Implications of 20 Years of CHC Cognitive-Achievement Research:

Back to the Future and Beyond CHC

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Abstract

Much has been learned about CHC COG→ACH relations during the past 20 years (McGrew & Wendling, 2010). This paper builds on extant research by first clarifying the definitions of *abilities*, *cognitive abilities*, *achievement abilities*, and *aptitudes* and then defining the differences between *domain-general* and *domain-specific* CHC predictors of school achievement. The promise of Kaufman's (1979; 2009) "intelligent" intelligence testing principle is demonstrated with two approaches to CHC-based *selective, referral-focused assessment* (SRFA). Next, a number of new *intelligent test design* (ITD) principles are described and demonstrated via a series of exploratory data analyses that employ a variety of data analytic tools (multiple regression, causal interpretation of SEM, multidimensional scaling). These ITD principles and analyses result in the proposal to construct *developmental-sensitive CHC-consistent scholastic aptitude clusters*, measures that can play an important role in contemporary third-method (pattern of strength and weakness [PSW]) approaches to specific learning disability (SLD) identification.

The need to move beyond simplistic conceptualizations of CHC COG→ACH relations and SLD identification models is argued and demonstrated via the presentation and discussion of CHC COG←→ACH models (causal SEM). Another proposal advanced is to identify and quantify *cognitive-aptitude-achievement trait complexes* (CAATCs). A revision in current third-method PSW SLD models is proposed that will integrate CAATCs. Finally, the need to incorporate the *degree of cognitive complexity* of tests and composite scores *within CHC domains* in the design and organization of intelligence test batteries (to improve the prediction of school achievement) is proposed. The fusion of proposals presented in this paper are a call to: (a) return to old ideas with new methods (i.e., "Back to the Future") and (b) embrace new ideas, concepts, and methods that require psychologists to move beyond the confines of the dominant CHC taxonomy of human cognitive abilities (i.e., "Beyond CHC").

Implications of 20 Years of CHC Cognitive-Achievement Research: Back to the Future and Beyond CHC

Let me begin by taking a few degrees of freedom to provide a personal introduction and context to help the reader understand the genesis of the wide-ranging ideas presented in this paper.

It is an honor and pleasure to write and present this invited paper at the *Inaugural Session of the Richard Woodcock Institute for Advancement of Contemporary Cognitive Assessment: The Evolution of CHC Theory and Cognitive Assessment*. As this paper evolved, it became clear that many of my thoughts, ideas, concepts, and approaches to data analyses reflected the influence of Dr. Richard Woodcock, a friend and mentor for over 25 years of my professional career. More than once, I wanted to change the focus and title of my paper to address a broader array of topics, many that build directly on the legacy of Dr. Woodcock's numerous innovative applied assessment contributions.

Dr. Woodcock's innovations and contributions include, but are not limited to:

- Publishing the first co-normed, individually administered cognitive-aptitude-achievement-interest battery of tests, which extend over most of the lifespan (preschool to late adulthood);
- Publishing the only individually administered co-normed cognitive and achievement batteries that provide scores based on both age and grade norms;
- Operationalizing and articulating a pragmatic decision-making model for test development and interpretation;
- Bridging the intelligence theory–IQ test gap as the first test author to base a cognitive-achievement battery on the extended Cattell-Horn *Gf-Gc* theory, later to be called Cattell-Horn-Carroll (CHC) theory;
- Initiating the practice of applying IRT Rasch test scaling methods to a clinical, individually administered battery of tests and the development of the crucial *W* score–growth score metric;
- Developing and advocating for better metrics for understanding human performance (e.g., real regression-to-the-mean adjusted discrepancy norms, norm-based intradiscrepancy and variation metrics, the Relative Performance Index, proficiency levels);

- Publishing an individually administered cognitive ability battery that also included differential scholastic aptitude clusters;
- Pioneering a series of CHC-organized joint- or cross-battery factor analyses of the major individually administered test batteries, resulting in birth of the concept of cross-battery assessment;
- Advocating for and providing methodology for examiners to engage in more flexible selective testing; and
- Providing technically sound solutions for test linking and equating, included the linking of a standardized battery of adaptive behavior (Scales of Adaptive Behavior; Scales of Adaptive Behavior—Revised) to a cognitive-achievement battery and the translation and adaptation of all three versions of the English-based WJ cognitive and achievement batteries to Spanish formats via equated U.S. norm methods.

This list is incomplete, but it demonstrates the breadth of Dr. Woodcock's contributions to the practice of psychological and educational assessment. On a more personal note, Dr. Woodcock has played a major role as a positive and critical mentor—one that has encouraged, prodded, and challenged me to always think about "raising the bar" when conceptualizing, implementing, and completing a research or test-development project.

Major portions of this paper draw on Dr. Woodcock's foundational contributions. In many respects, his fingerprints are all over this paper. He can claim partial credit for any of the ideas and innovations that are well received. I will assume 100% responsibility for any that fall flat or are misdirected. However, he will need to assume indirect responsibility for any material that may be characterized by the reader as, "Hmm…interesting idea—but are you serious?" since he contributed to the development of my professional mind—which shares much common variance with his—an intellectually restless mind that is driven to (a) look for new methods, research, and theories to address applied problems; (b) stretch available statistical methods and software in search of discovery; (c) look beyond the parochial boundaries of my training for seeds of ideas in other disciplines to cross fertilize with my existing professional schema; (d) challenge tradition and orthodoxy in the pursuit of best practice and on the basis of scientific evidence; and (e) relentlessly (stubbornly?) pursue purpose-driven research and creative thinking.

The above comments only partially describe the *purpose, passion, and serendipity*[1] theme that evolved as the core of my professional life, due in large part to Dr. Woodcock. This professional philosophy produced the CHC cognitive-achievement relations synthesis (McGrew & Wendling, 2010), which served as the springboard for the current paper. What may look like a coherent and logical set of propositions, proposals, and data analyses in this paper is more the result of a nonlinear, serendipitous, Woodcock-influenced journey "back to the future" and "beyond CHC."

My "Beyond CHC" Journey

A priceless gift from Dr. Woodcock has been unfettered access to the standardization data from all three editions of the WJ battery (Woodcock & Johnson, 1977; Woodcock & Johnson, 1989; Woodcock, McGrew, & Mather, 2001) and numerous special studies reported in the various technical manuals. I have had complete freedom to explore and play in what I call my private "WJ data sandbox." I have spent countless hours in this sandbox in the pursuit of answers to questions, hunches, theory-driven ideas, and serendipitous findings from prior data sandbox sessions. I have entered the data sandbox with many different data analytic tools and lenses. Many of the discoveries and insights have never reached formal publication as they satisfied my curiosity and, more importantly, resulted in new insights regarding the nature of intelligence and the WJ tests. That was sufficient reward. However, from time to time, I put my findings to word in the form of journal articles or book chapters—the current paper being one such product of my exploratory data sandbox activities.

No sooner than the WJ III was published in 2001, I began exploring the subtle nuances of the WJ III norm data. The corpus of findings has made it clear that a strict, linear-structural approach to understanding the nature of human intelligence, understanding the mental processes assessed in the WJ III® tests, and understanding cognitive, aptitude, and achievement relations requires the use of both CHC-grounded research and alternative non-CHC lenses. Starting in 2002, I engaged in a wide-ranging set of

[1] *Purpose, passion and serendipity* is the motto or philosophy of my web-based portal, *The MindHub*™ (www.themindhub.com).

exploratory analyses of the WJ III norm data and select WJ-R and WJ III cross-battery data sets. I dubbed this my "beyond CHC" project. From 2002 to today, I subjected these data sets to a variety of exploratory and analytic procedures (various variants of exploratory factor analysis, exploratory model-generating CFA, cluster analysis, and 2- and 3-D multidimensional scaling).

A pivotal point in my "beyond CHC" journey was a trip to stay and work with Jack Carroll in Fairbanks, Alaska, during the last week of May 2003 (McGrew, 2005), approximately one month prior to his death (July 1, 2003). During this visit, Carroll mentored me on the use of his self-written collection of exploratory factor analysis software (with Schmid-Leiman orthoganlization, EFA-SL). Under his tutelage, I completed a Carroll EFA-SL analysis of 50 WJ III tests in the WJ III norm data (ages 6 through adult samples). As noted elsewhere (McGrew, 2009), during his later years, Carroll had moved beyond sole reliance on his EFA-SL procedures to embrace confirmatory factor analysis (CFA) methods as an adjunct to fine tune his initial EFA-SL results. He blended the two methodologies as illustrated in his last published book chapter, *The Higher-Stratum Structure of Cognitive Abilities: Current Evidence Supports* g *and About Ten Broad Factors* (Carroll, 2003). By December 2003, I had completed the second CFA stage of the initial WJ III EFA-SL analysis started in Alaska with Dr. Carroll. The results of this analysis, which confirmed much of the CHC model, also suggested two equally plausible "beyond CHC" higher-order construct models with intermediate factors under *g*.[2]

Unfortunately, space does not allow the presentation of the wide-ranging set of exploratory data analyses I have completed since 2002. The remainder of this paper is a sample of select insights gleaned from my "beyond CHC" journey—a journey that has suggested the need to revisit old ideas and concepts that were either ahead of their time or have been ignored by myself and others who engage in psychological and educational assessment in school learning contexts. Thus, a need to go "back to the future."

The purpose of the current paper is to summarize a select portion of these findings and suggest how this knowledge can improve cognitive-achievement testing via selective, referral-focused assessments

[2] The results, with brief interpretations, are available at the following series of links:
http://www.iqscorner.com/2005/03/carroll-analysis-of-50-chc-designed.html
http://www.iqscorner.com/2005/03/carroll-analyses-of-50-chc-tests-rnd-2.html

(SRFA). This will be followed by suggestions of select new *intelligent test design* (ITD) principles for developing features that can be used to advance interpretation of intelligence test batteries, along with proposals for SLD identification models—innovations that require a combination of going "back to the future" and "beyond CHC."

CHC Model v2.0

The CHC model utilized in this paper is the recent CHC revision described by Schneider and McGrew (2012). A visual-graphic representation of the Schneider and McGrew summary is presented in Figure 1. This model and the Schneider and McGrew definitions are the foundation for this paper.[3]

Insert Figure 1 about here.

CHC COG→ACH Relations: What We Know Today

McGrew and Wendling (2010) recently provided the first systematically organized relations synthesis of contemporary Cattell-Horn-Carroll (CHC) cognitive-achievement (COG→ACH) research. Their review also included an integration of the narrative synthesis of the CHC COG→ACH research by Flanagan and colleagues (Flanagan, Ortiz, Alfonso, & Mascolo, 2006). McGrew and Wendling concluded that much has been learned from 20 years of CHC COG→ACH relations research. According to McGrew and Wendling (2010):

- *Almost all available CHC-designed COG→ACH research is limited to the WJ Battery.* Ninety-four percent of the reviewed research has been completed with the WJ battery (*Woodcock-Johnson® Psycho-Educational Battery–Revised* [WJ-R], Woodcock & Johnson, 1989, and the *Woodcock-Johnson III* [WJ III], Woodcock, McGrew, & Mather, 2001). Thus, caution is suggested in generalizing to other intelligence batteries until similar CHC-designed studies are completed with other commonly used cognitive batteries (e.g., *Differential Ability Scales®–II* [DAS-II], Elliott, 2007; *Kaufman Assessment Battery for Children, Second Edition*

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[3] An abridged summary of the Schneider & McGrew CHC v2.0 model can be accessed at: http://www.iqscorner.com/2011/06/chc-intelligence-theory-v20-broad-and.html

[KABC-II], Kaufman & Kaufman, 2004; *Wechsler Intelligence Scale for Children®–Fourth Edition* [WISC®-IV], Wechsler, 2008; *Stanford-Binet Intelligence Scales, Fifth Edition* [SB5], Roid, 2003).

- *The primary action in CHC COG→ACH relations is at the narrow-ability level*. Although broad CHC composites may be the best average predictors across a broad array of outcome measures, when the focus is on understanding, diagnosing, or suggesting academic interventions in sub-areas of achievement (e.g., word attack, reading comprehension, learning math facts, solving applied math problems), McGrew and Wendling's (2010) review suggested *narrow is better*. As stated by McGrew and Wendling, "consistent with the classic 'bandwidth-fidelity tradeoff' (Cronbach & Gleser, 1957) and the 'attenuation paradox' (Boyle, 1991; Loevinger, 1954) issues in the validity and reliability measurement literature….broad best predicts and explains broad. Narrow best predicts and explains narrow" (p. 669). New research, presented later, suggests that the "narrower is better" principle may not be 100% accurate and a more fundamental underlying principle is significant.
- *There is a future for "intelligent" intelligence testing, even in the current response-to-intervention* (RTI) *environment.* The disposal of the imperial IQ–ACH SLD discrepancy model, coupled with the publication of multiple contemporary cognitive batteries implicitly or explicitly grounded in (or interpretable from) CHC theory, and the extant CHC-based COG→ACH research knowledge provide assessment professionals with the opportunity to go "back to the future" and engage in the judicious, flexible, selective, *intelligent* (clinical skills + psychometric research) intelligence testing (Kaufman, 1979; Kaufman, 2009).

Figure 2 is a condensed, abridged summary of McGrew and Wendling's (2010) relations synthesis of contemporary CHC COG→ACH research. The figure conveys four important conclusions. First, academically related cognitive assessment should focus primarily on the measurement of narrow rather than broad CHC abilities. Second, certain CHC narrow abilities (e.g., *Gc* [language development], *Gsm* [working memory]) are important for both reading and math (*domain-general* CHC abilities). Third, some CHC narrow abilities are differentially related to reading (e.g., *Gc* [lexical knowledge], *Ga* [phonetic coding]) and math achievement (*Gf* [quantitative reasoning], *Gv* [visualization]) (*domain-specific* CHC abilities). Finally, conclusions 1 through 3, make it clear that in order to design assessments that address referral-specific concerns, assessment professionals and researchers need to understand the three-way interaction of *CHC narrow abilities* X *achievement domains* X *age* (*developmental status*).[4]

Insert Figure 2 about here.

Clarification of Ability Construct Terminology

Before proceeding, it is necessary to clarify and define some key terms. The terms *ability*, *cognitive ability*, *achievement*, *aptitude*, and *aptitude-achievement* are discussed in contemporary psychological and educational assessment circles, often without a clear understanding of the similarities and differences between and among the terms. For example, what does an "aptitude-achievement" discrepancy in the context of contemporary models of SLD identification (see Flanagan, Fiorello, & Ortiz, 2010) mean? Where are the aptitudes in the CHC model? It is argued here that it is critical for assessment professionals and researchers to use agreed-upon terms to avoid confusion, enhance collaboration, and facilitate research synthesis. In this spirit, Figure 3 illustrates the conceptual distinction between abilities, cognitive abilities, achievement abilities, and aptitudes. These conceptual distinctions are drawn primarily from Carroll (1993) and the work of Snow and colleagues (Corono et al., 2002). These definitions will be used in this paper.

Insert Figure 3 about here.

Figure 3 illustrates that all constructs in the CHC model are *abilities*. According to Carroll (1993), "*as used to describe an attribute of individuals,* ability *refers to the possible variations over individuals in the liminal levels of task difficulty (or in derived measurements based on such liminal levels) at which, on any given occasion in which all conditions appear favorable, individuals perform successfully on a defined*

[4] The abridged nature of Figure 2 excludes the age-related differential findings reported by McGrew and Wendling (2010). Readers should consult this source for information on the relation between age and significant CHC COG→ACH findings.

class of tasks" (p. 8, italics in original).[5] In simple terms, "every ability is defined in terms of some kind of performance, or potential for performance" (p. 4). The overarching domain of abilities includes cognitive and achievement abilities as well as aptitudes (see Figure 3). *Cognitive abilities* are abilities on tasks "*in which correct or appropriate processing of mental information is critical to successful performance*" (p. 10, italics in original). The key component to the definition of cognitive abilities is the *processing of mental information* (Carroll, 1993). *Achievement abilities* "refers to the degree of learning in some procedure intended to produce learning, such as an informal or formal course of instruction, or a period of self-study of a topic, or practice of a skill" (p. 17). As reflected in Figure 3, the CHC domains of *Grw* and *Gq* are consistent with this definition and Carroll's indication that these abilities are typically measured with achievement tests. Most assessment professionals use the terms "cognitive" and "achievement" abilities in accordance with these definitions. However, the term *aptitude* is often misunderstood.

Carroll (1993) uses a narrow definition of *aptitude* "to refer to a cognitive ability that is possibly *predictive* [emphasis added] of certain kinds of future learning success" (p. 16). The functional emphasis on prediction is the key to this narrow definition of aptitude and is indicated by the two horizontal arrows in Figure 3. These arrows, which connect domain-general and domain-specific abilities to the shaded CHC narrow abilities, combine to predict a achievement ability outcome domain and represent the narrow definition of "aptitude" used in this paper.

This definition is much narrower than the broad concept of aptitude reflected in the work of Richard Snow. Snow's notion of aptitude includes both cognitive and noncognitive (*conative*) characteristics of individuals (Corno et al., 2002; Snow, Corno & Jackson., 1996). The broader definition of aptitude focuses on "the characteristics of human beings that make for success or failure in life's important pursuits. Individual differences in aptitudes are displayed every time performance in challenging activities is assessed" (Corno et al., 2002, p. xxiii). Contrary to many current assumptions, aptitude is not the same as cognitive ability or intelligence. According to Corno et al., *ability* is the power to carry out some type of specific task and comes in many forms: reading comprehension, mathematical reasoning, spatial ability, perceptual speed, domain-specific knowledge (e.g., humanities), physical coordination, etc. This is

[5] As noted by Carroll (1993), *liminal* refers to specifying *threshold* values used "in order to take advantage of the fact that the most accurate measurements are obtained at those levels" (p. 8).

consistent with Carroll's definition of ability. According to Snow and colleagues, aptitude is more aligned with the concepts of readiness, suitability, susceptibility, and proneness, all which suggest a "predisposition to respond in a way that fits, or does not fit, a particular situation or class of situations. The common thread is potentiality—a latent quality that enables the development or production, given specified conditions, of some more advanced performance" (Corno et al., 2002, p. 3). This definition is similar to the definition in the *Shorter Oxford English Dictionary* (Brown, 2002) where the noun *aptitude* is defined as "[1.] Natural tendency, propensity, or disposition; [2.] Fitness, suitability, appropriateness; [3.] Natural ability; a talent (for); capacity to acquire a particular skills" (p. 107, bold in original). This broader definition includes noncognitive characteristics such as achievement motivation, freedom from anxiety, self-concept, control of impulses, and other noncognitive characteristics.

