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Specific cognitive aptitudes and gifted samples

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ABSTRACT

This paper explores the way in which the literatures on gifted education and specific cognitive aptitudes can be better integrated and inform one another to advance scientific knowledge. We first briefly review evidence accumulated to date on specific cognitive aptitudes and gifted samples and then explore what might be usefully investigated in the future. We consider measurement issues, value for applied uses of tests, specific cognitive aptitudes beyond what has been focused on to date and conclude with a discussion surrounding cross-field integration using the totality of evidence and consideration of policy. Continued research and better integration of research evidence across domains and translation to policy and practice might correspondingly improve basic scientific understanding of cognitive aptitudes.

There are numerous theoretical paradigms and operationalizations of what it means to be gifted or talented (for a review, see Subotnik, Olszewski-Kubilius, & Worrell, 2011). However, the specific cognitive aptitude framework (Carroll, 1993; Snow, 1990) is one reasonable, measurement-focused way of operationalizing and intersecting the literatures of cognitive aptitudes and academic or intellectual giftedness. Our definition of gifted focuses on students who have exceptional academic potential, particularly unusually high developed general reasoning capacity (g) or exceptional performance on developed specific cognitive aptitudes. Gifted students may also be defined by high current achievement in one or more domains (i.e., eminence; Subotnik et al., 2011). Paradigms of expertise development align well with this definition of giftedness (Simonton, 2001). We believe this approach accounts for the totality of the evidence from cognitive aptitudes research that *should* inform research on gifted students but is not widely appreciated or understood within the field of gifted education.

Many practitioner definitions of giftedness assume that students will have domains of particular expertise and patterns of strengths and weaknesses in their cognitive and non-cognitive skills. Therefore, the question of whether we can measure specific cognitive aptitudes in gifted samples has pragmatic implications for the identification of students with exceptional academic reasoning in K-12 schools as well as in understanding potential for expertise development throughout the educational and training spectrum. The findings on specific aptitudes among highly intellectually able groups suggest that assessing these aptitudes adds to the predictive power for future academic and professional success, alongside general reasoning, and is worth further focus and research.

In this paper, we briefly discuss what we know about specific cognitive aptitudes in gifted samples and then consider what might be fruitfully investigated in the future. We discuss measurement issues, value for applied uses of tests, specific cognitive aptitudes beyond what has been focused on to date, and conclude with a discussion surrounding cross-field integration using the totality of evidence and consideration of policy. Continued research and better integration of research evidence across domains and translation to other areas might correspondingly improve basic scientific understanding of cognitive aptitudes.

1. Specific cognitive aptitudes in gifted samples

Distinctions between *potential* and *current* achievement are made throughout state, U.S. federal, and other definitions of student characteristics that warrant gifted and talented educational programs (Rinn, Mun, & Hodges, 2020). Beyond this general distinction between cognitive aptitude and achievement, many programs serve students with potential or developed achievements in specific academic domains and are thus interested in specific cognitive aptitudes as predictors of future achievement that help identify areas of strength or greater potential. These educational programs are more consistent with models that include diverse specific cognitive aptitudes (e.g., Cattell-Horn-Carroll

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[CHC]; *g*-verbal-perceptual-image rotation [*g*-VPR]; Johnson & Bouchard, 2005).

In alignment with this focus on domains of performance, many programs use measures of G*f* and specific domain achievement (quantitative knowledge, reading, and writing; Carroll, 1993) in their selection procedures (Brodersen, Brunner, & Missett, 2017). Narrower forms of reasoning are sometimes used. Rarely are other broad factors from multi-stratum models (e.g., CHC, *g*-VPR) assessed, such as short- and long-term memory or processing capacities.

The distinction between current and potential high achievement is aligned with investment theories of cognitive aptitudes (Ackerman & Lakin, 2018). Snow (1990) framed the idea of an *aptitude* as "person-situation reciprocity" (p. 252), or the individual's developed potential for learning or action at a given developmental time point facilitated by appropriate circumstances. Both investment and aptitude theories argue that cognitive abilities are *developed* and malleable, up to a point, through talent development opportunities such as education and coaching (Lohman, 1993, 2005; Ritchie & Tucker-Drob, 2018; Subotnik et al., 2011). However, their value for predicting future learning requires alignment with the content or learning opportunity (Wee, 2018).

