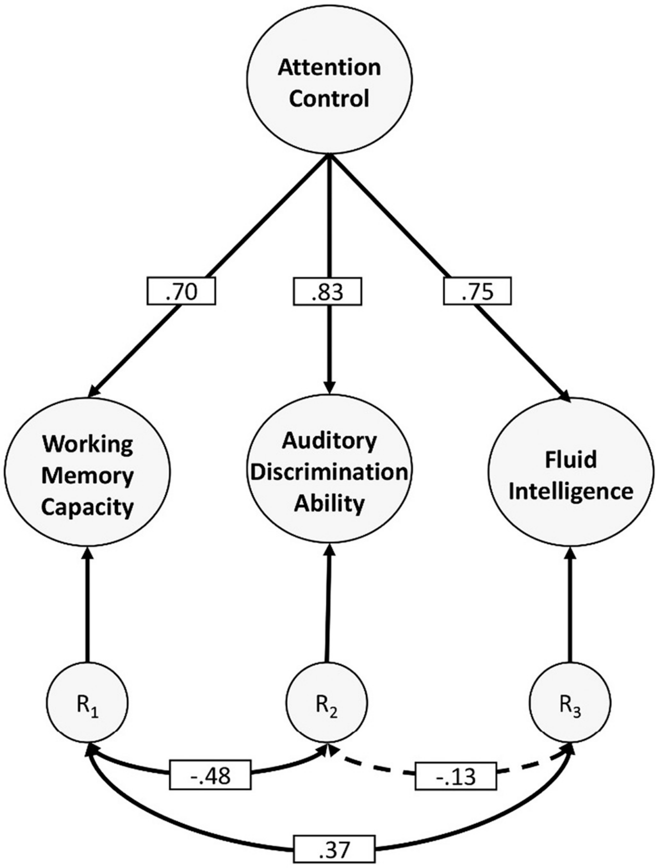

Fig. 7. Common-cause model ($N = 399$). $\chi^2(59) = 137.85$, $p < .001$, CFI $= .95$, RMSEA $= .06$ [.05, .07]. Factor indicators are identical to those depicted in Fig. 5 but are not shown for visual clarity.

The question of interest—whether attention control accounts for the positive manifold—is addressed by examining the magnitude of the residual correlations in the common-cause model (Fig. 7). If, for example, the residual correlations are no longer statistically significant, this would indicate that attention control fully explains the positive correlations among the broad cognitive abilities. On the other hand, the residual correlations may be statistically significant but weaker than the correlations in the correlated-factors model depicted in Fig. 5. We can test this by comparing the decrement in model fit when these correlations are freely estimated to when the residual correlations are constrained to be equal to the values of the correlated-factors model. If the model fits significantly worse when the residual correlations are constrained, this would suggest that attention control partially explains the positive correlations among broad cognitive abilities, but that other factors may also play a role.

As seen in Fig. 5, the correlations between the latent factors representing broad cognitive abilities were all positive, substantial, and statistically significant (average $r = .66$). The strongest correlation was observed between attention control and auditory discrimination ability ($r = .83$), whereas the weakest correlation, still moderate in magnitude, was between working memory capacity and auditory discrimination ability ($r = .38$). The results depicted in Fig. 5 are consistent with more than one hundred years of cognitive ability research; measures of cognitive ability tend to correlate positively with one another.

Next, we analyzed a second model to examine the relationship between the four latent factors and a general factor. Theoretically, if domain-general executive processes are largely responsible for the correlation between different cognitive abilities, and attention control captures these domain-general executive processes better than the other latent factors in the model, then attention control should have the highest loading on the general factor. As shown in Fig. 6, the attention control and general factor were virtually isomorphic to one another, with a loading of .98. All other loadings were also strong and positive, ranging from .72 to .81.

Finally, we ran a model with attention control standing in for *g* as a predictor of working memory capacity, auditory discrimination ability, and fluid intelligence, and estimated the residual correlations among the latent ability factors. Note that this model is *not* a hierarchical model, but rather a one-level structural equation model with one predictor factor (attention control) and three dependent variables/factors (working memory capacity, auditory discrimination ability, and fluid intelligence). As shown in Fig. 7, the correlations between broad cognitive abilities were largely explained by the attention control factor. That is, the path from attention control to each broad cognitive ability was substantial and significant, ranging from .70 to .83. More important for the present purposes, the residual correlations among the broad cognitive abilities after accounting for attention control were reduced to either non-significance, or were much smaller than those shown in the correlated factors model (Fig. 5). Specifically, the residual correlations between fluid intelligence and auditory discrimination ability was reduced to non-significance (compare $r = .58$, $p < .001$ in Fig. 5 to $r = -.13$, *ns* in Fig. 7). Although still statistically significant, the residual correlation between working memory capacity and fluid intelligence was drastically reduced (compare $r = .70$, $p < .001$ in Fig. 5 to $r = .37$, $p = .003$ in Fig. 7; the R^2 decreased from .49 to .14), and constraining the residual correlation to equal the bivariate correlation from Fig. 5 significantly reduced model fit, $\Delta\chi^2(1) = 40.41$, $p < .001$. The residual correlation between working memory capacity and auditory discrimination ability is more curious. While significantly different from the initial bivariate correlation, $\Delta\chi^2(1) = 68.95$, $p < .001$, accounting for attention control led to a significant, sign-reversed residual correlation between working memory capacity and auditory discrimination ability (compare $r = .38$, $p < .001$ in Fig. 5 to $r = -.48$, $p = .001$ in Fig. 7). We note that this is unsurprising given that the same pattern was observed in Tsukahara et al. (2020), and these analyses were conducted on the same data. That said, a substantive explanation for this sign-reversal is elusive. Our interpretation of these results is that attention control accounted for the *positive* relationship between working memory capacity and sensory discrimination ability.