As reflected in Figure 3, cognitive and achievement abilities differ primarily in the degree of emphasis on mental information processing (cognitive) and the extent to which the ability is an outcome acquired more from informal and formal instruction (achievement). Here, *aptitude* is defined as *the combination, amalgam or complex of specific cognitive abilities that, when combined, best predict a specific achievement domain*. This definition is consistent with Snow's (1987) assumption that "the term aptitude always implies prediction in some particular outer environment" (p. 13). Cognitive abilities are always cognitive abilities. Some cognitive abilities *contribute* to academic or scholastic aptitudes, which are pragmatic functional measurement entities—not latent, trait-like cognitive abilities. Different academic or scholastic aptitudes, depending on the achievement domain of interest, likely share certain common cognitive abilities (domain general) and also include cognitive abilities specific to certain achievement domains (domain specific). A simple and useful distinction is that cognitive abilities and achievements are more like unique abilities in a table of human cognitive elements, while different aptitudes represent combinations of different cognitive elements from this table that serve a pragmatic predictive function. For quantoid readers, the distinction between factor-analysis-based latent traits (cognitive abilities) and multiple-regression-based functional predictors of achievement outcomes (cognitive aptitude) may help clarify the sometimes murky discussion of cognitive and achievement abilities and aptitudes.

Finally, I believe the various third-method pattern-of-strength-and-weakness (PSW) SLD models referenced in this paper would benefit from being framed in a broader conceptual and theoretical framework. Regardless of the SLD model name (e.g., concordance–discordance, discrepancy–consistency, dual discrepancy–consistency), the models, at their core, are all based on the notion of a specific pattern or configuration of abilities, aptitudes, and achievements related to different types of SLD in different achievement domains (see Flanagan, Fiorello, & Ortiz, 2010). The visual-graphic representation of each model typically includes three shapes (representing construct domains) and simple discrepancy comparisons between the domains (typically designated by arrows; see Figure 11 later in this manuscript). Although clear and efficient for enhancing conceptual understanding, such models tend implicitly to suggest a simplistic, multiple-domain discrepancy-score approach to defining SLD. Furthermore, the rationales for these models reflect a parochial foundation in contemporary federal SLD regulations and contemporary research from the fields of special education, school psychology, school neuropsychology, and psychometric factor-analysis intelligence research. Seminal and historical research from other corners of psychology (e.g., individual differences, educational psychology) that has focused on the development of theories and methods for measuring and describing characteristic patterns or configurations of different human ability traits is largely ignored in contemporary SLD model literature.

Richard Snow's seminal study of *aptitude complexes* (which, at various times, he also referred to as compounds and configurations) (Corno et al., 2002; Snow, 1987) is the most prominent educational psychology example. Building on Snow's work, Ackerman's (1996) PPIK (intelligence-as-process, personality, interests, intelligence-as-knowledge) model of intelligence has produced intriguing research-based insights into trait complexes. In an *Annual Review of Psychology* article on individual differences in intelligence (Scientific and Social Significance of Assessing Individual Differences: "Sinking Shafts at a Few Critical Points"), Lubinski (2000) recognizes the similarity of the work of Snow and Ackerman (and others) via the discussion of the *constellations* of cross-domain attributes. Although these research programs have typically dealt with a broader array of human trait domains (intelligence, achievement, motivation, personality, interests, etc.), the focus on patterns or configurations across and within domains is similar to the focus of contemporary SLD third-method models.

I believe that research and conceptualization of third-method PSW SLD models could benefit from being viewed as a narrow subset of a larger set of trait complexes. Contemporary SLD assessment research could benefit from the conceptual and methodological progress demonstrated by trait-complex organized research (e.g., see Ackerman, 1996, 2000; Ackerman, Bowen, Beier, & Kanfer, 2001; Ackerman, Chamorro-Premuzic, & Furnham, 2011).[6] For example, this historical research would serve to remind contemporary assessment personnel that aptitude-achievement relations are not readily captured in simple linear relations (and figures) and often require interactions and the conceptualization of relations in multidimensional hyperspace (see Snow, 1987). To advance this idea , I suggest the various third-method SLD models be considered attempts to understand and measure cognitive-aptitude-achievement trait complexes. Borrowing liberally from Ackerman (Ackerman, 1997; Beier & Ackerman, 2005), who in turn drew from the seminal work of Cronbach (1967) and Snow (1989), a *trait complex* is defined in the most general sense as "sets of traits that combine to affect some type of outcome…the sets of traits are sufficiently interrelated to suggest exploration of mutually causal interdependencies" (Ackerman, 1997, p. 187). This definition is consistent with the definition in the *Shorter Oxford English Dictionary* (Brown, 2002), which defines the noun *complex* as "**1.** A complex whole; a group of related elements…**2.** **Chemistry**. A substance or species formed by the combination of simpler ones" (p. 468, bold in original). In the current context, I define a *cognitive-aptitude-achievement trait complex* (CAATC) as a *constellation or combination of related cognitive, aptitude, and achievement traits that, when combined together in a functional fashion, facilitate or impede the acquisition of academic learning*. I will return to CAATCs later—in the form of exploratory data analyses that may offer hope for better measuring, describing, and explaining school learning—with implications for revisions of current third-method SLD identification models.

[6] The use of this broader context also serves as a necessary reminder (and link to research) that one of the primary goals of cognitive-aptitude-achievement testing is the identification of aptitude-treatment-interactions (ATIs) that can inform instructional interventions (see Corno et al., 2002).

CHC-Selective, Referral-Focused Assessment Strategies

A General CHC-Selective, Referral-Focused Assessment Approach

Given the CHC v2.0 model and CHC COG→ACH relations research synthesis summarized in Figure 2, it is now possible for the field of school-based cognitive assessment to move toward more flexible selective, referral-focused assessment (SRFA) approaches. Unfortunately, linear constraints of the written word combined with the heterogeneous universe of possible learning problems in the sphere of human experience do not allow for the presentation of multiple SRFA scenarios. Instead, two fictitious examples (see Figure 4) are presented to demonstrate how the information summarized in Figure 2 can be used.

Insert Figure 4 about here.

Figure 4 presents the assessment logic for a student who is 7 years of age and who is referred for continuing problems in basic reading skills (BRS) acquisition.[7] In both scenarios, all relevant domain-general and domain-specific abilities listed for BRS (see Figure 3) are considered in the selection of possible tests to administer by the examiner during Stage 1. It should be noted in Figure 4 that not all possible WJ III tests associated with BRS (see Figure 2) are listed during Stage 1 of the assessment scenario. The more detailed age-based summaries provided by McGrew and Wendling (2010) were consulted to select the initial pool of possible tests to administer in Stage 1 of the SRFA process. In both scenarios, the decision was made to administer eight WJ III tests (identified by black flags) that correspond to the CHC domains designated on each branch of the figure. Given that referral and background information suggested a possible language–*Gc* deficit, the examiner decided to measure at least three narrow CHC abilities via the selection of three WJ III *Gc* tests (Verbal Comprehension, Oral Comprehension, and Picture Vocabulary). These three tests provided indicators of of domain-general language development (*Gc*-LD) and listening ability (*Gc*-LS), and domain-specific lexical knowledge (*Gc*-VL). Also, given that the WJ III Picture Vocabulary test can be considered a pictorial general verbal information test (McGrew, 1986, 1994), the examiner decided not to administer the WJ III General

[7] This figure is not intended to represent *the* figure or flow chart to follow in a lockstep manner. It is a visual schematic intended to represent the underlying logic for explanatory purposes.

Information test at Stage 1. Rather, the Picture Vocabulary score at Stage 1 would guide the examiner's decision whether to administer General Information during Stage 2 of the assessment. Reflecting an awareness of the age-based findings of McGrew and Wendling (2010), where both associative memory (*Glr*-MA) and naming facility (*Glr*-NA, similar to rapid automatized naming [RAN], or speed of lexical access) are significantly related to BRS achievement, two WJ III *Glr* tests were selected for administration (Visual-Auditory Learning and Rapid Picture Naming). Finally, the domain-general abilities of perceptual speed (*Gs*-P [WJ III Visual Matching]) and working memory (*Gsm*-MW [Numbers Reversed]) and the BRS domain-specific ability of phonetic coding (*Ga*-PC [a.k.a., phonemic awareness, WJ III Sound Blending]) were selected to be administered. This collection of eight WJ III tests, based on the CHC COG→ACH information summarized in Figure 1, represents the most time-efficient and BRS-targeted set of CHC narrow cognitive ability WJ III tests for taking a first look at the student during Stage 1 of SRFA.

As designated in Figure 4 by the downward pointing arrows, this hypothetical subject displayed relative deficits on the WJ III Verbal Comprehension, Oral Comprehension, and Picture Vocabulary tests when scores were compared to a complete set of SRFA Stage 1 tests. Relative strengths are noted in *Gsm*-MW, *Glr*-MA/NA, *Gs*-P, and *Ga*-PC, suggesting the hypothesis that the student's difficulties are likely not related to cognitive CHC deficits in these domains. These fictitious results suggest a broad *Gc* deficit as indicated by weaknesses in language development, listening ability, and lexical knowledge. As noted in Figure 4, the examiner is then faced with the Stage 2 decision whether to consider administering additional WJ III tests to verify this hypothesized broad *Gc* deficit (e.g., General Information or Academic Knowledge for general [verbal] information, Understanding Directions for listening ability). If sufficient other test information, parent and teacher reports (e.g., *Children's Psychological Processes Scale* [CPPS], Dehn, 2012), and school records provide additional convergent evidence of a broad language–*Gc* deficit, it would not be unreasonable for an examiner to stop additional *Gc* testing and generate the hypothesis of a broad *Gc* deficit as contributing to the student's BRS learning difficulties. However, if the examiner was not convinced or it was determined that it was important to gather more detailed information for making within-*Gc* narrow ability comparisons, then the four tests listed in Stage 2 might be considered.

Scenario 2 illustrates how a different pattern of cognitive strengths and weaknesses (after Stage 1) for another seven year old student would lead to a different Stage 2 question and SRFA strategy. In this scenario, relative strengths were suggested in *Gc*, *Gsm*-MW, *Gs*-P, and *Ga*-PC. Hypothesized *Glr*-related deficits were suggested, in associative memory and naming facility. The weakness on the WJ III Picture Vocabulary test could also be consistent with the initial hypothesis of long-term storage and retrieval deficits, as this test requires a subject to look at pictures and retrieve from their lexicon the appropriate name for the picture. As noted in the Stage 2 portion of this scenario, initial test results suggest the *Gc* problems reported by school personnel do not appear related to lack of language abilities or limitations in the student's breadth of vocabulary or general information. Rather, they suggest that the presenting learning behaviors may be more related to problems in storing newly acquired *Gc* knowledge or in problems with efficient retrieval. In contrast to Scenario 1 where, at Stage 2, further assessment was focused primarily on additional confirmation evidence of a highly probably broad *Gc* deficit, Stage 2 (in Scenario 2) is still focusing on generating a hypothesis about cognitive deficits that likely need further exploration. As can be seen in Figure 3, additional SRFA would appear wise to investigate and compare this student's associative memory (WJ III Memory for Names) and naming facility (WJ III Retrieval Fluency and Decision Speed). Depending on the Stage 2 results, the examiner may feel confident in forming a hypothesis regarding this particular student's pattern of cognitive strengths and weakness and discontinue formalized testing or, if necessary, enter a third iteration of assessment by supplementing the WJ III *Glr*-MA/NA tests with tests of these abilities from other assessment batteries (Flanagan, Ortiz, & Alfonso, in press; Flanagan, Ortiz, Alfonso, & Mascolo, 2006).

These two hypothetical examples do not cover the entire array of possible test patterns that may emerge after Stage 1 or some that might take the Stage 2 assessment into other domains (e.g., phonemic awareness, working memory, processing speed). If the assessment is only to aid instructional hypothesis generation, the testing completed (as described above) may be sufficient to suggest evidence-based interventions that are then monitored with curriculum-based methods. If eligibility for SLD services is under consideration, it might be possible for the examiner to conclude from the pool of all administered tests that the individual's relative strengths provide sufficient evidence of average or normal cognitive abilities, a requirement for SLD diagnosis. If not, the examiner may need to engage in additional SRFA with WJ III tests that are good proxies for general intelligence, and more importantly, are tests of abilities that are less related to BRS learning problems. A review of less BRS-salient CHC domains in Figure 3 suggests that the best candidate strength tests for this hypothetical case might come from the CHC *Gf* domain.

CHC-Consistent, Aptitude-Selective, Referral-Focused Assessment: Back to the Future

The third-method approach to SLD identification has been advanced primarily by Flanagan and colleagues (2006, 2011, in press), as well as Hale and colleagues (Hale, Wycoff, & Fiorello, 2011) and Naglieri (2011) (see Flanagan, Fiorello, and Ortiz, 2010, for an overview and discussion). A central concept of the third-method SLD models is that an individual with a possible SLD must demonstrate cognitive deficits that are empirically or theoretically established as being those most related to the achievement domain where the person is experiencing their primary achievement difficulties. That is, the individual's cognitive domain-general or domain-specific deficits are consistent or *concordant* with the person's academic deficits in the context of other cognitive and achievement strengths that suggest strengths in non-SLD areas (i.e., a consistent pattern of strengths and weaknesses [PSW]).

Inherent in these SLD models is the notion of *aptitude-achievement consistency* or *concordance*. This use of "aptitude" is consistent with the previously defined notion of cognitive aptitude for a specific academic domain, hereafter called *scholastic aptitude*.[8] It is important to note that aptitude is *not* the same as general intelligence and is *not* a CHC cognitive ability trait—it is a combination or complex of cognitive abilities that best predict a specific achievement domain. For reading and math, these are the domain-general and domain-specific CHC narrow abilities summarized in Figure 3.

Back to the Future vis-à-vis Scholastic Aptitude Measures. The importance of scholastic aptitude as a core component of the consistency models of SLD assessment and identification, in many respects, is a call to go "back to the future." The WJ (Woodcock & Johnson, 1977) and WJ-R (Woodcock & Johnson, 1989) batteries both included scholastic aptitude (SAPT) clusters as part of the WJ/WJ-R *pragmatic decision-making discrepancy model* (McGrew, 1986, 1994; Woodcock, 1984). Of particular

[8] The term *scholastic* aptitude is used instead of *academic* aptitude to afford continuity with early attempts to provide differential academic aptitude clusters in the WJ and WJ-R—measures that were called Scholastic Aptitude clusters.

relevance was the WJ and WJ-R *Type I aptitude-achievement discrepancy*, which provided a discrepancy between obtained and expected achievement (a prediction based on curriculum-specific SAPTs). The original WJ and WJ-R SAPTs were *not* presented as part of the explicitly defined comprehensive discrepancy-based consistency–concordance SLD identification models as advanced by Flanagan et al. (2006, 2011, in press), Hale et al. (2011), and Naglieri (2011). Instead, the original SAPTs were presented as part of a general psychoeducational pragmatic decision-making model. However, it is clear that the WJ and WJ-R SAPTs were ahead of their time because, philosophically, they now align with the aptitude portion of the aptitude-achievement consistency–concordance component of contemporary SLD models.

The WJ SAPTs were differentially weighted combinations of the four best cognitive tests that predicted reading, math, writing, or knowledge. The differential weights were the same across all age ranges. For example, the WJ Reading Aptitude cluster was a differentially weighted combination of Antonyms-Synonyms (*Gc*-LD/VL: .42), Visual-Auditory Learning (*Glr*-MA: .23), Analogies (*Gc*-LD/VL: .18), and Blending (*Ga*-PC: .17). The WJ Math Aptitude cluster was a differentially weighted combination of Antonyms-Synonyms (*Gc*-LV: .39), Analysis-Synthesis (*Gf*-RG: .27), Visual Matching (*Gs*-P: .26), and Concept Formation (*Gf*-I: .08). In the WJ-R, the SAPTs were equally weighted, four-test combinations. Although derived primarily via the atheoretical empirical power of multiple regression statistical models, the specific CHC abilities included in the WJ Reading and Math SAPTs demonstrate overlap with the critical CHC cognitive abilities listed for reading and math in Figure 2. As articulated by McGrew (1986) when discussing the Woodcock-Johnson Tests of Cognitive Abilities (WJTCA), "because of their differential weighting system, the [*Woodcock-Johnson Tests of Cognitive Abilities*] WJTCA Scholastic Aptitude clusters should provide some of the best curriculum-specific expectancy information available in the field of psychoeducational assessment" (p. 217). When discussing the Woodcock-Johnson Tests of Cognitive Abilities—Revised (WJTCA-R) SAPTs, McGrew (1994) reiterated "the purpose of the WJTCA-R differential aptitude clusters is to provide predictions of *current* levels of achievement. If a person obtains low scores on individual tests that measure cognitive abilities related to a specific achievement area and these tests are included in the aptitude cluster, then the person's current achievement expectancies should also be lowered. This expectancy information will be more accurately communicated by the narrower WJTCA-R different aptitude clusters than by any broad-based score from the WJTCA-R or other tests" (p. 223, italics in original). Woodcock (1984), in a defense of the SAPTs in *School Psychology Review*, made it clear that the composition of these clusters was to make the best possible aptitude-achievement comparison. Woodcock stated that "the mix of cognitive skills included in each of the four scholastic aptitude clusters represents the best match with those achievement skills that could be obtained from the WJ cognitive subtests" (p. 359).

The value of the WJ and WJ-R SAPTs was not fully appreciated largely due the dominant IQ–ACH discrepancy model that constrained assessment professionals from using the SAPTs as intended (McGrew, 1994). This, unfortunately, led to their elimination in the WJ III and replacement with the Predicted Achievement (PA) option, which provided achievement domain-specific predictions of achievement based on the age-based optimal weighting of the seven individual tests that compose the WJ III GIA-Standard (GIA-Std) cluster. Although the WJ III PA option is a stronger predictor of achievement than the WJ III GIA-Std, the PA option never captured the attention of assessment professionals and tends to be atheoretical—and thus not intuitively understandable to clinicians. In a sense, the field has now caught up with the WJ/WJ-R operationalization of SAPTs.