2. Which specific aptitudes?

The specific cognitive aptitudes with the most research supporting their use in predicting future domain performance are verbal, mathematical, and spatial reasoning (see Lubinski & Benbow, 2000 for an integrated framework). Historically, Terman's (1925) longitudinal study of gifted youths and the Study of Mathematically Precocious Youth (SMPY; see Lubinski & Benbow, 2021 for a current summary of core findings) have been important investigations of the gifted where students have been followed throughout the lifespan (Lubinski, 2016). Taken together, these studies illustrate that the specific cognitive aptitudes of verbal, mathematical, and spatial reasoning are each uniquely important to educational, work, and life outcomes. The relative performance of students in these cognitive aptitude domains predicts life outcomes in ways that *g* does not. For example, individuals with higher spatial and mathematical talents tend to gravitate towards educational, occupational, and creative trajectories in math, computer science, physics, and engineering disciplines, whereas individuals with higher verbal talents tend to gravitate towards the arts and humanities (Kell, Lubinski, Benbow, & Steiger, 2013; Wai, Lubinski, & Benbow, 2009). Research has found this to be the case even for individuals with *g* scores in the top 1% or higher, who are conceivably capable of excelling in any domain of expertise. Even then, the area of particular strength is predictive of where their expertise develops.

The value of specific abilities is also supported by population-representative longitudinal studies examining cognitive aptitudes similar to those investigated among the gifted (Lakin & Wai, 2020; Wai, 2014). Both the level and pattern or "tilt" of specific cognitive aptitudes matter for later life outcomes (Coyle, 2018, 2019; Kell et al., 2013; Park, Lubinski, & Benbow, 2007). Tilt research generally relies on manifest variables, not considering how measurement error affects individual scores or contaminates the tilt estimate, which is simply the difference in the observed scores for the specific aptitudes under study (Coyle & Greiff, 2021). If anything, this makes the predictive validity of tilt even more impressive. The correlation of tilt scores with outcomes might be even higher if they excluded individuals "without tilt" (i.e., those whose scores are not statistically different). Profiles research, which takes measurement error into consideration, indicates there is useful variation in the specific cognitive aptitude patterns of gifted students (Lohman, Gambrell, & Lakin, 2008).

Practitioner value is also important. Schneider (2013) explained the value that clinicians obtain from the nuances of group factors that go beyond what *g* can offer. Clinicians want to understand differences in performance or outcomes between individuals with similar overall aptitude, and, therefore, Schneider (2013) argues for more research and effort to create assessments for group factors that are useful for these purposes. Researchers and practitioners in education also seek similar nuance. Whereas *g* predicts many general life outcomes (Brown, Wai, & Chabris, 2021), including the level of expertise that individuals may develop, it is not as effective in predicting *which* of many life outcomes are likely (especially if they are similar in complexity) or in aligning individuals to the most advantageous training or career pathway at a particular developmental time point (Ackerman, 2018; Schneider & Newman, 2015). Furthermore, prediction from *g* is far from perfect and we can observe differences in outcomes, including among gifted students, that may be explained further if we had more detailed information about the wide array of students' specific aptitudes. In other words, our lived experiences suggest there should be useful specific aptitudes that guide individuals to develop specific areas of skills. If current tests do not adequately predict those differences, then research should endeavor to improve assessments to capture them, not abandon the concept of specific cognitive aptitudes.

These lines of research converge to demonstrate that there is potential to measure specific aptitudes in verbal, mathematical, and spatial reasoning that matter (above and beyond *g*) in educational, vocational, and life outcomes and thus should be accounted for throughout development.

3. Future directions and recommendations

3.1. *Conceptualizing and studying giftedness: implications of theory and method*

There is a long-standing tension between generality and specificity when defining intellectual giftedness (e.g., Kaufman & Sternberg, 2008; Silverman, 2009). We believe that this topic has been somewhat overlooked, especially in light of newer models of cognitive aptitudes that have arisen in the past 15 years. Despite their enduring antagonism, these two ideas of giftedness are likely more inextricably tied together than many realize.