More broadly, it seems that attention control accounted for most—but not all—of the positive correlations observed among the broad cognitive ability factors in the present dataset. Of course, a different set of cognitive ability factors could lead to a different pattern of results, and other factors could still play a role after accounting for attention control. It would be interesting to include measures of crystallized intelligence in future work, because the present analyses are primarily focused on fluid abilities. Whether attention control would load as highly on the *g*-factor or account for as much of the positive manifold if crystallized intelligence measures were included in the model is an open question. In future work, we plan to extend this approach by including additional measures of each construct, including more broad cognitive abilities in the model, and recruiting a larger sample to test whether attention control explains *more* of the positive manifold in lower-ability samples relative to higher-ability samples, a hypothesis consistent with Spearman's (1927) Law of Diminishing Returns as well as process overlap theory (Kovacs et al., 2019).

5. Discussion

A growing body of evidence suggests that attention control can explain most of the covariation between many broad cognitive abilities, such as fluid intelligence, working memory capacity, and sensory discrimination. In the analyses presented above, we showed that: 1) latent factors reflecting broad cognitive abilities correlate positively with one another; 2) when a higher-order *g* factor is specified to explain the covariance between these latent factors, an attention control factor has the strongest loading on the g factor; and 3) when attention control is specified as the higher-order factor, it largely accounts for the positive manifold, because the residual correlations among the broad cognitive ability factors are reduced substantially, at times to non-significance.

This is not to say that attention control *fully* explains the correlation between all broad cognitive abilities; our models lacked a crystallized intelligence factor as well as other cognitive ability factors, and after accounting for attention control, some residual correlations remained statistically significant. How might the results have differed had we included other measures of cognitive abilities? If attention control is more important for fluid abilities than for crystallized abilities, then including knowledge-based measures of cognitive ability might have rendered attention control less closely related to the *g*-factor than it was in the present study. As is the case in all psychological research, our conclusions are limited by the kind and quality of the measures that were administered to participants. Another limitation of the modeling approach we used is that we could not correlate the residuals of the lower-order cognitive ability factors in the hierarchical *g*-factor model (Fig. 6) because the model would be locally underidentified. Presumably, a *g*-factor identified only by the positive correlations between lower-order cognitive ability factors would outperform any other factor in terms of accounting for the correlations among the lower-order cognitive ability factors. This appears to be a necessary consequence of the statistical modeling approach that allows for the specification of a higher-order *g*-factor that is only identified by the positive correlations among measures. With these limitations in mind, the evidence presented here suggests that attention control is a piece of the intelligence puzzle, and perhaps a bigger piece than was considered until recently. We interpret this evidence as *suggestive*, not *conclusive*, and hope to unpack the specific mechanisms by which attention control explains the correlations between broad cognitive abilities in future work.

The preceding analyses were motivated in part by process overlap theory, which argues that cognitive tests tap domain-general executive processes and domain-specific processes, and that the positive manifold is caused by tests' mutual dependence on domain-general executive processes (Kovacs & Conway, 2016). In general, our executive attention perspective is consistent with process overlap theory, although it also differs in significant ways. We agree that performance on any single task is likely determined by multiple domain-specific and domain-general processes. We also agree that domain-general executive processes likely serve as a bottleneck constraining task performance, and that domain-general processes are heavily sampled by tests of fluid intelligence and working memory capacity, although this premise requires further elaboration. As of yet, domain-general executive processes have remained largely unspecified by process overlap theory. Addressing this gap, we have suggested that *maintenance* and *disengagement* are two domain-general executive functions that are supported by attention control and are sampled to different degrees in working memory capacity and fluid intelligence tests. Finally, we also agree that on its own, a higher-order *g* factor lacks a cognitive mechanism and is merely a statistical explanation for the positive manifold.

Where we diverge from process overlap theory is in our emphasis on attention control as a latent construct that can be reliably and validly measured and one that explains much—though probably not all—of the positive manifold. We think of attention control as an ability which allows individuals to organize cognitive processing around objectives. People that can organize cognition in a goal-relevant manner (i.e., those with high attention control) will perform well on many types of tasks, whereas those lacking the ability to control attention will struggle on many types of tasks. Our definition and measurement of attention control does not negate the existence of distinct domain-general executive processes. In fact, it includes at least two such functions, maintenance and disengagement, which are deployed by the executive control of attention to meet the processing demands of the task.