Intelligent Test Design (ITD): Developmental-Sensitive, CHC-Consistent Scholastic Aptitude Clusters

WJ/WJ-R type SAPTs could now serve an important role in contemporary aptitude-consistency SLD models. With advances in CHC theory and measurement and computerized test scoring, it is now possible to develop better SAPTs for SLD identification and other purposes—what I call *developmental-sensitive CHC-consistent scholastic aptitude clusters*, an example of a more "intelligent" *intelligence test design* (ITD) principle. I next use the WJ III norm data to illustrate an ITD approach to the development of CHC-consistent SAPTs because (a) as a coauthor, I have ready access to the complete data set, (b) over 90% of the extant CHC COG→ACH research has been based on the WJ-R or WJ III, and (c) the WJ III includes the most complete array of individual tests that sample from the widest array of CHC domains relevant to academic achievement. The WJ III norm data for all subjects from ages 5 through 18 were used in the analyses described next.

<u>Developmental-Sensitive CHC-Consistent Scholastic Aptitude Clusters</u>. Prior WJ-R/WJ III CHC COG→ACH research has demonstrated systematic developmental relations between WJ-R/WJ III cognitive *clusters* and achievement (Floyd, McGrew, & Evans, 2008; McGrew, 1993; McGrew & Hessler, 1995). This is consistent with the conclusions of McGrew and Wendling (2010) and indicates that CHC-consistent SAPTs should incorporate this developmental information. More important, these prior studies provide an ITD approach to capture the age-nuanced CHC COG→ACH relations. The ITD procedures described below for the prediction of the WJ III Basic Reading Skills cluster are the same procedures used in the prediction of WJ III Math Reasoning.

All WJ III individual tests (that were classified as measuring CHC narrow abilities related to basic reading skills as summarized in McGrew and Wendling, 2010) served as the initial pool of potential predictor tests. CHC theory and logic-based multiple regression models were crafted. First, all tests in the initial predictor pool were entered into a single, full multiple-regression model. Next—instead of running a software application to implement automatic backward or forward multiple regression stepping of test variables—an author-controlled backward elimination of predictor/test-predictor strategy occurred. Tests with high negative loadings were eliminated one-by-one, and the output inspected after each step.[9] Tests that were nonsignificant in the prediction of BRS were then eliminated one at a time. After a final pool of statistically significant contributors to the BRS model remained, previously eliminated tests that theory, research, or partial correlation monitoring suggested as potentially related to BRS were reentered (one at a time) to insure they were still not significant predictors that should have been retained in the final model. Multiple iterations of this test predictor reentry process occurred before the BRS prediction model was finalized. Six tests were retained in the BRS model based on the entire sample of 5 through 18 year olds: Verbal Comprehension, Sound Awareness, Numbers Reversed, Visual Matching, Sound Blending, and Visual-Auditory Learning.[10]

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[9] The partial correlations for all tests after each step were closely monitored to identify tests that may have been "bridesmaid" predictors—i.e., would likely have stayed in the model if another test with which the bridesmaid test was highly correlated had not been present.
[10] In the Math Reasoning regressions, the WJ III Number Series test eliminated from the initial pool of potential predictor variables given that the Quantitative Concepts test in the Math Reasoning cluster includes some number series items.

Next, thirteen separate multiple regression models were run at each age from ages 5 through 18. The standardized regression coefficients for each predictor were plotted as a function of age. The plotted raw standardized coefficients demonstrated clear systematic developmental trends, but with noticeable "bounce" due to sampling error. Smoothed curves, using a nonlinear smoothing function through the plot of each set of age-specific standardized regression coefficients, were generated. The smoothed curves represent the best estimate of the population parameters. This technique of smoothing sample values to estimate population parameters has been used previously in a variety of studies (see McGrew, 1993, and McGrew & Wrightson, 1997) and was employed in the development of WJ III GIA-Standard and GIA-Extended *g*-weighted clusters and the developmental-sensitive WJ III Predicted Achievement (PA) score (McGrew & Woodcock, 2001). The raw and smoothed results for Verbal Comprehension and Visual-Auditory Learning are presented in Figure 5 for illustrative purposes. The raw, standardized coefficients demonstrate sampling error bounce, but visual inspection suggests clear developmental trends. The smoothed curves are interpreted as the best estimates of the population parameters for Verbal Comprehension and Visual-Auditory Learning from ages 5 through 18. It is clear that the relative importance of Verbal Comprehension and Visual-Auditory Learning increase and decrease systematically, respectively, as a function of age. Figures 6 and 7 present the final smoothed results for the CHC-consistent SAPT tests for the prediction of the WJ III Basic Reading Skills and Math Reasoning clusters.

Insert Figure 5–7 about here.

There is much that can be discussed from a review of Figures 6 and 7. The most salient conclusions are:

- *SAPTs require a mixture of domain-general and domain-specific CHC cognitive abilities*. The composition of CHC-consistent SAPT clusters make theoretical and empirical (CHC COG→ACH research synthesis, see Figure 3) sense. For example, *Gc*-LD/VL (Verbal Comprehension) is a domain-general predictor as it is salient for BRS and MR at all ages and systematically increases in importance with age. In BRS, visual-auditory-paired associative memory (Visual-Auditory Learning [*Glr*-MA]) is very important during the early ages (ages 6–9), but then disappears from importance in the prediction model. Visual-Auditory Learning (*Glr*-MA) is not in the MR model. *Glr*-MA, as measured by Visual-Auditory Learning, is classified as a BRS domain-specific ability. *Gf* abilities (quantitative reasoning [RQ], Number Matrices; general sequential reasoning [RG], Analysis-Synthesis) are important throughout all ages when predicting math reasoning achievement. In fact, both increase in relative importance with age, particularly for the measure of *Gf*-RQ (Number Matrices). These two *Gf* tests are absent from the BRS model, which defines them as MR domain-specific abilities. Instead of measures of *Gf*, measures of *Ga* abilities (Sound Blending, Sound Awareness) are BRS domain-specific abilities. *Gs* and *Gsm*-MW (domain-general cognitive efficiency variables) are classified as domain-general since they are present in both the BRS and MR models.

- *Developmental trends are critically important in aptitude-achievement comparisons*. The age-based plots (see Figures 6 and 7) provide a more precise picture of the developmental nature of the relations between CHC abilities and achievement than the McGrew and Wendling (2010) and Flanagan and colleagues reviews (2006, 2011). The current findings suggest, when selecting tests for SRFA, it is crucial that examiners know the developmental nature of CHC COG→ACH relations research. The fact that some specific narrow CHC tests show such dramatic changes across age suggests that *those who implement an aptitude-achievement consistency–concordance SLD model must be cautious and not use a "one size fits all" approach when determining which CHC COG abilities be examined for the aptitude portion of the consistency model.* An ability that may be very important at certain age levels may not be as important at other age levels (e.g., Visual-Auditory Learning in the WJ III BRS aptitude cluster).
- *SAPTs are better predictors of achievement than* g-*based composites*. The amount of explained variance (multiple *R*-squared, see Tables in Figures 6 and 7) is higher for the CHC-

consistent SAPT clusters when compared to the WJ III General Intellectual Ability (GIA-Std) clusters. This is particularly true at the oldest ages for MR.[11]

- *SRFA requires three-way interaction thinking*. The above results reinforce McGrew and Wendling's (2010) conclusion that development of more "intelligent" SRFA strategies requires a recognition of the *three-way interaction of CHC abilities* X *achievement domains* X *age* (developmental status).

It is time to consider bringing the SAPTs back...back to the future. The logic of their design is a nice fit with the aptitude component of the aptitude-achievement consistency–concordance SLD models. The field is now ready for this type of conceptualized and developed measure. However, the original concept can be improved upon via two new ITD procedures:

- *Test developers should utilize the extant CHC COG→ACH relations literature when selecting the initial pool of tests to include in the prediction models.* This extant research literature should also guide the selection of variables in the final models. The models should not be driven by raw empiricical prediction. This varies from the WJ and WJ-R SAPTs, which were designed primarily based on empirical criteria, although their composition often made considerable theoretical sense when viewed via a post hoc CHC lens. Test batteries that do not include indicators of all major achievement-relevant cognitive domains (e.g., *Glr, Ga*, and *Gs* are missing from some individually administered cognitive test batteries) will have a hard time developing CHC-consistent SAPTs. Test developers or independent researchers will need to explore means by which supplemental indicators of missing key CHC SAPT-important tests might be statistically linked to the other tests in these more limited CHC batteries. This problem also holds for the WJ III, albeit to a lesser extent, when SRFA requires "drilling down" deeper into certain narrow CHC cognitive ability domains.

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[11] Of course, these values capitalize on chance factors due to the sample-specific nature of multiple regression procedures and would likely shrink somewhat in independent, sample cross validation. However, the results are consistent with prior reviews of the superior predictive ability of WJ/WJ-R SAPTs when compared to WJ/WJ-R *g*-based composite scores as well as composites from earlier editions of the Wechsler batteries, SB, and KABC (McGrew, 1986, 1994).

- *Provide age-based developmental weighting of the tests in the different CHC-consistent SAPTs.* The authors of the WJ III demonstrated the necessary technology to make this possible when they implemented age-based, differential-weighted GIA *g* and Predicted Achievement scores in the WJ III computer scoring software (*Woodcock-Johnson III Normative Update* [WJ III NU] *Compuscore® and Profiles Program* [Compuscore], Schrank & Woodcock, 2007). The same technology can be applied to the development of CHC-designed SAPTs with developmental shifting weights (per the smoothed curves in the models above). For WJ III users, the WJ III NU-based *Compositator* program (Schneider, 2010) can be used to develop CHC-consistent SAPTs within the WJ III battery; although, the age-based correlation matrices that serve as the program's software engine are not provided in single-year increments, but rather mirror that broader age range reported for the WJ III test intercorrelations as reported in the WJ III NU technical manual (McGrew & Woodcock, 2001; McGrew, Schrank, & Woodcock, 2007).

A CHC-Consistent SAPT SRFA Strategy. The composition of the example WJ III BRS and MR SAPTs suggests another wrinkle for SRFA. Instead of pursuing the General CHC SRFA Approach described previously (see Figure 3 and 4 and related text for BRS example), examiners could choose to administer the six BRS SAPT tests presented in Figure 6 during Stage 1 of the assessment process. This would provide the most time-efficient initial assessment that would include indicators of the key BRS CHC-related cognitive abilities. Examiners would then examine the relative pattern of strengths or weaknesses within the initial six tests and continue per the logic and methods described previously with regard to the example presented in Figure 4. Of course, the six BRS SAPT tests could be supplemented at Stage 1 with additional tests based on available referral and background information.

An additional advantage, aside from time-efficient SRFA, would be the ability to generate predicted or expected achievement scores that could then be evaluated for statistical significance to determine aptitude-achievement consistency (or the aptitude-achievement component of the BRS cognitive-aptitude-achievement trait complex described later in this paper) as used in contemporary consistency SLD models. Currently, if one is using the WJ III battery, the *Compositator* (Schneider, 2010) program could serve this function. Hopefully, in the future, intelligence test developers will include a broad array of tests that measure the most important narrow CHC COG→ACH relations, or statistical links to supplemental co-normed batteries, that would allow for CHC-consistent SAPT construction across co-normed or equated batteries.

CHC COG→ACH Relations: Concluding Comments—ITD and Back to the Future

The dethroning of the imperial IQ–Achievement discrepancy model of SLD identification, combined with (a) the emergence of the CHC taxonomy of cognitive abilities, (b) the publication of a variety of cognitive intelligence batteries that are either implicitly or explicitly grounded in (or can be interpreted from) CHC theory, and (c) the emergence of CHC COG→ACH research synthesis (which indicates school-learning-related cognitive assessments should focus primarily on narrow CHC abilities) provide opportunities for assessment professionals to go "back to the future" to embrace "intelligent" intellectual assessment. Assessment professionals can throw off the shackles of the knee-jerk "give everyone a standard or complete IQ battery" mentality and, instead, embrace a CHC SRFA assessment strategy.

SRFA assessment is consistent with Alan Kaufman's "intelligent testing" approach, first articulated in 1979. The *intelligent testing* skill set requires the combination of knowledge of clinical principles and expertise in understanding the quantitative features of each individual test in an intelligence battery (e.g., reliability, specificity, *g*-loadings, different theoretical interpretations, CHC COG→ACH relations, etc.). This demands "a very high standard of clinical expertise" (Fletcher-Janzen, 2009, p. 16) as the model requires the bringing together of "empirical data, psychometrics, clinical acumen, psychological theory, and careful reasoning to build an assessment of an individual leading to the derivation of an intervention to improve the life circumstances of the subject" (Reynolds, 2007, p. 1133). The CHC COG→ACH research synthesis summarized here and elsewhere (Flanagan et al., 2006; McGrew & Wendling, 2010) provides a crucial missing link to the intelligent testing approach that, for years, was handicapped by (a) the lack of a comprehensive taxonomy of human cognitive abilities (CHC theory) by which to study cognitive-achievement relations, (b) the lack of applied intelligence batteries that sampled a sufficient range of CHC abilities related to academic achievement (e.g., the WISC-R, which dominated the early years of SLD research, did not include measures of *Glr*, *Ga*, and *Gf*, abilities that have been reported to be significantly related to reading or math achievement), and (c) dominant research methods that focused primarily on prediction and the incremental partitioning of variance (e.g., multiple regression) and not on explanation and causal relations (e.g., structural equation modeling) (McGrew, Flanagan, Keith, & Vanderwood, 1997).

The above developments, as well as the recent emphasis on aptitude-achievement consistency in third-method SLD models, also beckons assessment professionals to go “back to the future”—to embrace Woodcock’s (1984) concept SAPTs, a measurement option first operationalized in the individually administered WJ cognitive-achievement battery and then the WJ-R. Use of ITD principles, as demonstrated by the *developmental-sensitive CHC-consistent SAPTs*, can now provide the best possible academic expectancy information available from contemporary cognitive test batteries.

Beyond CHC Theory

The astute reader may recognize the hypocrisy in the above criticism of pre-CHC COG→ACH research (for its reliance on multiple regression prediction models) and my presentation of CHC-consistent SAPTs built on the statistical machinery of multiple regression methods. Guilty as charged. In my defense, it is important to note that the construction of proposed multiple-regression-based, developmental-sensitive CHC-consistent SAPTs was not turned over to the blind automatic variable entry and removal stepping algorithms of multiple regression software. Instead, they were designed via theory and research-driven considerations at each step in the process (i.e., ITD). Nevertheless, everything presented above is most likely wrong—to some extent.

Why? Because using linear models to represent the nonlinear nature of reality is bound to represent inaccurately the real-world reality of the complex interactions between cognitive-aptitude-achievement trait complexes. Horn and Noll (1997), when discussing the limitations of linear factor analysis methods to define cognitive ability taxonomies, make this important point (which is also relevant to studying cognitive-aptitude-achievement trait complexes) when they state:

> A fundamental limitation of any theory built on a rectilinear system of factors is that it is not of a form that well describes natural phenomena. It is thus unlikely to be fully adequate. It is a system that can accurately describe rectangular structures built by humans…but not the rounded and irregular structures of mother nature. The phenomena of nature are not usually well described by the linear equations of a Cartesian coordinate system….The equations that describe the out structure and convolutions of brains must be parabolas, cycloids, cissoids, spirals, foliums [sic] exponentials, hyperboles, and the like. (p. 84)

I have tried to embrace Horn and Noll's (1997) characterization of human abilities as being inadequately described by linear statistical models and methods. Although not completely free from the shackles of linear models, I have attempted to move beyond CHC by applying more complex interacting linear CHC COG→ACH causal structural equation modeling (SEM) as well as moving beyond the statistical constraints of factor analysis methods via the use of more historical (and underutilized) data analysis tools such as cluster analysis and multidimensional scaling (MDS) (McGrew, 2005; Schneider & McGrew, 2012). Two sets of my "back to" and "beyond" analyses are presented next. The first set is an investigation that integrated CHC theory with information processing (IP) research. The second set was the search for CHC cognitive-aptitude-achievement trait complexes, a journey that resulted in the serendipitous discovery of a potentially new conceptual twist for SLD identification models based on the configurations of a person's cognitive, aptitude, and achievement strengths and weaknesses.

Beyond CHC: CHC COG→ACH Information Processing (IP) Causal Models

Drawing on the intriguing IP + psychometric research that has explored the relation between working memory (MW) and higher-order cognition, a research topic that has "occupied researchers for the past 20 years" (Kane, Bleckley, Conway, & Engle, 2001, p. 169), I previously published the results of WJ III norm sample-based causal models that investigated the relations between measures of information processing efficiency (viz., *Gs*, *Gsm*-MS, and *Gsm*-MW) and complex cognitive ability (operationalized in the form of *g*) (McGrew, 2005). The results were consistent with the previously summarized working memory→*g* research literature. Across five age-differentiated WJ III norm samples, the working memory→*g* direct effect path ranged from .73 to .93. Clearly, working memory was interpreted as exerting a large causal effect on complex cognitive performance, which was defined by a latent *g*-factor based on the combination of five latent CHC factors (i.e., *Gf*, *Gc*, *Glr*, *Ga*, *Gv*). Also of interest was the finding, consistent with research on the *developmental cascade* hypothesis (Fry & Hale, 1996, 2000), that *Gs* did not demonstrate a direct effect on *g* in the childhood samples. However, starting at late adolescence, *Gs* begins to demonstrate small, yet significant, direct effects on *g* and a much more substantial effect at middle childhood and beyond. A beyond-CHC extension of these original CHC–IP analyses is the exploration of causal models that add achievement-dependent variables to the CHC–IP models. A few illustrative models are presented next.

Figure 8 presents the results from an illustrative CHC–IP COG→ACH causal SEM for WJ III norms subjects from ages 6 through 8 years of age. The *g* + *Gs* + *Ga*→word attack model suggests that understanding the acquisition of word attack skills may require an understanding of a variety of direct and indirect effects (mediated via other abilities) for the cognitive abilities of general intelligence (*g*), processing speed (*Gs*), memory span (*Gsm*-MS), working memory (*Gsm*-MW), and auditory processing (*Ga*).[12] The effect summary table (see Figure 8) suggests that *g* (.59), working memory (*Gsm*-MW: .54), and processing speed (*Gs*: .59) are most relevant to understanding the development of word attack skills. Although lower, the total effects for memory span (*Gsm*-MS: .34) and auditory processing (*Ga*: .27) implicate these abilities in understanding word attack skill performance. This is a much more complex model for explaining or predicting a component of basic reading skills (viz., word attack) when compared to the simple multiple regression SAPT model (see Figure 6). Also, it is important to note that the model fit of this was not practically different from the more parsimonious *g*→Word Attack (.73) model.