A general definition of giftedness emphasizes scores on *g* or *Gf* (which are frequently correlated at or near unity; Gustafsson, 1984; Kvist & Gustafsson, 2008), with performance on latent specific abilities merely serving as "indicators" to provide an estimate for the ultimate construct of interest, general reasoning (Schmidt, 2012a, 2012b). Domain-specific definitions of intellectual giftedness center on cognitive aptitudes tied to specific content domains (e.g., quantitative, verbal, visuospatial). The fact that scores on all aptitude tests are almost inevitably positively correlated might suggest that the distinction between broad and narrow "types" of giftedness is trivial, but it is not. Emphasizing generality or specificity when defining intellectual giftedness can sometimes lead to different individuals being classified as gifted and talented or not.

Most fundamentally, despite the positive manifold, the average correlation between test scores is "only" about 0.30 (Carroll, 1993) – and it will tend to be lower among individuals on the precipice of being identified as gifted, given that the general factor tends to account for less variance among test scores among high scorers than low scorers (see the later section on Spearman's Law of Diminishing Returns [SLODR]). This degree of intercorrelation leaves substantial room for intraindividual variation in standing on individual specific cognitive aptitudes. In other words, many individuals could demonstrate exceptional potential in a specific cognitive aptitude even if their general score is less impressive. Moreover, there is also often substantial skew in the intellectual profiles of gifted children, meaning they typically score quite a bit higher in one domain (e.g., verbal) than another (e.g., mathematical) (Achter, Benbow, & Lubinski, 1997; Achter, Lubinski, & Benbow, 1996; Lubinski & Benbow, 2021). More broadly, using a population representative sample, Wai et al. (2009) found that 70% of individuals scoring in the top 1% in visuospatial reasoning did not score in the top 1% in quantitative or verbal reasoning. Obviously, then, if giftedness is defined in terms of proficiency in a specific intellectual domain, but few specific intellectual aptitudes are sampled by a test battery, it is likely that some gifted children will be missed. For example, as has been noted many times previously (e.g., Wai & Kell, 2017; Wai & Worrell, 2016), Terman's (1925) study did not include future Nobel Prize winners Luis Alvarez and William Shockley, likely because the single measure used to determine intellectual giftedness was the Stanford-Binet test, which is highly loaded with verbal content. Had mathematical and/or visuospatial content played a larger role in Terman's assessment, it is quite likely these individuals – and perhaps others – would have been selected for inclusion.

Whereas Terman was satisfied with using only a single test to estimate individuals' general intellectual standing, decades of research have shown that this approach is inadequate, and that many more tests (and sampling multiple content domains; Lakin & Kell, 2020) are typically needed to obtain an adequate estimate of general reasoning (e.g., Floyd, Clark, & Shadish, 2008; Major, Johnson, & Bouchard Jr., 2011). Attempting to estimate general reasoning from just one or two formats (such as only administering the Raven's Progressive Matrices) may seem consistent with a general (*g*-centric) conception of giftedness, but the resulting scores will be a hodgepodge of variance due to whatever specific abilities those tests measure mixed with *g* itself; selection will, in reality, be based on an ill-defined specific notion of giftedness, rather than a general one. Inadequacies in a test battery could lead to individuals erroneously being rejected (or selected) based on a general criterion of giftedness that is not relevant to the educational services being offered.

Regardless of how general giftedness is ascertained (e.g., composite of all test scores, latent variable modeling, principal component extraction), it will ultimately be represented by some type of mean score across all the tests comprising the assessment instrument (cf. van Bork, Epskamp, Rhemtulla, Borsboom, & van der Maas, 2017). If there is substantial skew in some test-takers' intellectual profiles (e.g., top 1% in verbal reasoning, top 60% in mathematical reasoning) it is possible that they will not qualify as "generally gifted" even if they qualify as gifted within one or more given content domains, as their performance in one domain could substantially drag down their overall, average score. The issue is only further complicated when taking into consideration the fact that the *g*-loadings of tests (which index the degree to which those tests will contribute to the estimation of the general factor) can vary substantially across content domains and as a function of the composition of the entire test battery, along with the characteristics of the sample assessed (Johnson, 2018).