Some have argued that there is no need to posit an overarching, or supervisory, executive attention system governing multiple distinct executive functions. For example, Rey-Mermet, Gade, and Oberauer (2018) examined the factor structure of 10 inhibition measures that were computed using response time difference scores in a sample of 232 younger and older adults. They found that a model with two correlated latent factors—one representing inhibition of pre-potent responses and another representing resistance to distractor interference—provided better fit to the data than a single-factor model or an orthogonal two-factor model as indicated by chi-square tests. That said, many of the factor loadings were low, and furthermore, Bayesian hypothesis testing did not provide strong evidence in favor of any of the models compared to the alternatives. On the basis of these results, Rey-Mermet et al. (2018) concluded that "tasks used to assess inhibition do not measure a common underlying construct, but the highly task-specific ability to resolve the interference arising in that task" (p. 515). More recently, Rey-Mermet, Gade, Souza, von Bastian, and Oberauer (2019) used accuracy-based difference score measures of executive control and found similar results: the measures did not cohere on a unitary latent factor and also had weak relationships with fluid intelligence and working memory capacity. There are many reasons why some researchers may struggle to find measures that cohere on a latent attention control factor, and we discuss a number of plausible explanations for Rey-Mermet et al.'s results elsewhere (see Draheim et al., 2021, pp. 265–266). As we have noted, there are serious methodological issues impacting the measurement of individual differences in attention control (e.g., the use of difference scores) that continue to stymie efforts to build and test comprehensive theories of intelligence.

6. Challenges associated with measuring cognitive processes

For instance, because no single task is a process-pure measure of the construct it is intended to measure, it is difficult to identify the cognitive processes underlying individual differences in performance. One reason is that just because a cognitive process is required to perform a task does not necessarily mean that the cognitive process will be reflected in individual differences in task performance. There needs to be sufficient demand on a cognitive process to reveal differences *between* individuals on that process. The demand that is placed on a cognitive process will depend on many factors including task design, the strategy used by the individual, their knowledge and abilities, and even their demographic characteristics (e.g., children vs. adults).

Process overlap theory shifts the focus away from **g** as a psychological or biological explanation of the positive manifold and instead emphasizes the overlap of cognitive processes that are tapped by various tasks. The challenge for researchers moving forward is to better understand the cognitive processes that give rise to individual differences in task performance in order to understand why one measure may correlate more strongly with some measures than others. As highlighted above, this is no easy feat and will likely require us to think simultaneously as experimentalists and differential researchers. Although the two disciplines think of reliability and validity in different ways, both bring strengths to the table that the other does not (e.g., Burgoyne et al., 2020; Cronbach, 1957).

Part of the tension between the experimentalist and differential traditions stems from the question of "how can we isolate cognitive processes?" For the differential researcher, one can administer multiple heterogeneous tasks that are thought to tap common and unique processes and then use latent factors to pull apart the common variance from the unique variance at the between-subject level. For the experimentalist, one can systematically manipulate features of a task to control for extraneous and confounding variables at the within-subject level. When measuring attention control, for example, experimentalists have often used difference scores to subtract performance in one condition largely thought to reflect automatic processes (e.g., Flanker congruent trials) from another condition largely thought to reflect controlled processes (e.g., Flanker incongruent trials).

In general, however, the use of difference scores is based on the highly questionable assumption of additive factors. In fact, Draheim et al. (2021) pointed out that reaction time difference scores in Flanker and Stroop tasks are not process pure, despite the use of contrasting conditions, and are contaminated with individual differences in processing speed. Furthermore, the cognitive processes brought to bear on single trials and/or in contrasting conditions are not isolated but instead overflow across the entire administration of a task; in other words, cognition is a dynamic process. This is demonstrated in phenomena such as the sequential congruency effect and post-error slowing. These nuances, among others, make it challenging to validate and specify what domain-specific and domain-general processes are contributing to individual differences in task performance.

There are promising modeling techniques to better combine differential and experimental methods, such as hierarchical linear modeling (Rouder & Haaf, 2019), generative modeling (Haines et al., 2021), and fixed-links modeling (Schweizer, 2006). Additionally, combining physiological measures (EEG, eye tracking, heart rate, neuroimaging) with behavioral data can help elucidate the processes underlying task performance (see Fukuda & Vogel, 2009; Vogel, McCollough, & Machizawa, 2005). These techniques may pave the way for greater understanding in future research.

7. Conclusion

Process overlap theory provides a plausible account of the positive manifold. That said, some key aspects of the theory, such as whether *g* is formative or reflective, may benefit from greater elaboration and specification. More importantly, there is still considerable work to be done addressing measurement limitations before the theory can be empirically substantiated or falsified in a convincing manner. Nevertheless, knowing ‘where to point the microscope’ will help organize researchers around a common goal and likely generate new discoveries in the years ahead.

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