Insert Figure 8 about here.

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[12] Although the use of the inferential fit statistics are inappropriate due to the previously described exploratory model generation methods used, for the record, select model fit statistics for the model in Figure 8 were GFI = .93, AGFI = .91, PGFI = .74, and RMSEA = .055 (.051 – .058). A model with a single path from *g* to word attack produced a direct *g* effect of .73 and model fit statistics that are nearly equivalent (GFI = .90, AGFI = .91, PGFI = .73, RMSEA = .069 [.066 – .073]).

When the criterion latent factor was basic reading skills (BRS), fewer non-*g* paths were significant in two equally plausible alternative *g* + models.[13] In the *g*→BRS model, the *g* direct effect was .81. An alternative *g* + *Gs*→BRS model produced a *g* direct effect of .64 plus a direct *Gs* effect of .24. In the second alternative BRS model, (*g* + MW→BRS), the direct *g* effect decreased to .38 while a much larger MW direct effect was found (.44). A similar pattern was found when models were specified with letter-word identification (LWID) being the criterion latent variable. In the *g*→LWID model, the direct *g* effect was .76. The direct *g* effect decreased to .58 in the alternative *g* + MW→LWID model, with the *Gs* direct effect being .25. An equally plausible *g* + MW→LWID model produced a direct *g* effect of .28 and a direct MW effect of .50.

Although the amount of model "tinkering" that occurs to obtain good model fits is often not reported and is typically unknown (Horn, 1989), I admit the above models are ripe with ad hoc model tweaking and tinkering. The more complex models violate *Occam's razor* (the law of parsimony), which would typically result in the rejection of the model in Figure 8 (as well as all other *g* + →ACH models presented earlier in this paper) in favor of a single *g*→word attack model. Nevertheless, I cautiously resonate to the position of Stankov, Boyle, and Cattell (1995) who stated, within the context of research on human intelligence that "while we acknowledge the principle of parsimony and endorse it whenever applicable, the evidence points to relative complexity rather than simplicity. Insistence on parsimony at all costs can lead to bad science" (p. 16).

The power of the inferential fit statistics for these reported causal models has been neutered—and I did it willingly. The above analyses are presented as illustrations of new ideas and approaches I hope others will pursue. According to John Horn (1989), Lloyd Humphries was the first to describe factor analysis as "little more than efforts to slice smoke" (p. 38). But, Horn extended the slicing smoke metaphor by saying that "it is reasonable, however, to fan smoke in ways that are meaningful and useful" (p. 37), and "it is possible to move smoke around in ways that show we know where it is" (p. 38). The CHC–IP COG→ACH causal models presented above should be viewed as intelligent, well-reasoned attempts to move and fan the smoke of COG→ACH relation research. This initial attempt indicates the need for CHC

[13] The fits statistics for the models described in this paragraph are not presented. The findings were very similar to those reported for the word attack models with the various models not being practically different.

COG→ACH relations research to go beyond simple linear models. Yes, causal SEMs are based on a system of linear equations, so the nonlinear nature of reality is not adequately captured. Yet, it is possible to specify models that are more complex and that would include interaction terms, nonlinear effects, age (developmental) variables, models without *g*, and models with causal relations between and among the narrow–broad cognitive and achievement abilities (e.g., see Benson, 2008;). Schneider and McGrew (2012) and Floyd and Kranzler (2012) have presented conceptual CHC–IP models or frameworks that would be good starting points from which to specify more dynamic CHC–IP COG →ACH causal models. Moving beyond CHC requires both looking beyond the linear, factor-based model via the incorporation of research from other areas (e.g., information processing and neurocognitive research) and also moving beyond traditional (and largely linear) research methods to capture better the real-world nuances of CHC COG→ACH relations.

Although models similar to the CHC–IP COG→ACH causal model presented in Figure 8 can suggest abilities–tests that may be most relevant to SRFA, integration of such models in SLD identification models requires much additional development and innovation. One intriguing possibility is assessing the degree to which an individual's pattern of test scores conforms to or is a variance from a norm-group-validated CHC–IP COG→ACH causal model (like the one in Figure 8). The predominant use of fit indices in CFA and SEM has been to evaluate the fit of a model in a sample of data or across multiple sample groups. However, techniques have been suggested for the development of SEM *person-fit* (Reise & Widaman, 1999). I would encourage those with quantitative skills much better than mine to explore the development of applied methodology that would allow for the evaluation of whether the configuration or pattern of a person's cognitive and achievement test scores are consistent, or at variance with, a validated normative CHC–IP COG→ACH model. Even more exciting would be the development of person-to-SEM fit metrics that could suggest which causal paths (e.g., *Ga*→word attack in Figure 8) may be the reason for the person's model misfit—possibly suggesting cognitive ability deficits that explain a person's deficient functioning on the achievement-dependent variable. Person-normative model misfit methods have the potential to provide metrics that may better operationalize the diagnosis and understanding of SLD, cognitive-aptitude-achievement trait complexes, and school learning in general.

Beyond CHC: CHC Cognitive-Aptitude-Achievement Trait Complexes

I have previously argued that alternative nonfactor analysis methodological (e.g., multidimensional scaling [MDS]) and theoretical lenses need to be applied to validated CHC measures to better understand "both the *content* and *processes* underlying performance on diverse cognitive tasks" (McGrew, 2005, p. 172). When MDS-*faceted*[14] methods have been applied to data sets previously analyzed by exploratory or confirmatory factor methods, "new insights into the characteristics of tests and constructs previously obscured by the strong statistical machinery of factor analysis emerge" (Schneider & McGrew, 2012, p. 110).[15] Despite the empirical status of these methods being characterized as "quite impressive" (Süß & Beauducel, 2005, p. 319), American psychology and mainstream quantitative school psychology have expressed little interest in these useful methodological lenses (Tucker-Drob & Salthouse, 2009) in favor of what I call *Jöreskog syndrome*[16]—an almost blind allegiance to and belief in structural equation modeling confirmatory factor analysis (SEM-CFA) methods as the *only* way to see the "true light" of the structure of intelligence and intelligence tests. ITD requires test developers and researchers to embrace a wider array of data analytic tools to understand better the various nuances of the measures being developed or evaluated. Singular use of one tool (e.g., CFA) to analyze intelligence test batteries represents Kaplan's (1964) *law of the instrument*: "Give a small boy a hammer, and he will find that everything he encounters needs pounding" (p. 15).

Following methods similar to those explained and demonstrated by Beauducel, Brocke, and Liepmann (2001), Beauducel and Kersting (2002), Süß and Beauducel (2005), Tucker-Drob and Salthouse

[14] Facet theory is considered a metatheory that enables researchers to define formal hypotheses in a manner that makes systematic data collection and testing of hypotheses transparent. "A *facet* [emphasis added] may be any way of categorizing observations in usually mutually exclusive and exhaustive categories and can be formally described as a set consisting of a finite number of elements. Facet theory is based on the Cartesian product of a finite number of sets…therefore, a facet is simply a set involved in a Cartesian product…in faceted models of intelligence, the behavior or tasks typically are classified as "*operations* [emphasis added] (the most prominent cognitive demand of a task, *contents* [emphasis added] (the different classes of task content), or *complexity* [emphasis added]" (Süß & Beauducel, 2005, p. 313).
[15] See Süß and Beauducel (2005) and Tucker-Drob and Salthouse (2009) for excellent descriptions of these methods and illustrative results.
[16]Karl Gustav Jöreskog is coauthor of the statistical program LISREL, which, when it was released—by most accounts—was considered a watershed, ushering in the tsunami of structural equation modeling research in the field of intelligence and intelligence testing. I must confess that I previously suffered from this syndrome, but now see that SEM-CFA models are just one set of powerful tools for understanding intelligence and intelligence tests. I now recognize the need for complimentary alternative methodological and theoretical lenses by which to study and explore human intelligence—although, I am still very much CHC-centric.

(2009), and Wilhelm (2005), I subjected all WJ-R standardization subjects (McGrew, Werder, & Woodcock, 1991) with complete sets of scores (i.e., list-wise deletion of missing data) for the WJ-R Broad Cognitive Ability-Extended (BCA-Ext), Reading Aptitude (RAPT), Math Aptitude (MAPT), Written Language Aptitude (WLAPT), *Gf-Gc* cognitive factors (*Gf*, *Gc*, *Glr*, *Gsm*, *Gv*, *Ga*, *Gs*), Broad Reading (BRDG), Broad Math (BMATH), and Broad Written Language (BWLANG) achievement clusters to a Guttman radex MDS analysis (*n* = 4,328 subjects from early school years to late adulthood).[17] MDS procedures have more relaxed assumptions than linear statistical models and allow for the simultaneous analysis of variables that share comment variables or tests—a situation that results in nonconvergence problems (due to excessive multicolinearity) when using linear statistical models. This feature made it possible to explore the degree of similarity of the WJ-R operationalized measures of the constructs of cognitive abilities, general intelligence (*g*), scholastic aptitudes, and academic achievement in a single analysis. That is, it was possible to explore the relations between and among the core elements of CHC-based cognitive-aptitude-achievement trait complexes (CAATCs). The results are presented in Figures 9 and 10.

Insert Figures 9 and 10 about here.

WJ-R MDS Analysis: Basic Interpretation

- In Guttman radex models, variables closest to the center of the 2-D plots are the most cognitively complex. The following is concluded from the results in Figure 9:
    - The WJ-R *g* measure (BCA-Ext) is almost directly at the center of the plot and is the most cognitive-complex variable. This makes theoretical sense given that it is a composite common to 14 tests from seven of the CHC *Gf-Gc* cognitive domains. Proximity to the center of MDS plots is sometimes considered evidence for *g*.

[17] The WJ-R battery was analyzed since it was the last version of the WJ series to include scholastic aptitude clusters.

- Reading and Writing Aptitude (GRWAPT) and Math Aptitude (MAPT) are also cognitively complex. Both the GRWAPT[18] and MAPT clusters are composed of four equally weighted tests of four different *Gf*-*Gc* abilities. Thus, the finding that they are also among the most cognitively complex WJ-R measures is not surprising. The CHC *Gf*-*Gc* cognitive measures of *Gf* and *Gc* are much more cognitively complex than *Gv*, *Glr*, *Ga, Gsm*, and *Gs*.[19]

- In Guttman radex models, the variables are located along two continua or dimensions that often have substantive theoretical interpretations. The two dimensions in Figure 9 are labeled A←→B and C←→D. The following is concluded from a review of Figure 9:
  - The A←→B dimension reflects the ordering of measures per stimulus *content*, a common finding in MDS analyses. The cognitive variables on the left side of this continuum midline (*Gv*, *Glr*, *Gf*, *Gs*, MAPT) are composed of measures with predominant *visual-figural* or *numeric-quantitative* stimulus characteristics. The majority of the variables on the right side of the continuum midline (GRWAPT, *Gc*, *Ga*, *Gsm*, BRDG, BWLANG) are characterized as more *auditory-linguistic, language,* or *verbal*. This *visual-figural/numeric-quantitative-to-auditory-linguistic/language-verbal* content dimension is very similar to the figural, numeric, and verbal content demonstrated by the *Berlin Model of Intelligence Structure* (BIS) (Süß & Beauducel, 2005).[20]

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[18] As noted in Figure 9, the Reading and Written Language Aptitude clusters, which were separate variables in the analysis, shared three of four common tests and nearly overlapped in the MDS plot. Thus, for simplicity, they were combined into the single GRWAPT variable in Figure 9. This is also consistent with the factor analysis of reading and writing achievement variables that typically produce a single *Grw* factor and not separate reading and writing factors.

[19] The primary *narrow* abilities measured by each of the cognitive *Gf*-*Gc* clusters are included in the label for each cluster. Contrary to the WJ III, the WJ-R *Gf*-*Gc* clusters were not all operationally constructed as *broad Gf*-*Gc* abilities (see McGrew, 1997; McGrew & Woodcock, 2001). Only the WJ-R *Gf* and *Gc* clusters can be interpreted as measuring broad domains per the requirement that broad measures must include indicators of different narrow abilities (e.g., Concept Formation [*Gf*-I] and Analysis-Synthesis [*Gf*-RG]). The other five WJ-R *Gf*-*Gc* clusters are now understood to be valid indicators of narrow CHC abilities (*Gsm*-MS, *Ga*-PC, *Glr*-MA, *Gv*-MV/CS, *Gs*-P).

[20] The BIS model is a heuristic framework, derived from both factor analysis and MDS facet analysis, for the classification of performance on different tasks and is not to be considered a trait-like structural model of intelligence as exemplified by the factor-based CHC theory. Nevertheless, Guttman radex MDS models often show strong parallels to hierarchical, factor-based models that are based on the same set of variables (Kyllonen, 1996; Süß & Beauducel, 2005; Tucker-Drob & Salthouse, 2009).

- The C←→D dimension reflects the ordering of variables per *cognitive operations* or *processes*, another common finding in MDS analyses. The cognitive variables above the continuum midline (*Gv*, *Glr*, *Ga*, *Gc*, *Gsm*, BCA-Ext, GRWAPT) are composed primarily of cognitive ability tasks that involve mental processes or operations. Conversely, although not as consistent, three of the lowest variables below this continuum midline are the achievement ability clusters (BRDG, BWLANG, BMATH). Thus, the C←→D dimension is interpreted as representing a *cognitive operations/processes-to-acquired knowledge/product* dimension.
- In contrast to factor analysis, interpretation of MDS is more qualitative and subjective. Variables that may share a common dimension are typically identified as lying on relatively straight lines or planes, in separate quadrants or partitions, or tight groupings (often represented by circles or ovals or connected as a shape via lines). The AC quadrant (see Figure 9) is interpreted as representing (excluding BCA-Ext, which is near the center) cognitive operations with visual-figural content (*Gv*, *Glr*). The CB quadrant is interpreted as representing auditory-linguistic/language-verbal content-based cognitive operations. The BC quadrant includes only the three broad achievement clusters and is thus an achievement or an acquired knowledge dimension. Finally, the DA quadrant can be interpreted as cognitive operations that involve quantitative operations or numeric stimuli (e.g., *Gf* is highly correlated with math achievement, McGrew & Wendling, 2010; one half of the *Gs*-P cluster is the Visual Matching test, which requires the efficient perceptual processing of numeric stimuli, *Glr*-N).[21] The interpretation of these four quadrants is consistent with the BIS content-faceted *content-by-operations* model research.
- Theoretical interpretation of the two continua and four quadrants provides potentially important insights into the abilities measured by the WJ-R. More importantly, the conclusions provide potentially significant theoretical insights into the nature of human intelligence—insights that typically fail to emerge when using factor analysis methods

[21] The MAPT cluster also includes the two *Gf* tests and Visual Matching.

(Schneider & McGrew, 2012; Süß & Beauducel, 2005). In other MDS analyses I have completed, similar *visual-figural/numeric-quantitative-to-auditory-linguistic/language-verbal* and *cognitive operations/processes-to-acquired knowledge/product* continua dimensions have emerged (McGrew, 2005; Schneider & McGrew, 2012). When I have investigated a handful of 3-D MDS[22] models, the same two dimensions emerge along with a third, *automatic-to-deliberate/controlled cognitive processing* dimension, which is consistent with the prominent dual-process models of cognition and neurocognitive functioning (Evans, 2008, 2011; Barrouillet, 2011; Reyna & Brainerd, 2011; Ricco & Overton, 2011; Stanovich, West, & Toplak, 2011) that are typically distinguished as Type I–II or System I–II (see Kahneman's, 2011, highly acclaimed *Thinking, fast and slow*).[23]

These higher-order cognitive processing dimensions, which are not present in the CHC taxonomy, suggest that intermediate strata (or dimensions that cut across broad CHC abilities) might be useful additions to the current three-stratum CHC model. These higher-order dimensions may be capturing the essence of fundamental neurocognitive processes and argue for moving "beyond CHC" to integrate neurocognitive research to better understand intellectual performance.

WJ-R MDS Analysis: Cognitive-Aptitude-Achievement Trait Complex (CAATC) Interpretation

Figure 10 is an extension of the results presented in Figure 9. Two different CAATCs are suggested. These were identified by starting first with the BMATH and BWLANG-BRDG achievement variables and next connecting these variables to their respective SAPTs (MAPT, GRWAPT). Next, the closest cognitive *Gf-Gc* measures that were in the same general linear path were connected (the goal was to find the math- and reading-related variables that were closest to lying on a straight line). Ovals where then superimposed on the figure to represent the areas comprising the two CAATCs. Finally, a dotted line representing the approximate bisection of each of the CAATC vectors was drawn. The approximate correlation (r = .55, see

[22] WJ III 3-D MDS model for norm subjects ages 9–13 is available at http://www.iqscorner.com/2008/10/wj-iii-guttman-radex-mds-analysis.html
[23] A similar dimension emerged as a plausible higher-order cognitive processing dimension in the previously mentioned Carroll type analysis of 50 WJ III test variables (see footnote 2).

Figure 10) between the two multidimensional CAATCs was estimated via measurement of the angle between the CAATC vector dotted lines.[24]

As presented in Figure 10, Math and Reading-Writing CAATCs are suggested as a viable perspective from which to view the relations between cognitive abilities, aptitudes, and achievement abilities. The following primary conclusions, insights, and questions are drawn from Figures 9 and 10:

- It appears that potential exists to empirically identify CAATCs via the use of CHC-grounded theory, the extant CHC COG→CH relations research, and multidimensional scaling. It also appears possible to estimate the correlation between different trait complexes (see math/reading-writing trait complex r = .55 in Figure 10). I suggest these preliminary findings may help the field of cognitive-achievement assessment and research to better approximate the multidimensional nature of human cognitive abilities, aptitudes, and achievement abilities.
- Although the WJ-R battery is not as comprehensive a measure of CHC abilities as the WJ III, the cognitive abilities within the respective math and reading-writing CAATCs are very consistent with the extant CHC COG→ACH relations research (McGrew & Wendling, 2010). The reading-writing trait complex (see Figure 10) includes *Ga*-PC, *Gc*-LD/VL, and via the GRWAPT, *Gs*-P and *Gsm*-MS; abilities that are listed as domain-general and domain-specific in Figure 3. In the case of math, the trait complex includes indicators of *Gf*-RG, *Gv*-MV, and via the MAPT, *Gs*-P (Visual Matching, which might also tap *Gs*-N) and *Gc*-LD/VL; abilities that are either domain-general or domain-specific for math (see Figure 3). Working memory (*Gsm*-MW) is not present (see Figure 3) as the WJ-R battery did not include a working memory cluster that could enter the analysis.