All of these nuances exist merely in the context of well-established, factorial models of general and specific cognitive aptitudes. The two major types of factorial models featuring both general and specific reasoning are hierarchical, in that they feature different strata of reasoning capacities (Mulaik & Quartetti, 1997; Yung, Thissen, & McLeod, 1999).[1] Higher-order models feature a fundamental general factor that causes variance in specific cognitive aptitudes and it is those specific aptitudes that cause variance in performance on test items; the general factor is inferred from the positive intercorrelations among the specific factors. Nested-factor or bifactor models feature uncorrelated general and specific aptitudes, both of which directly account for variance on tests. Although there are subtle differences in these models – not the least of which being that psychological interpretation of the general factor may differ among them (Benson, Beaujean, McGill, & Dombrowski, 2018) – they nonetheless assume that both specific cognitive aptitudes and a pervasive general reasoning capacity actually exist. Several newer models (Kovacs & Conway, 2016; van der Maas et al., 2006) – along with a refurbishment of a much older one (i.e., Thomson's bonds; Bartholomew, Allerhand, & Deary, 2013) – *deny* the existence of a psychological, causal general factor underlying the positive manifold. Such theories often fit the statistical data equally as well as models featuring a general factor (Kievit et al., 2017; Kievit, Hofman, & Nation, 2019), meaning that the ultimate arbiter among them will have to come from outside the psychometric realm (Eysenck, 1997; Jensen, 1987; Protzko & Colom, 2021).

Until the tension among these theories is resolved, gifted theorists and practitioners must grapple with the implications of these non-*g* theories. From the perspective of these theories, does it make psychological sense to hold general conceptions of giftedness? It is certainly possible to compute "general intellectual" scores for individuals across tests and use cut-scores on those measures to define and identify giftedness – but those scores are explicitly held in these newer traditions to be formative, not reflective, in nature, and not representative of any deeper reality. From this perspective, choosing gifted and talented individuals based on these scores would be roughly equivalent to choosing "size gifted" people based on sums of their heights and weights (which are correlated about 0.40 in the general population; Meyer et al., 2001). Such composites have practical usefulness (as do indices of socioeconomic status and country-level economic growth), but they do not refer to any underlying scientific variable, which is often implicit in general definitions of giftedness.

It is important to note that general and specific cognitive aptitudes are inextricably intertwined, regardless of which conceptualization of either cognitive aptitudes or giftedness is chosen. In the case of common factorial models (e.g., higher-order, nested-factors), adequate estimation of general reasoning requires many tests that sample multiple cognitive aptitudes while in non-factorial models the general factor emerges from the interactions of specific cognitive aptitudes. In both cases, general reasoning cannot be accurately measured without also properly measuring specific reasoning. There is a flip side to this coin, however: Methodologically, it is possible to separate general and specific factors. Specific aptitude factors in bifactor models can be estimated as partialled latent variables that are independent of the *g* variance. In reality, however – whether performing everyday tasks, creative endeavors, or taking cognitive assessments – performance itself is *manifest*, not latent, and is influenced by both general and specific cognitive aptitudes. From the perspective of higher-order models the influence of *g* may be indirect, while from the perspective of nested-factor models it may be direct, but that influence remains. In the dynamic flux of behavior, the influence of general and specific aptitudes cannot be disentangled, making research with partialled *g* and specific factors irrelevant for many applied purposes. As Schneider (2013) noted: "We care about a sprinter's ability to run quickly, not residual sprinting speed, after accounting for general athleticism" (p. 188). Similarly, regardless of whether one holds a general or specific conception of giftedness, the two definitions – at least implicitly – cannot be wholly disentangled from one another, practically.