  Also of interest are the three WJ-R cognitive factors (*Gsm*-MS, *Glr*-MA, *Gs*-P) that are *excluded* from the hyperspace representations of the proposed math and reading-writing CAATCs. Although highly speculative, it is possible their separation (i.e., independence) from the narrower-designated trait complexes—if known to be related to reading-writing or

[24] Using trigonometry, the *cosine* of the intersection of the two trait complex vectors was converted to a correlation. I thank Dr. Joel Schneider for helping fill the gap in my long-lost expertise in basic trigonometry via a spreadsheet that converted the measured angle to a correlation.

math achievement—indicates that they represent domain-general abilities. *Glr*-MA and *Gs*-P are both listed as domain-general abilities in Figure 3. For CHC measures known to be significantly related to achievement, additional work is needed to determine if independence from identified CAATCs indicates domain-general abilities. Alternatively, it is very possible, given the previously demonstrated developmental nuances of CHC COG→ACH relations, the results presented in Figures 9 and 10 (which used the entire age range of the WJ-R measures) may mask or distort findings in unknown ways.

Those knowledgeable of the CHC COG→ACH relations research will note the inclusion of certain *Gv* abilities (Vz, SR, MV) in Figure 3 as well as the inclusion of the WJ-R *Gv*-MV/CS cluster (see Figure 10) as part of the proposed math CAATC, despite the lack of consistently reported significant CHC *Gv*→ACH relations. McGrew and Wendling (2010) recognized that some *Gv* abilities have clearly been linked to reading and math achievement (especially the later) in non-CHC-organized research. They speculated that the "*Gv* Mystery" (p. 665) may be due to certain *Gv* abilities being *threshold* abilities or that the cognitive batteries included in their review did not include *Gv* measures that measured complex *Gv*-related Vz or MV processes. Given this context, it may be an important finding (via the methods described earlier in this paper) that the WJ-R *Gv* measure is unexpectedly included in the math CAATC. This may support the importance of *Gv* abilities in explaining math and concurrently indicate a problem with the operational *Gv* measures.

- The long distance from the WJ-R *Gv* measure to the center of the diagram (see Figure 9) indicates that the WJ-R *Gv* measure, which included tests classified as indicators of MV and CS, is not cognitively complex. This conclusion is consistent with Lohman's (1979) seminal review of *Gv* abilities where he specifically mentions MV and CS as representing low-level *Gv* processes and "such tests and their factors consistently fall near the periphery of scaling representations, or at the bottom of a hierarchical model" (pp. 126–127). I advance the hypothesis that the math CAATC in Figure 10 suggests that *Gv* **is** *a math-relevant domain*, but more complex *Gv* tests (e.g., 3-D mental "mind's eye" rotation, complex visual working memory), which would be closer to the center of the MDS hyperspace, need to be developed and included in cognitive batteries. This suggestion is consistent with Wittmann and Süß's concept of *Brunswick Symmetry*, which, in turn, is founded on the fundamental concept of *symmetry,* which has been central to success in most all branches of science (Wittmann & Süß, 1999). The Brunswick Symmetry model argues that in order to maximize prediction or explanation between predictor and criterion variables, one should match the level of *cognitive complexity*[25] of the variables in both the predictor and criterion space (Hunt, 2011; Wittmann & Süß, 1999). The WJ-R *Gv*/WJ-R BMATH relation may represent a low (WJ-R *Gv*)-to-high (WJ-R BMATH) predictor–criterion complexity *mismatch*, thus dooming any possible significant relation. These findings are expanded upon later in this paper.

Researchers and practitioners in the area of SLD should recognize that when third-method PSW "aptitude-achievement" discrepancies are evaluated to determine "consistency," the combination of domain-general and domain-specific abilities that composes an aptitude for a specific achievement domain is in many ways a miniproxy for general intelligence (*g*). In Figures 9 and 10, the BCA-Ext and MAPT and GRWAPT variables are in close proximity (which represents high correlation) and are all near the center of the MDS radex model. The manifest correlations between the WJ-R BCA-Ext (in the WJ-R data used to generate the CAATCs in Figure 10) and RAPT, WLAPT, and MAPT clusters are .91, .89, and .91, respectively. This reflects the reality of the CHC COG→ACH research in both reading and math achievement: Cognitive tests or clusters with high *g*-loadings (viz., measures of *Gc* and *Gf*), as well as shared domain-general abilities, are always in the pool of CHC measures associated with the academic deficit. However, the placement of GRWAPT and MAPT in the different content–processes quadrants in Figures 9 and 10 suggests that more differentiated CHC-designed achievement domain SAPT measures might be developed. The manifest correlations between MAPT and the two GRWAPT measures were .82 to .84, suggesting approximately 69% shared variance. GRWAPT and MAPT are strongly related SAPTs; yet,

[25] Cognitive complexity is defined later in this paper.

there is still unique variance in each. Furthermore, the WJ-R SAPT measures used in this analysis were equally weighted clusters and not the differentially weighted clusters as in the original WJ. As presented earlier in this paper, research suggests that intelligent, test-developed optimal SAPT prediction requires developmentally shifting weights across age. It is my opinion that the evolution of developmental-sensitive CHC-consistent SAPTs will result in lower correlations between RAPT and MAPT measures.

Beyond CHC Theory: Cognitive-Aptitude-Achievement Trait Complexes and SLD Identification Models

The possibility of measuring, mapping, and quantifying CAATCs raises intriguing possibilities for reconceptualizing approaches to the identification of SLD. Figure 11 presents the generic representation of the prevailing third-method SLD models and a formative proposal for a conceptual revision. As noted previously, the prevailing PSW model (left side of Figure 11), although useful for communication and enhancing understanding of the conceptual approach, is simplistic. Implementation of the model requires successive calculations of simple (and often multiple) discrepancies, which fail to capture the multidimensional and multivariate nature of human cognitive, aptitude, and achievement abilities. I believe the CAATC representations in Figure 10, although still clearly imperfect and fallible representations of the nonlinear nature of reality, may better approximate the multifaceted nature of cognitive-aptitude trait complex relations. The right side of Figure 11 is an initial attempt to conceptualize SLD within a CAATC framework. In this formative model, the bottom two components of the current third-method models (i.e., academic and cognitive weakness) have been combined into a single, multidimensional CAATC domain.

Insert Figure 11 about here.

CAATCs better operationalize the notion of consistency among the multiple cognitive, aptitude, and achievement elements of an important academic learning domain or domain of SLD. As noted in the definition of CAATC presented earlier, the emphasis is on a *constellation* or combination of elements that are *related* and *combined* together in a functional fashion. These characteristics imply a form of central, inwardly directed force that pulls elements together much like magnetism. *Cohesion* appears the most appropriate term for this form of multiple-element bonding. Cohesion is defined by the *Shorter English Oxford Dictionary* (Brown, 2002) as, “the action or condition of sticking together or cohering; a tendency to remain united” (p. 444). Element bonding and stickiness are also conveyed in the *APA Dictionary of Psychology* (VandenBos, 2007) definition of cohesion as “the unity or solidarity of a group, as indicated by the strength of the bonds that link group members to the group as a whole” (p. 192). In the CAATC-based SLD proposal in Figure 11, cohesion within a CAATC is designated by overlapping circular shapes. Determining the *degree of cohesion* within a CAATC is an integral and critical step to ascertaining whether a particular academic domain deficit is present. The stronger the within-CAATC cohesion, the more confidence one can place in the identification of a CAATC as possibly indicative of an SLD. This focus on quantifying the CAATC cohesion is seen as a necessary, but not sufficient, first step in attempting to identify SLD based on a multivariate PSW. If the CAATC demonstrates very weak cohesion, the hypothesis of a possible SLD should receive less consideration. If there is significant (yet to be operationally defined), moderate-to-strong CAATC cohesion, then the comparison of the CAATC to the cognitive–academic strengths portion of the conceptual model is appropriate for SLD consideration. To simplify, PSW-based SLD identification would be based first on the detection of weakness in a *cohesive-specific* CAATC, followed by determination of significant discrepancy in relative strengths from other cognitive and achievement domains. Of course, additional variations of this model require further exploration. For example, should discrepant–discordant comparisons be made between other empirically identified and quantified CAATCs? Would CAATC-to-CAATC comparisons between highly empirical and theoretically correlated CAATCs (e.g., basic reading skills and basic writing skills) when contrasted to less empirically and theoretically correlated CAATC-to-CAATC domains (e.g., basic reading skills and math reasoning) be diagnostically important? I have more questions than answers at this time.

Yes—this proposed CAATC framework and integration into SLD models is speculative and in the formative stages of conceptualization. It is not yet ready for prime-time, in-the-field applied practice. It is, however, based on exploratory data analyses inspired by theoretical considerations and well-reasoned logic. Of course, appropriate statistical metrics and methods for operationalizing the degree of domain cohesion are required, but I do not see this as an insurmountable hurdle. Metrics based on Euclidean distance (e.g., Mahalanobis distance) can quantify the cohesion between CAATCs as well as measure the distance from the *centroid* of a CAATC (see Schneider, 2012). Alternately, statisticians much smarter than I might apply centroid-based multivariate statistical measures to quantify and compare CAATC domain cohesion. I urge those with such skills and interest to pursue the development of these ITD metrics. Also, the current limited exploratory results with the WJ-R data should be replicated and extended in more contemporary samples with a larger range of both CHC cognitive, aptitude, and achievement tests and clusters. I would encourage split-sample CAATC model development and cross validation in the WJ III norm data.

Additional research and development, some of which I have suggested in this paper, will provide promising methodologies as well as ideas with limited validity, and possibly some with too many practical constraints, thus, rendering them hard to implement. Nevertheless, the results presented here suggest possible incremental progress toward better defining SLD and learning complexes that are more consistent with nature—with the identification of CAATC *taxa*[26] that better approximate "nature carved at the joints" (Meehl, 1973, as quoted and explained by Greenspan, 2006, in the context of MR–ID diagnosis). Such a development would be consistent with Reynolds and Lakin's (1987) plea, 25 years ago, for disability identification methods that better represent dispositional taxa rather than *classes* or *categories* based on specific cutting scores grounded in "administrative conveniences with boundaries created out of political and economic considerations" (p. 342).

Beyond CHC: ITD—Within-CHC-Domain Complexity-Optimized Measures

Optimizing Cognitive Complexity of CHC Measures

The Brunswick-Symmetry-derived Berlin Model of Intelligence Structure (BIS) (Wittmann & Süß, 1999) was mentioned previously as an important framework for understanding predictor-criteria relations and, more importantly, as a framework to better maximize these relations via matching the predictor-criteria space on the dimension of cognitive complexity. What is cognitive complexity? Why is it important? More important, what role should it play in designing intelligence batteries to optimize CHC COG→ACH relations?

[26] The *Shorter Oxford English Dictionary* defines a *taxon* as "a taxonomic group of any rank, as species, family, class, etc; an organism contained in such a group" (p. 3193) and *taxonomy* as "classification, esp. in relation to its general laws or principles; the branch of science, or of a particular science or subject, that deals with classification; *esp.* the systematic classification of living organisms" (p. 3193, italics in original).

Cognitive complexity is often operationalized by inspecting individual test loadings on the first principal component from principal component analysis (Jensen, 1998). The high *g*-test rationale is that performance on tests that are more cognitively complex "invoke a wider range of elementary cognitive processes (Jensen, 1998; Stankov, 2000, 2005)" (McGrew, 2010, p. 452). High *g*-loading tests are often at the center of MDS radex models—but this isomorphism does not always hold. David Lohman, a student of Snow's, has made extensive use of MDS methods to study intelligence and has one of the best grasps of what cognitive complexity, as represented in the hyperspace of MDS figures, contributes to understanding intelligence and intelligence tests. According to Lohman and Lakin (2011), those tests closer to the center are more cognitively complex due to five possible factors: a larger number of cognitive component processes; accumulation of speed component differences; more important component processes (e.g., inference); increased demands of attentional control and working memory; and/or more demands on adaptive functions (assembly, control, and monitoring). Schneider and McGrew's (in press) *level of abstraction* description of broad CHC factors is similar to cognitive complexity. Using the example of a 100-meter sprint hurdle race, one must independently measure 100-meter sprinting speed and then measure performance in jumping hurdles (both examples of narrow abilities). However, competing in a 100-meter sprint hurdle race is not the mere sum of the two narrow abilities and is more of a nonadditive combination and integration of narrow abilities. This analogy captures the essence of cognitive complexity. In the realm of cognitive measures, cognitively complex tasks involve more of the five factors listed by Lohman and Lakin (2011) during successful task performance.

Of critical importance is the recognition that factor or ability domain breadth (i.e., broad or narrow) is *not* synonymous with cognitive complexity. More important, cognitive complexity has not always been a test design concept (as defined by the Brunswick Symmetry and BIS models; see Wittmann & Süß, 1999; Süß & Beauducel, 2005) *explicitly* incorporated into ITD. A number of tests have incorporated the notion of cognitive complexity in their design plans, but I believe this type of cognitive complexity is different from the within-CHC-domain cognitive complexity discussed here.

For example, according to Kaufman and Kaufman (2004), "in developing the KABC-II, the authors did not strive to develop 'pure' tasks for measuring the five CHC broad abilities. In theory, *Gv* tasks should exclude *Gf* or *Gs*, for example, and tests of other broad abilities, like *Gc* or *Glr*, should only measure that ability and none other. In practice, however, the goal of comprehensive tests of cognitive ability like the KABC-II is to measure problem solving in different contexts and under different conditions, with *complexity* [emphasis added] being necessary to assess high-level functioning" (p. 16). Although the Kaufmans address the importance of cognitively complex measures in intelligence test batteries, their CHC-grounded description defines complex measures as those that are factorially complex or mixed measures of abilities from more than one broad CHC domain. The Kaufmans also address cognitive complexity from the non-CHC, neurocognitve, three-block functional Luria model when they indicate it is important to provide measurement that evaluates the "dynamic integration of the three blocks" (p. 13). This emphasis on neurocognitive integration (and thus, complexity) is also an explicit design goal of the latest Wechsler batteries. As stated in the WAIS-IV manual (Wechsler, 2008), "although there are distinct advantages to the assessment and division of more narrow domains of cognitive functioning, several issues deserve note. First, cognitive functions are interrelated, functionally and neurologically, making it difficult to measure a pure domain of cognitive functioning" (p. 2). Furthermore, "measuring psychometrically pure factors of discrete domains may be useful for research, but it does not necessarily result in information that is clinically rich or practical in real world applications (Zachary, 1900)" (Wechsler, p. 3). Finally, Elliott (2007) similarly argues for the importance of recognizing neurocognitive-based "*complex* [emphasis added] information processing" (p. 15) in designing the DAS-II, which results in tests or composites measuring across CHC-described domains.

The ITD principle explicated and proposed here is that of striving to develop cognitively complex measures *within* broad CHC domains—that is, not attaining complexity via the blending of abilities across CHC broad domains and not attempting to directly link to neurocognitive network integration.[27] The

[27] This does not mean that cognitive complexity may not be related to the integrity of the *human connectome* or different brain networks. I am excited about contemporary brain network research (Bressler & Menon, 2010; Cole, Yarkoni, Repovš, Anticevic & Braver, 2012; Toga, Clark, Thompson, Shattuck, & Van Horn, 2012; van den Heuvel & Sporns, 2012), particularly that which has demonstrated links between neural network efficiency and working memory, controlled attention and clinical disorders such as ADHD (Brewer, Worhunsky, Gray, Tang, Weber, & Kober, 2011; Lutz, Slagter, Dunne, & Davidson, 2008; McVay & Kane, 2012). The *Parietal-Frontal Integration* (P-FIT) theory of intelligence is particularly intriguing as it has been linked to CHC psychometric measures (Colom, Haier, Head, Álvarez-Linera, Quiroga, Shih, & Jung, 2009; Deary, Penke, & Johnson, 2010; Haier, 2009; Jung & Haier, 2007) and could be linked to CHC cognitive-optimized psychometric measures.

Brunswick-Symmetry-based BIS model (Wittmann & Süß, 1999) provides a framework for attaining this goal via the development and analysis of test complexity by paying attention to cognitive *content operations* and *process* facets.

Figure 12 presents the results of a 2-D MDS radex model of most key WJ III broad and narrow CHC cognitive and achievement clusters (for all norm subjects from approximately 6 years of age through late adulthood).[28] The current focus of the interpretation of the results in Figure 12 is only on the degree of cognitive complexity (proximity to the center of the figure) of the broad and narrow WJ III clusters within the same domain. Within a domain, the *broadest* three-test *parent* clusters are designated by black circles.[29] Two-test broad clusters are designated by gray circles. Two-test narrow *offspring* clusters within broad domains are designated by white circles. All clusters within a domain are connected to the broadest parent broad cluster by lines. The critically important information is the within-domain cognitive complexity of the respective parent and offspring clusters as represented by their relative distances from the center of the figure. A number of interesting conclusions are apparent.

Insert Figure 12 about here.

First, as expected, the WJ III GIA-Ext cluster is almost perfectly centered in the figure—it is clearly the most cognitively complex WJ III cluster. In comparison, the three WJ III *Gv* clusters are much weaker in cognitive complexity than all other cognitive clusters with no particular *Gv* cluster demonstrating a clear cognitive complexity advantage. As expected, the measured reading and math achievement clusters are primarily cognitively complex measures. However, those achievement clusters that deal more with basic skills (e.g., Math Calculation [MTHCAL] and Basic Reading Skills [RDGBS]) are less complex than the application clusters (Math Reasoning [MTHREA] and Reading Comprehension [RDGCMP]).

The most intriguing findings in Figure 12 are the differential cognitive complexity patterns within CHC domains (with at least one parent and at least one offspring cluster). For example, the narrow

[28] Only reading and math clusters were included to simplify the presentation of the results and the fact, as reported previously, that reading and writing measures typically do not differentiate well in multivariate analysis—and thus the *Grw* domain in CHC theory.
[29] GIA-Ext is also represented by a black circle.