3.2. Spearman's Law of Diminishing Returns (SLODR)

As alluded to previously, gifted or high cognitive aptitude samples are particularly well-suited to studying SLODR. SLODR holds that the amount of variance in test scores that *g* accounts for decreases as the aptitude level of the group being tested increases (Spearman, 1927; see also, Detterman, 1991; MacKintosh, 2011). A meta-analysis of SLODR

[1] Here, we treat factors and constructs as synonymous (cf. Royce, 1963), with cognitive aptitudes being a variety of construct/factor. We ascribe them causal status because we interpret them from a realist point of view (Haig & Evers, 2015), meaning that in this treatment we leave open the possibility that entities could one day be discovered that correspond to the "promissory notes" (Rozeboom, 1962) currently labeled simply "general aptitude" and "specific aptitude". The history of science shows that some classes of hypothesized entities were eventually definitively discovered and observed (e.g., electron, gene) while others were disconfirmed (e.g., miasma, phlogiston) (Kell, 2019). Although we adopt a realist perspective on constructs in this article, other, purely descriptive outlooks on constructs are equally viable (Fried, 2017; Jonas & Markon, 2016; Kell, 2018; Slaney & Racine, 2013).

studies (Blum & Holling, 2017) found that SLODR was consistently found as average ability increased in a sample, but this trend was complicated by a growing influence of *g* developmentally, so that SLODR effects were less pronounced in older respondents.

SLODR suggests that, among gifted samples, specific aptitudes may show more predictive value relative to *g* than they would in a mixed ability sample. Consistent with this expectation, many studies have shown that specific aptitudes show more reliable profiles (patterns in scores) in higher ability samples (Breit, Brunner, & Preckel, 2021). The observation of SLODR also suggests that caution should be taken in extrapolating studies of specific aptitudes from a gifted sample to the full distribution. Gifted education researchers are often seeking measures of new or alternative indicators of academic promise. Demonstrating a low correlation between a new construct and *g* in a high aptitude sample would not preclude a finding that the construct is heavily *g* saturated in the full distribution.

Many methodological approaches to profiles, *g* saturation, and factor structures have been found to lead to substantively and quantitatively different results related to SLODR (Breit, Scherrer, & Preckel, 2021; McGill, 2015). Some evidence against SLODR is hampered by a weak range of measures of specific and general aptitudes as well as contrasting just low/high aptitude groups (g., Arden & Plomin, 2007; Hartmann & Reuter, 2006; Legree, Pifer, & Grafton, 1996). The temporal stability of specific aptitude profiles among gifted children and decreasing *g*-loadings on aptitude tests as the average standing within a given sample increases (Reynolds, 2013) have been taken as evidence supportive of SLODR – while others have produced evidence suggesting that SLODR may be a statistical artifact due to heteroscedastic error residuals (Molenaar, Dolan, Wicherts, & van der Maas, 2010; Murray, Dixon, & Johnson, 2013). At the very least, the impact of latent score distributions and specific aptitude scores on the observation of SLODR is complex (Sorjonen, Madison, & Melin, 2021).

When studies are done well, gifted samples represent "natural experiments" that can be used to investigate SLODR more comprehensively, given that over one third of the range in general reasoning scores lies within the top 1% (Lubinski, 2009). If SLODR is a substantive phenomenon, rather than a statistical artifact, it would be expected that *g* would account for consistently less variance in specific aptitude scores as one moves continuously up the general reasoning continuum – and, accordingly, that the prevalence of extreme discrepancies in specific cognitive aptitude profiles (cf. M. Lang, Matta, Parolin, Morrone, & Pezzuti, 2019; Lohman et al., 2008) grows more common as assessment moves from the "merely" gifted to the highly, exceptionally, and profoundly gifted (Silverman, 2009). Other studies use continuous measures, but do not oversample in the gifted range to get adequate sample sizes (such as studies based on normative samples; e.g., Reynolds, 2013; Reynolds & Keith, 2007; Reynolds, Keith, & Beretvas, 2010).

To explore SLODR effectively, especially among highly gifted samples, assessments are needed that provide adequate measurement precision in the extreme right tail (e.g., within the top 1% or above). For example, to generate samples of adequate size, the highest aptitude group in Detterman and Daniel's (1989) study had a minimum IQ-equivalent score of 122 – not as high as the typical cutscore for intellectual giftedness (Silverman, 2009).