Perceptual Speed (PERSPD [*Gs*-P]) offspring cluster is more cognitively complex than the broad parent *Gs* cluster. The broad *Gs* cluster is composed of the Visual Matching (*Gs*-P) and Decision Speed (*Gs*-R9, *Glr*-NA) tests, which measure different narrow abilities. In contrast, the Perceptual Speed cluster is composed of two tests that are classified as both measuring the same narrow ability (perceptual speed). This finding appears, on first blush, counterintuitive as one would expect a cluster composed of tests that measure different content and operations to be more complex (per the above definition and discussion) than a cluster composed of two measures of the same narrow ability. However, one must task analyze the two Perceptual Speed tests to realize that, although both are classified as measuring the same narrow ability (perceptual speed [*Gs*-P]), they differ in both stimulus content and cognitive operations. Visual Matching requires processing of numeric stimuli. Cross Out requires the processing of visual-figural stimuli. These are two different content facets in the BIS (Wittmann & Süß, 1999) model. The Cross Out visual-figural stimuli are much more spatially challenging than the simple numerals in Visual Matching. Furthermore, the Visual Matching test requires the subject to quickly seek out, discover, and then mark two-digit pairs that are identical. In contrast, in the Cross Out test, the subject is provided a target visual-figural shape, and the subject must then quickly scan a row of complex visual images and mark two that are identical to the target. It is interesting to note, in other unpublished "WJ III data sandbox" analyses that I have completed, the Visual Matching test often loads on groups with quantitative achievement tests while Cross Out has frequently shown to load on a *Gv* factor. Thus, task analysis of the content and cognitive operations of the WJ III Perceptual Speed tests suggests that although both are classified as narrow indicators of *Gs*-P, they differ markedly in task requirements. More important, the Perceptual Speed cluster tests, when combined, appear to require more cognitively complex processing than the broad *Gs* cluster. This finding is consistent with Ackerman, Beier, and Boyle's (2002) research that suggests perceptual speed has another level of factor breadth via the identification of four subtypes of perceptual speed (i.e., pattern recognition, scanning, memory, and complexity; see McGrew, 2005, and Schneider & McGrew, 2012, for discussion of a hierarchically organized model of speed abilities). Based on Brunswick Symmetry–BIS cognitive complexity principles, one would predict that a *Gs*-P cluster composed of two parallel forms of the same task (e.g., two Visual Matching or two Cross Out tests) would be less cognitively complex than broad *Gs*.

A hint of the possible correctness of this hypothesis is present in the inspection of the *Gsm* parent and offspring clusters reported in Figure 12.

The WJ III *Gsm* cluster is the combination of the Numbers Reversed (MW) and Memory for Words (MS) tests. In contrast, the WJ III Auditory Memory Span (AUDMS [*Gsm*-MS]) cluster is much less cognitively complex when compared to *Gsm* (see Figure 12). Like the Perceptual Speed (*Gs*-P) cluster described in the context of the processing speed family of clusters, the Auditory Memory Span cluster is composed of two tests (Memory for Words and Memory for Sentences) with the same memory span (MS) narrow ability classification. Why is this narrow cluster less complex than its broad parent *Gsm* cluster while the opposite held true for *Gs*-P and *Gs*? Task analysis suggests that the two memory span tests are more alike than the two perceptual speed tests. The Memory for Words and Memory for Sentences tests require the same cognitive operation—simply repeating back, in order, words or sentences spoken to the subject. This differs from the WJ III Perceptual Speed cluster as the similarly classified narrow *Gs*-P tests most likely invoke both common and different cognitive component operations. Also, the Auditory Memory Span cluster is composed of stimuli from the same BIS content facet (i.e., words and sentences, auditory-linguistic/language-verbal). In contrast, the *Gs*-P Visual Matching and Cross Out tests involve two different content facets (numeric and visual-figural).

Likewise, the WJ III Working Memory (WRKMEM [*Gsm*-MW]) cluster is more cognitively complex. This finding is consistent with the prior WJ III *Gs*–Perceptual Speed and WJ III *Gsm*–Auditory Memory Span discussion. The WJ III Working Memory cluster is composed of the Numbers Reversed and Auditory Working Memory tests. Numbers Reversed requires the processing of stimuli from one BIS content facet—numeric stimuli. In contrast, Auditory Working Memory requires the processing of stimuli from two BIS content facets: numeric and auditory-linguistic/language-verbal (i.e., numbers and words). The cognitive operations of the two tests also differ. Both require the holding of presented stimuli in active working memory space. Numbers Reversed then requires the simple reproduction of the numbers in reverse order. In contrast, the Auditory Working Memory test requires the storage of the numbers and words in separate chunks, and then the production of the forward sequence of each respective chunk (numbers or words), one chunk before the other. Greater reliance on divided attention is most likely occurring during the Auditory Working Memory test.

In summary, the results presented in Figure 12 suggest that it is possible to develop cluster scores that vary by degree of cognitive complexity within the same broad CHC domain. More important is the finding that the classification of clusters as broad or narrow does not provide information on the measures' cognitive complexity. Cognitive complexity, as defined in the Lohman and Lakin (2011) sense, can be achieved within CHC domains without resorting to mixing abilities across CHC domains. Finally, some narrow clusters can be more cognitively complex, and thus likely better predictors of complex school achievement, than broad clusters or other narrow clusters.

Implications for Test Battery Design and Assessment Strategies

Currently the construction of assessments featuring broad CHC clusters fail to recognize the importance of cognitive complexity during the design process. I plead guilty to contributing to this viewpoint via my role in the WJ III, which focused extensively on broad CHC domain construct representation. (Most WJ III narrow CHC clusters require the use of the *Woodcock-Johnson III Diagnostic Supplement to the Tests of Cognitive Abilities*, Woodcock, McGrew, Mather, & Schrank, 2003.) Also, guilty as charged in the dominance of broad CHC factor representation in the development of the original cross-battery assessment principles (Flanagan & McGrew, 1997; McGrew & Flanagan, 1998). Additionally, I have determined the "narrow is better" conclusion of McGrew and Wendling (2010) may need modification. Revisiting the McGrew and Wendling results suggests that the narrow CHC clusters more predictive of academic achievement likely may have been so not necessarily because they are narrow, but because they are more cognitively complex. I offer the hypothesis that a more correct principle is that "cognitively complex measures" are better. I welcome new research focused on testing this principle.

In retrospect, given the universe of WJ III clusters, a broad + narrow hybrid approach to intelligence battery configuration (or cross-battery assessment) may be more appropriate. Based exclusively on the results presented in Figure 12, the clusters that appear might better be featured in the "front end" of the WJ III or a selective-testing constructed assessment—those clusters that examiners should consider first within each CHC broad domain: Fluid Reasoning (*Gf*)[30], Comprehension-Knowledge (*Gc*), Long-Term Retrieval (*Glr*), Working Memory (*Gsm*-MW), Phonemic Awareness 3 (*Ga*-PC), and Perceptual Speed (*Gs*-P). No clear winner is apparent for *Gv*, although the narrow Visualization cluster is slightly more cognitively complex than the *Gv* and *Gv*3 clusters. The above suggests that if broad clusters are desired for the domains of *Gs*, *Gsm,* and *Gv*, then additional testing beyond the front end or featured tests and clusters would require administration of the necessary *Gs* (Decision Speed), *Gsm* (Memory for Words) and *Gv* (Picture Recognition) tests. Utilization of ITD principles for optimizing within-CHC cognitive complex clusters suggests that a different emphasis and configuration of WJ III tests might be more appropriate. It is proposed that the above WJ III cluster complexity priority or feature model would likely allow practitioners to administer the best predictors of school achievement. I further hypothesize that this cognitive-complexity-based, broad + narrow test-design principle most likely applies to other intelligence test batteries that have adhered to the primary focus of featuring tests that are the purest indicators of two or more narrow abilities within the provided broad CHC interpretation scheme. Of course, this is an empirical question that begs research with other batteries. More useful will be similar MDS radex cognitive complexity analyses of cross-battery intelligence data sets.[31]

Summary and Conclusions

McGrew and Wendling's (2010) CHC COG→ACH relations review was the springboard for this paper. My initial plan was to add greater clarity to McGrew and Wendling concerning the importance of differentiating between domain-general and domain-specific predictors of school achievement. Next, I was to demonstrate approaches to CHC-based selective referral-focused assessment (SRFA). The need to go "back to the future" was initially going to focus on new opportunities for assessment professionals to engage in more *intelligent*, flexible intelligence testing (à la Alan Kaufman, 1979) and the need to resurrect the idea of WJ/WJ-R Scholastic Aptitude clusters (SAPTs). Finally, another original goal was to present

[30] Although the WJ III Fluid Reasoning 3 cluster (*Gf*3) is slightly closer to the center of the figure, the difference from Fluid Reasoning (*Gf*) is not large and time efficiency would argue for the two-test *Gf* cluster.

[31] It is important to note that the cognitive complexity analysis and interpretation discussed here is specific to *within the WJ III battery only*. The degree of cognitive complexity in the WJ III cognitive clusters in comparison to composite scores from other intelligence batteries can only be ascertained by cross-battery MDS complexity analysis.

summaries of select exploratory analyses completed in my ten-year, "beyond CHC" adventure—analyses that have provided many insights into the nature of intelligence and the characteristics of the WJ III tests. I believe all of these goals were accomplished.

As this paper evolved, new conceptual, theoretical, and data-based insights lead me to drill deeper into a number of ideas and concepts—in varying stages of formative development—to ascertain their merit. The results were unexpected and hold great promise for: (a) formulating and implementing fresh conceptual principles in new *intelligence test design* (ITD),[32] (b) exploring more CHC-based COG←→ACH causal models to better understand the real-world nuances of COG←→ACH relations, (c) developing *person-fit indices* to validate CHC COG←→ACH causal models for potential diagnostic and instructional purposes, (d) identifying methods that may help recognize and quantify *cognitive-aptitude-achievement trait complexes* (CAATCs), (e) revising current PSW third-method SLD models to integrate CAATCs, and (f) incorporating and quantifying the degree of cognitive complexity of tests and composite scores into the ITD process.

Of all the ideas presented, that of intelligence *CHC-based SRFA* can be immediately implemented by assessment professionals. The assessment, statistical data, and computer-scoring-based technology are available for relatively quick generation of *developmental-sensitive CHC-designed scholastic aptitude clusters* for batteries with a sufficient breadth of CHC cognitive and achievement tests. The statistical machinery (viz., MDS) to investigate the cognitive complexity of individual tests and composite scores has existed for decades and can be used immediately to address the ITD principle of within-CHC-domain cognitive complexity in test design and test battery organization.

The remaining proposals will require additional research and development, although progress is already nearing completion for the necessary metrics to implement portions of the CAATC approach to understanding COG→ACH relations (i.e., ability domain cohesion; see Schneider, 2012) and incorporate

[32] I currently define *intelligence test design* (ITD) as the process of using more theory and research-based knowledge to approach the development and evaluation of intelligence tests. A handful of ITD concepts were articulated in this paper. They are by no means exhaustive. These are intended to go beyond already accepted and well-validated psychometric test design concepts (e.g., methods based on the "new rules of measurement," Embretson, 1996; Embretson & Hershberger, 1999). In time, I hope a more complete set of ITD principles will be articulated by a collection of intelligence test researchers and test developers.

them into SLD identification models. I encourage other intelligence researchers to become more comfortable in moving from a less confirmatory approach to test development and research to a dynamic hybrid model of exploratory and confirmatory models and analytic tools. My exploratory journey over the past decade has resulted in the discovery of new insights and hypotheses that produced a number of the new ideas proposed in this paper. I encourage others to embark on similar "back to" and "beyond" research and theory-based journeys to improve the state of the art of intelligence theories, test batteries, and interpretation.

To some, the test design and interpretation features presented here will be viewed as the primary contribution of this manuscript. I will be pleased with such an outcome. However, I believe an equally important outcome is the demonstration of the evolution of new ideas via unconstrained theory and research-based exploratory data analysis. I am very much in agreement with the multiple method (factor analysis plus MDS) recommendation of Tucker-Drob and Salthouse (2009) who stated:

> We agree with Snow and colleagues' argument that theories of ability organization are "at least partly determined by the techniques used to analyze the interrelationships"…that is, just as it is important to test hypotheses in a variety of populations, using various operationalizations (e.g., multiple indicators), it is also important to test hypotheses using alternative analytic methods. Turkheimer, Ford, and Oltmanns (2005) have similarly argued that any structural taxonomy is "meaningful but arbitrary," at best, and is only useful insofar as it communicates and emphasizes the important and salient features of the multivariate data. By applying two parallel methodologies, we were able to identify such features. (p. 284)

The fusion of ideas presented here are a call to go "back to the future" and "beyond CHC—to return to old ideas with new methods and embrace new ideas, concepts, and strategies that move beyond the confines of dominate CHC taxonomy. These proposals compliment—they do not replace—confirmatory-based research methods; however, the possibilities of exploratory discovery in the "sandbox" of scientific investigation are exciting, and the promise of reward for future intelligent ITD is great. Dr.

Richard Woodcock, throughout his long and accomplished career, has demonstrated that the need to move forward, beyond simplistic perceptions of intelligence to advance the art and practice of psychological and educational assessment requires the heart and vision of an adventurer. One who is willing to ask questions and respond creatively to the answers. The essence of this purpose-driven research—to seek the unknown for the unexpected reward—is captured in Merton and Barber's (2003) book *The Travels and Adventures of Serendipity: A Study in Sociological Semantics and the Sociology of Science*:

> Many a scientific adventurer sails the uncharted seas and sets his course for a certain objective only to find unknown land and unsuspected ports in strange parts. To reach such harbors, he must ship and sail, do and dare; he must quest and question. These chance discoveries are called "accidental" but there is nothing fortuitous about them, for laggards drift by a haven that may be a heaven. They pass by ports of opportunity. Only the determined sailor, who is not afraid to seek, to work, to try, who is inquisitive and alert to find, will come back to his home port with discovery in his cargo. (p. 177)

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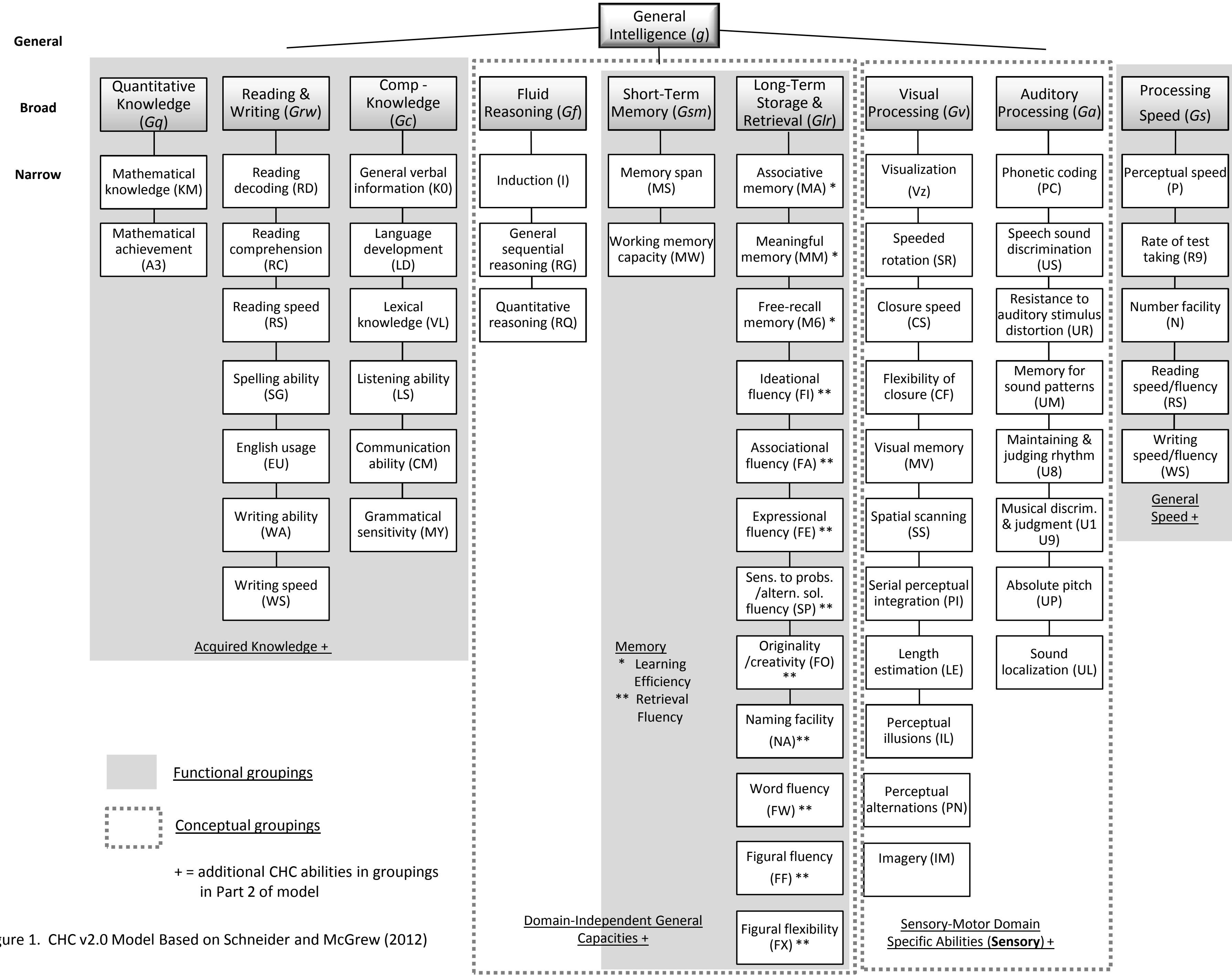


Figure 1. CHC v2.0 Model Based on Schneider and McGrew (2012)