Measures of very high reasoning capacity are rare and difficult to develop. A simpler solution relies on measuring cognitive aptitude with achievement measures, including above-level testing in studies with children up to their early teens. Above-level testing consists of administering a standardized cognitive assessment to individuals of younger ages or earlier grade levels than the assessment is intended for (LeBeau, Assouline, Mahatmya, & Lupkowski-Shoplik, 2020; Stanley, 1990). For example, the participants in SMPY were identified in early adolescence (11–13 years old) based on their scores on the SAT (Lubinski & Benbow, 2006). Administering such assessments allows for differentiating degrees of cognitive aptitude within the top 1% of *g* with greater precision, and which would otherwise be obscured if a typical assessment was used to determine giftedness (Lubinski, 2009). Doing so would allow for testing of SLODR within samples comprised of both the general population (e.g., SAT-takers ages 16–18) and gifted populations (e.g., SAT-takers ages 11–13), representing a fuller range of cognitive aptitude than is typically present in many studies of SLODR.

3.3. Intellectual profiles: math, spatial, and verbal – and beyond

Another area for future research could extend the literature on cognitive aptitude tilt and profiles in high aptitude groups. Much of the specific aptitudes literature focuses on individually administered reasoning tests, such as the Wechsler and Woodcock Johnson tests. However, these studies focus on the full distribution, rather than gifted samples. On the other hand, similar studies of gifted samples primarily focus on reading and math achievement alone, because these are most commonly available in educational testing. Survey programs, such as Project TALENT, are widely used in this area of research because they offer a greater breadth of measures and, therefore, potential specific aptitudes that can be estimated. However, the selection of measures at the time of testing from the Project TALENT dataset may make it challenging to extract broad cognitive aptitudes beyond Gc, Gf, and visuospatial reasoning. Therefore, we are limited in studying the possible role of short-term memory or other factors in directing the area of expertise that develops.

Coyle (2018) called for, and, later, provided, a similar expansion of tilt research to technical-academic or vocational-academic tilt (Coyle, 2019). However, tilt research is limited in that (1) it can only contrast two specific aptitudes and (2) considers only manifest differences in test scores. In contrast, score *profiles* can include many different specific aptitudes and often takes into account the impact of measurement error on the difference scores. Allowing for some individuals not to have tilt (i.e., two scores that are statistically equivalent) could strengthen the contrast of groups with meaningful tilt (Lohman et al., 2008). We would like to see more research, especially with large samples and longitudinal designs, study a wider range of aptitudes.

Another consideration for practitioners is what differences in broad cognitive aptitudes have meaningful implications for outcomes (Schneider, 2013). As mentioned earlier, tilt scores do not take into account measurement error between scores, but even after using latent variables or accounting for measurement error, such scores would not necessarily yield tilt values that are practically meaningful or actionable in every case. Further research is needed to explore potential thresholds in tilt that are associated with differential outcomes.

3.4. Applied value of specific aptitudes beyond g among the gifted

One limitation in the specific cognitive aptitudes literature is the reliability and validity of the measures of specific aptitudes. Many individually administered cognitive reasoning tests use just two formats to estimate the specific aptitude scores. Composite scores, of course, are based on a large number of these specific aptitude measures, so it is not surprising that they are more reliable due to larger numbers and a wider variety of test items. The shared variance from a heterogeneous cognitive battery should be a better measure of *g* than one that is skewed towards one type of aptitude or content. Some of the research attempting to explore specific versus general factors relies on single tests (Wee, 2018), which is consistent with Spearman's (1927) original conception of specific factors but does not accurately represent current conceptions of specific aptitudes. Methodologists find that at least three specific measures (item formats) are needed to average out the task specific influences to measure a meaningful specific aptitude (Süß & Beauducel, 2005). If the goal is to determine if there is a stratum of capacities with broad application to a range of outcomes, a relatively heterogeneous measure of the specific aptitude is needed as well.

The value of specific aptitudes above and beyond *g* has typically been evaluated using hierarchical regression, regressing a given criterion (e.

g., grades) first on *g*, with specific aptitude scores entered in the second step. The appropriateness of this approach depends on the theoretical model of cognitive aptitudes an investigator adopts, however, as the variable(s) entered in the first step of a regression are presumed to have causal priority over those entered in later steps (Cohen, Cohen, West, & Aiken, 2003). As noted previously, higher-order models of cognitive aptitudes posit that *g* is a source of variance in specific aptitudes, but other models of cognitive aptitudes posit there is no causal relationship among *g* and group factors (e.g., bifactor models) or that specific aptitudes are the cause of variance in a formative *g* factor (e.g., Process Overlap Theory; Kovacs & Conway, 2016). If one of these perspectives is adopted, incremental validity analysis is inappropriate, as not only will variance shared between the criterion and *g* be attributed to *g*, so will whatever variance is shared among specific aptitudes, *g*, and the criterion (Kell & Lang, 2017; Lang, Kersting, Hülsheger, & Lang, 2010). When *g* is not presumed to causally influence group factors, alternative methodologies must be adopted in order to accurately represent the unique contributions of *g* and specific aptitudes to predicting a given outcome. Depending upon the model an investigator adopts and the data available, such methodologies include nested-factors modeling (Reeve, 2004), relative importance analysis (Lang & Kell, 2020), and psychometric network analysis (Kan, van der Maas, & Levine, 2019).

Another recommendation is for scholars not to be stymied by the old adage "not much more than *g*" (Ree & Earles, 1991) when investigating practical outcomes (e.g., academic achievement, occupational performance). Although few doubt the predictive value of *g* (cf. Richardson & Norgate, 2015), the conclusion that group factors add nothing to prediction beyond it is premature (e.g., Coyle & Greiff, 2021; Dipboye, 2007; Schneider & Newman, 2015). Indeed, evidence for meaningful increments in validity beyond *g* has been accumulating for at least 15 years (e.g., Mount, Oh, & Burns, 2008; Reeve, 2004; Trippe, 2005; Ziegler, Dietl, Danay, Vogel, & Bühner, 2011), with a recent meta-analysis (Nye, Ma, & Wee, 2022) strongly supporting the usefulness of specific aptitudes for forecasting job performance.

Where incremental validity analyses have often borne out the "not much more than *g*" stance, application of alternative methodologies has often resulted in very different findings. For instance, application of dominance weights has shown that specific cognitive aptitudes independent of *g* often account for meaningful variance in career success (Lang & Kell, 2020), job performance (Lang et al., 2010), foreign language learning (Stanhope & Surface, 2014), academic performance (Wee, 2018), and performance in the U.S. Army (Lang & Bliese, 2012) and Air Force (ALMamari & Traynor, 2021) – and sometimes account for greater variance than *g* itself. Further, the assumption that a small amount of incremental validity is not valuable is shortsighted, as even small effects can cumulate over time and across large samples to culminate to meaningful practical effects (Funder & Ozer, 2019; Kuncel, Hezlett, & Ones, 2001; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). Nonetheless, such studies also suggest the existence of moderating effects that influence the relative importance of *g* and group factors. For example, Lang et al. (2010) found that *g* was more important, vis-à-vis specific aptitudes, for predicting performance in high rather than low complexity jobs (the opposite of what might be predicted by SLODR).

In light of these developments, we recommend that research into the practical utility of specific aptitudes be continued, with more explicit attention paid to the cognitive aptitude model adopted that guides the investigation and appropriate alignment of the quantitative method(s) used with that model. Acknowledging that, in some cases, group factors can be as or more important than *g* does not imply that *g* is necessarily unimportant – indeed, many of the investigations referenced that used relative importance analyses found that *g* accounted for meaningful variance in outcomes in addition to specific aptitudes. Rather than artificially pitting *g* and specific aptitudes against each other when predicting real-world outcomes, a more fruitful approach would be to identify moderating conditions that consistently influence these factors' relative importance.