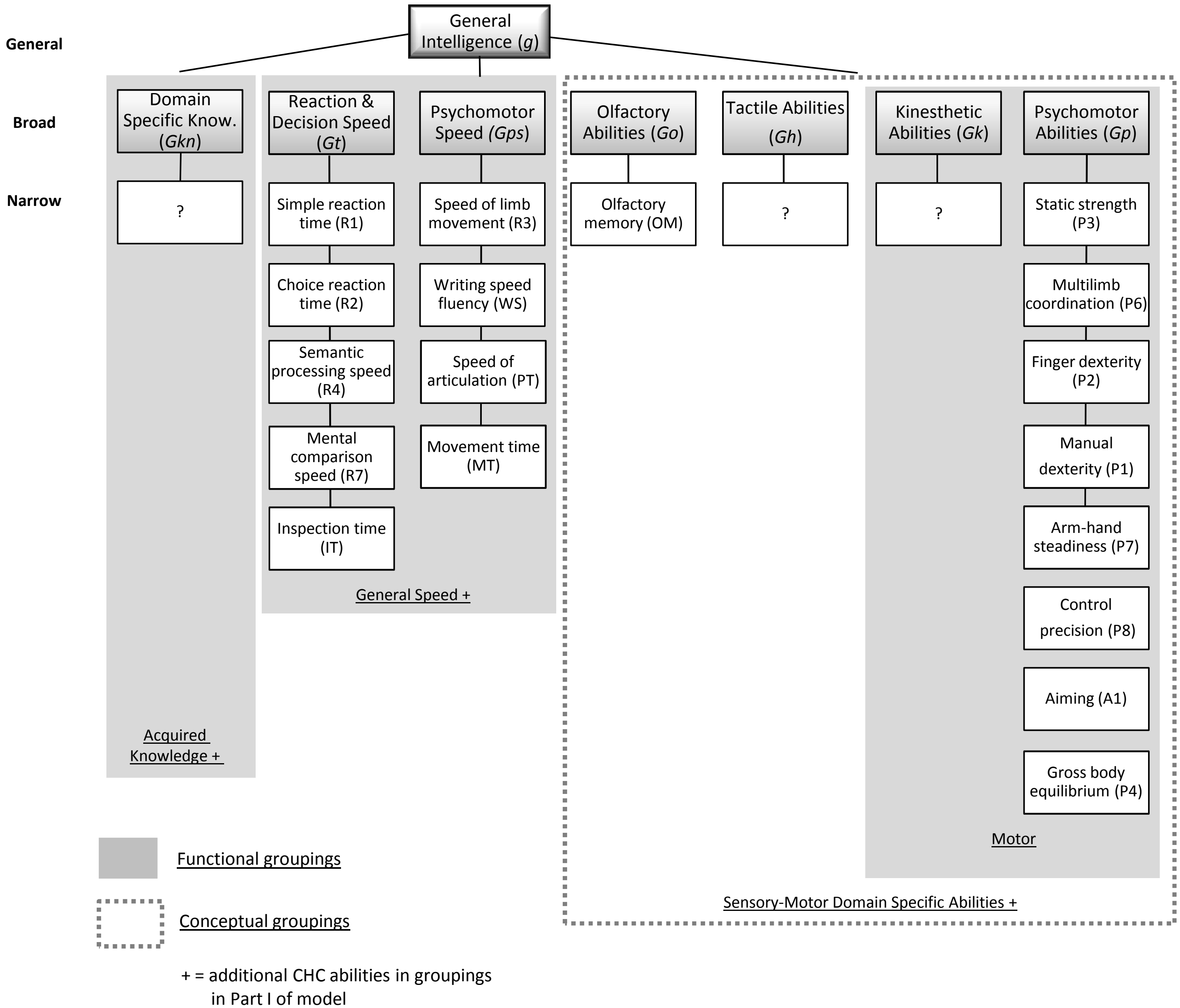
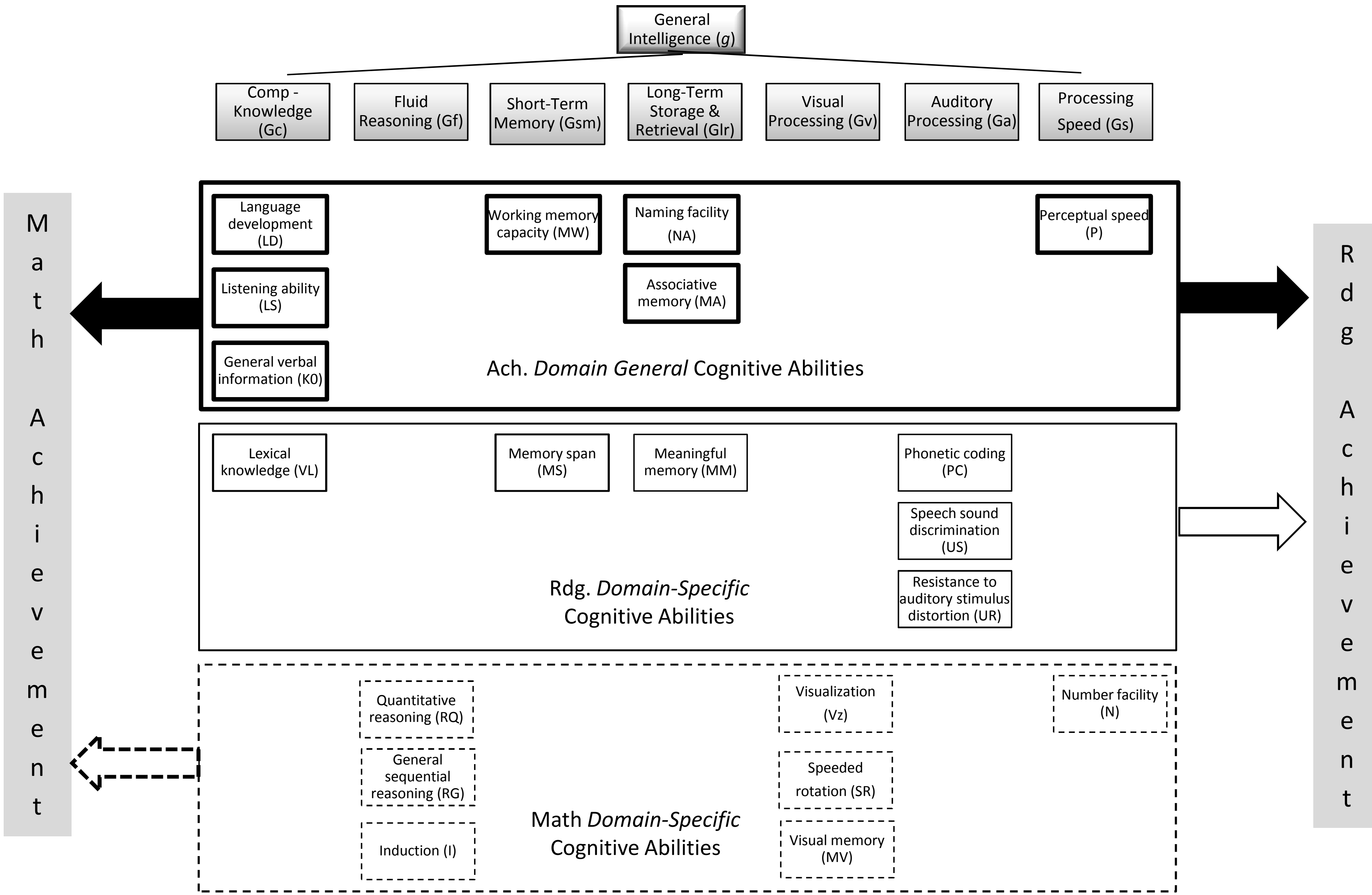


Figure 1 (continued). CHC v2.0 model based on Schneider and McGrew (2012)



(Developmental [age-based] differences are not captured by this abridged summary. See McGrew & Wendling [2010]for this information.)

Figure 2. Established Narrow CHC→Rdg./Math Achievement Relations Abridged Summary

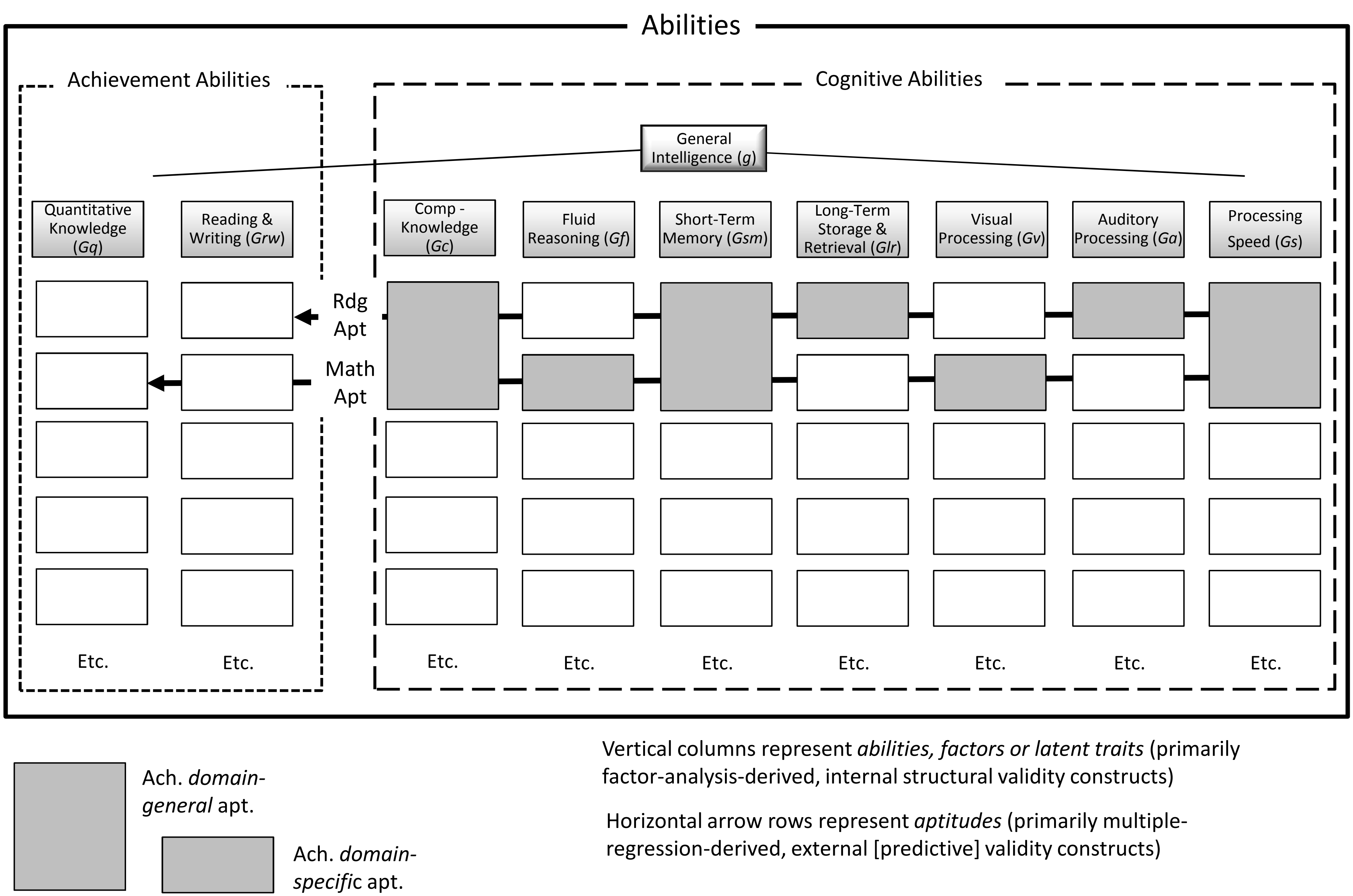


Figure 3. Conceptual Distinction Between Abilities: Cognitive Abilities, Achievement Abilities, and Aptitudes

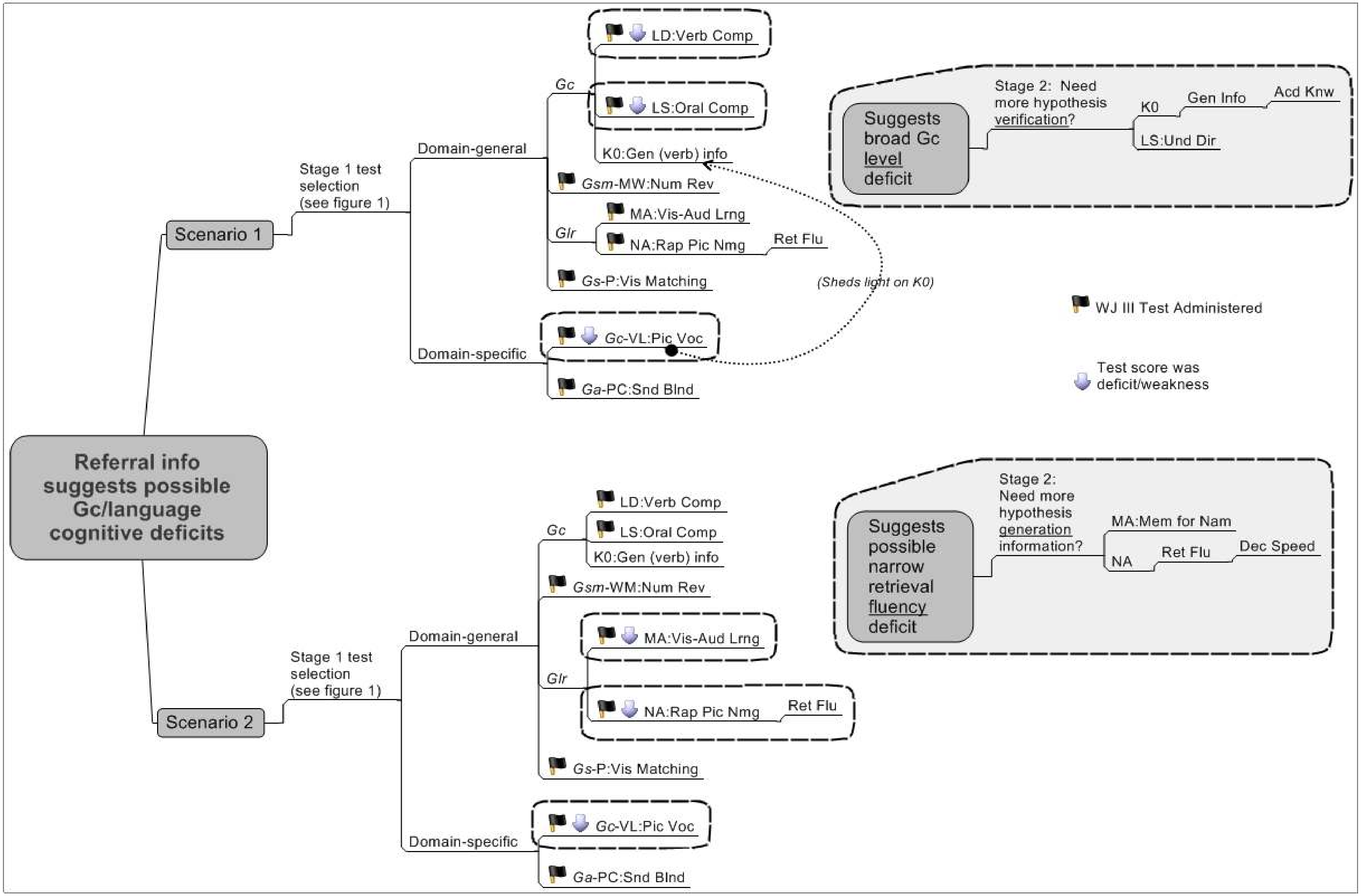
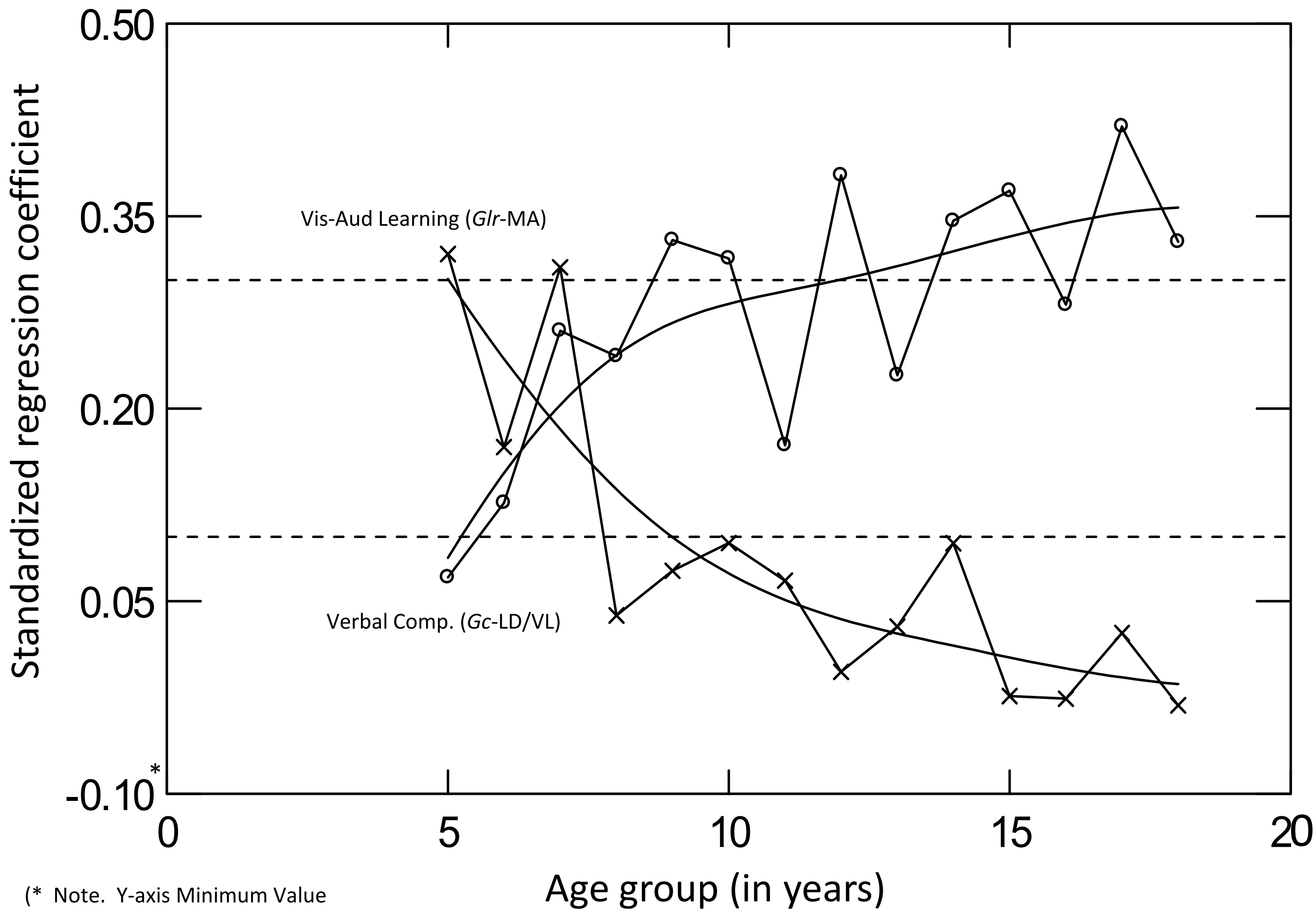
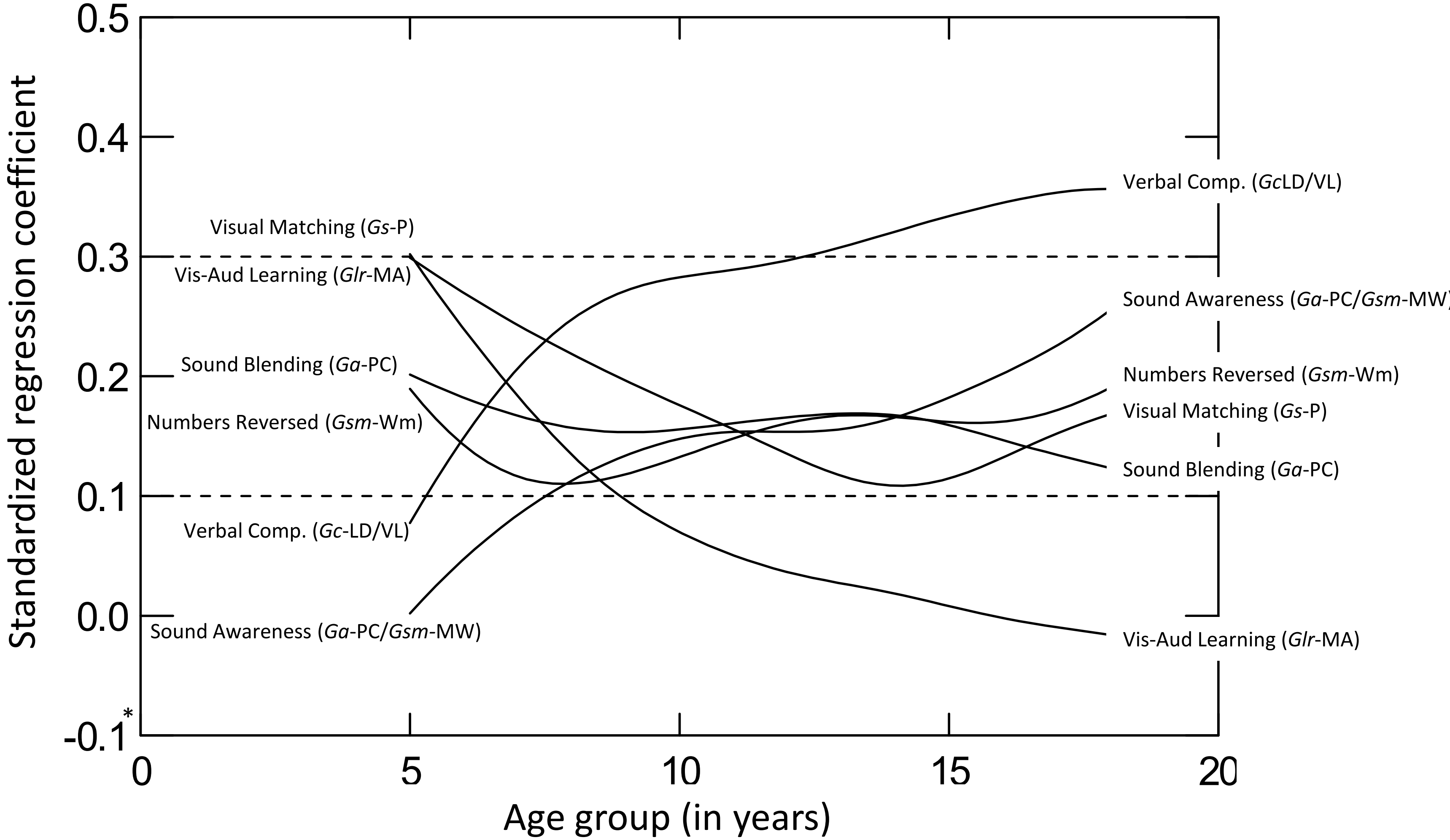