One intriguing "condition" that we urge investigating is the extent to which specific cognitive aptitudes contribute to prediction above and beyond *g* in the general population versus in intellectually gifted samples – and also samples that differ in their degrees of giftedness. Recent research suggests that even using incremental validity analysis, specific aptitudes can contribute meaningfully to the prediction of academic achievement beyond *g* (McGill, 2015), although findings have not been entirely consistent (McLarnon, Goffin, & Rothstein, 2018).[2] These findings suggest that it may be inappropriate to generalize the philosophy of "not much more than *g*" – even from an incremental validity standpoint – to gifted samples, where the influence of SLODR may be prevalent, weakening the influence of the general factor. We encourage continued investigation of this topic, in addition to extending it to the prediction of non-academic outcomes, such as job performance and career success. Jobs that require strong cognitive reasoning will largely be occupied by individuals high on *g* – and thus featuring a disproportionate number of gifted adults and favoring the effects of SLODR.[3] These investigations would benefit from approaching the issue of the practical value of general vis-à-vis specific aptitudes from multiple methodological standpoints (e.g., incremental validity, nested-factors modeling, relative importance analysis).

3.5. *Gifted research can inform our understanding of specific aptitudes*

Most of our future research directions have focused on how specific aptitudes as studied in gifted samples can inform our broader understanding of abilities research. However, the context and way in which gifted education researchers have studied specific aptitudes in determining appropriate placement in educational programming can also potentially inform our understanding of specific aptitudes. For example, one avenue of future research would be to include improved measures of specific aptitudes into gifted education samples when services are aligned to domain-specific expertise versus when the focus is general academic development. We can then learn more about students' response to instruction is more or less aligned to their areas of strengths. Such research on the alignment of services and specific abilities will allow us to understand how those aptitudes develop at the high end, and that in turn might inform our understanding of the structure and functioning of specific aptitudes in the right tail of the distribution. Generalization to the full distribution might also be possible, although the effect of SLODR may be to create greater distinctions between specific abilities in gifted samples that may be blurred in other samples.

4. Conclusion

This commentary primarily sought to explore new ways in which the rapidly developing research literature on specific cognitive aptitudes can be leveraged to inform our understanding of gifted samples and inform gifted education research as well as to provide recommendations

[2] Part of this effect can be attributed to the fact that there is limited variance in *g* in gifted samples, especially when a general conceptualization of giftedness is held. However, if the population of interest truly is *only* intellectually gifted individuals, scores on *g* are not range restricted, which is defined relative to the given population of interest (Kell & Wai, 2019).

[3] Lang et al.'s (2010) results do not support this hypothesis, as they found that the relative importance of *g* vis-à-vis specific abilities was *stronger* among incumbents in high complexity jobs. However, due to the nature of their dataset they could only divide jobs into high, medium, and low complexity categories, which may be too coarse to capture the potential effects of SLODR and impact of large numbers of gifted incumbents. This is a fertile area for future research, as two contrasting predictions firmly rooted in prior research and theory – SLODR versus performance in high complexity jobs being heavily reliant on *g* (Ackerman & Lakin, 2018; Farrell & McDaniel, 2001) – can be directly pitted against each other.

on future areas of research that would be fruitful at the intersection of these two fields. The fields of gifted education research and cognitive aptitudes research could benefit from each other, translating the basic science of cognitive reasoning to its practical application to advanced academic instruction (though, see Wai & Worrell, 2021 for discussion of the challenges of integrating these fields). Of course, gifted samples are just one field in which specific cognitive aptitudes research is useful, and numerous other fields could also be informed by the cognitive aptitudes literature, and in turn those fields might inform our understanding of specific cognitive aptitudes in various contexts. Additionally, more consideration of how the literature on specific cognitive aptitudes might best inform issues of policy and practice would be worth considering (e.g., for one take focused on education policy see Wai & Bailey, 2021), such as the idea of expanding gifted identification to use measures of spatial reasoning or other aptitudes (e.g., Kell & Lubinski, 2013; Lakin & Wai, 2020; Wai & Lakin, 2020). Finally, the research on specific cognitive aptitudes should consider multidisciplinary perspectives and approaches (Lyall, 2019), which may help basic research translate more effectively to problems of research, policy, or practice, where such evidence is important as a starting point.

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