Figure 4. Two Illustrative CHC General Selective Referral-Focused Assessment (SRFA) Scenarios: BRS problems for ages 6 to 8 yrs



(* Note. Y-axis Minimum Value of -0.10 Used as Some Regression Coefficients Were Less Than Zero and Negative)

Figure 5. Raw and Smoothed Standardized Regression Coefficients for WJ III Verbal Comprehension and Visual-Auditory Learning Tests as Predictors of WJ III Basic Reading Skills (BRS) Cluster from Ages 5 Through 18

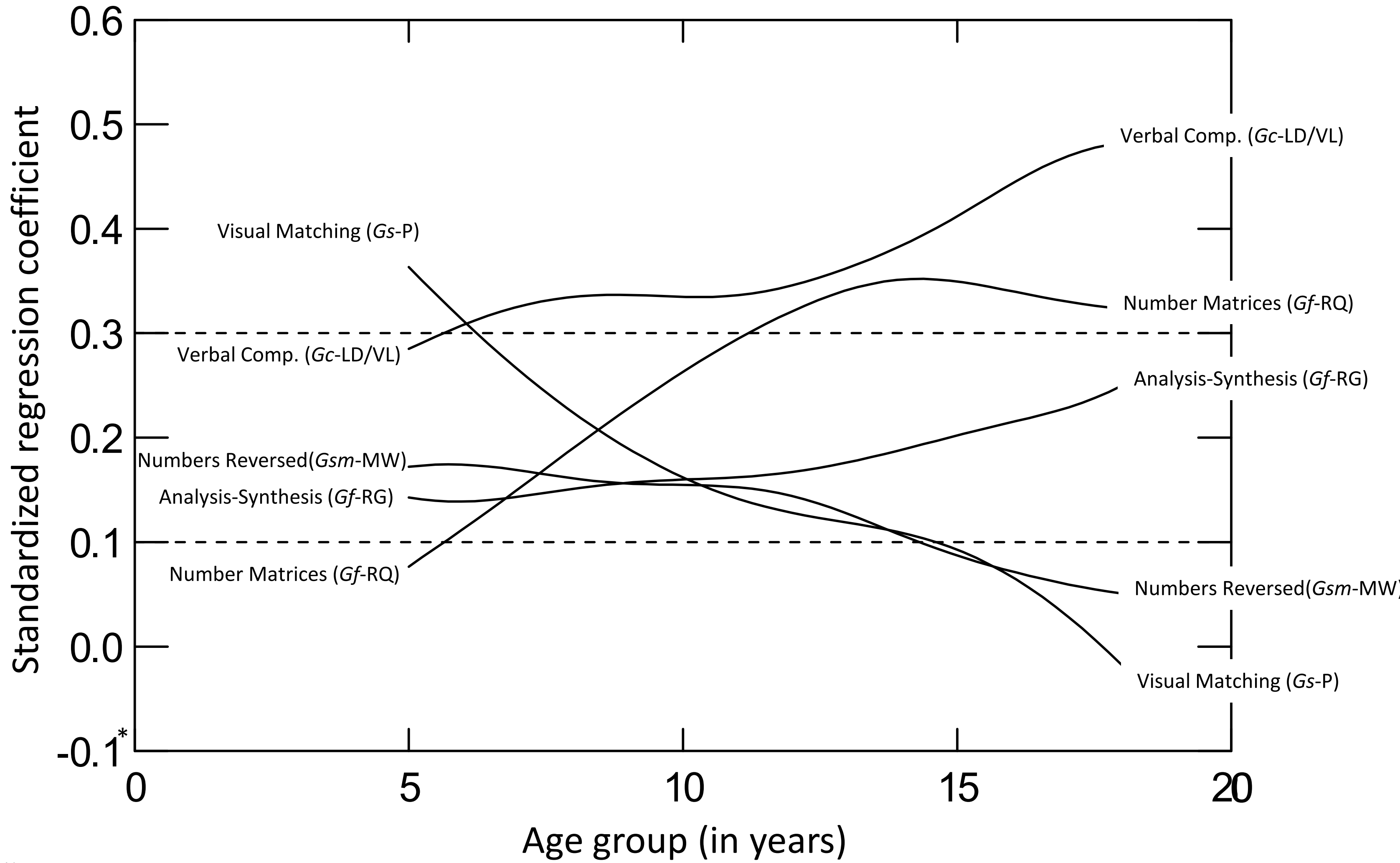


(* Note. Y-axis Minimum Value of -0.1 Used as Some Regression Coefficients Were Less Than Zero and Negative)

Age	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
GIA-Std	33	40	42	39	41	50	43	35	43	48	48	48	59	45
BRS Apt	50	49	50	48	45	56	48	43	50	54	52	52	63	52
Difference	**17**	**9**	**8**	**9**	**4**	**6**	**5**	**8**	**7**	**6**	**4**	**4**	**4**	**7**

Figure 6. Smoothed Standardized Regression Coefficients of Best Set of WJ III Cognitive Test Predictors of WJ III Basic Reading Skills (BRS) Cluster from Ages 5 Through 18

Table is percent of BRS variance accounted for by GIA-Std and BRS Aptitude as constructed and weighted per the figure.

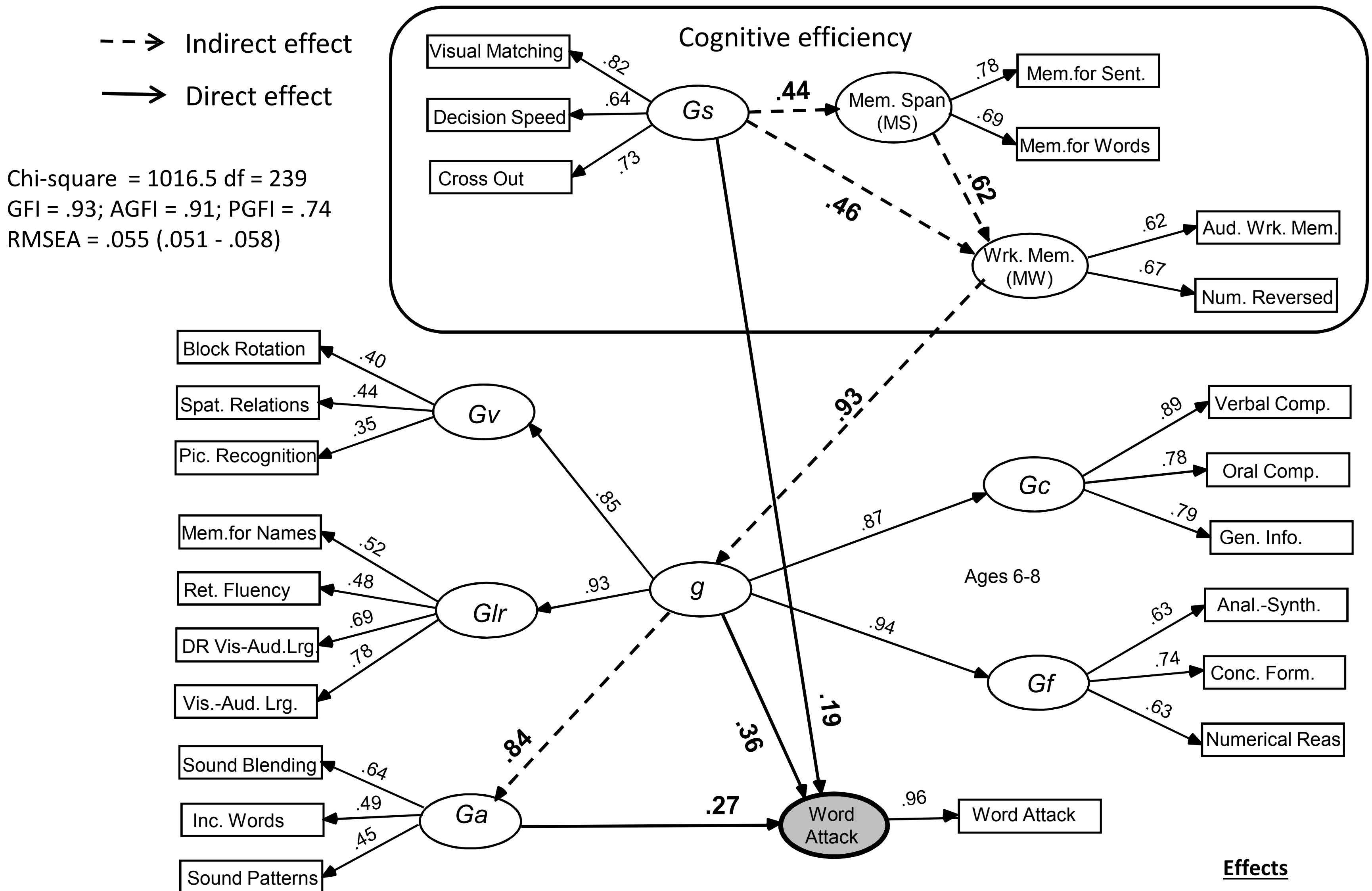


(* Note. Y-axis Minimum Value of -0.1 Used as Some Regression Coefficients Were Less Than Zero and Negative)

Age	5	6	7	8	9	10	11	12	13	14	15	16	17	18
GIA-Std	32	39	44	46	53	56	50	60	64	56	53	65	53	47
MR Apt	46	42	47	53	56	61	62	63	71	72	64	77	64	66
Difference	**14**	**3**	**3**	**7**	**3**	**5**	**12**	**3**	**7**	**12**	**11**	**12**	**11**	**19**

Figure 7. Smoothed Standardized Regression Coefficients of Best Set of WJ III Cognitive Test Predictors of WJ III Math Reasoning (MR) Cluster from ages 5 thru 18

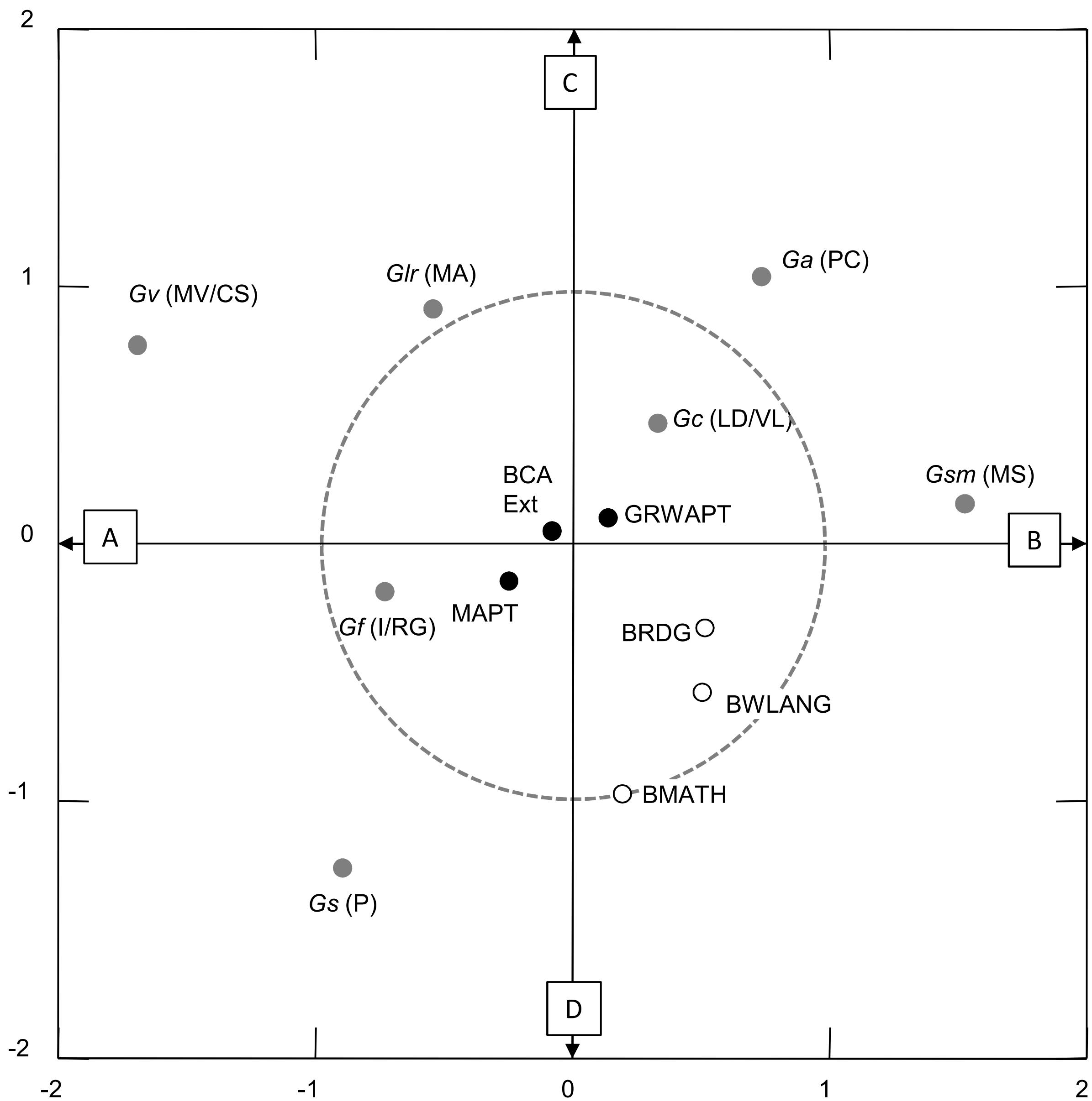
Table is percent of MR variance accounted for by GIA-Std and MR Aptitude as constructed and weighted per the figure



Effects

	Direct	Indirect	Total
Gs	0.19	0.40	**0.59**
***Gsm*-MS**	0.00	0.34	**0.34**
***Gsm*-MW**	0.00	0.54	**0.54**
g	0.36	0.23	**0.59**
Ga	0.27	0.00	**0.27**

Figure 8. Plausible CHC/IP COG→Word Attack Causal Model in WJ III Norm Data (ages 6 - 8)



A:B = Visual-figural/numeric-quantitative - auditory-linguistic/language-verbal dimension
C:D = Cognitive operations/processes - acquired knowledge/product dimension

<u>Notes on WJ-R Derived Scholastic Aptitude Clusters (SAPTs)</u>

<u>GRWAPT</u> = ***Gc*(LD/VL) + *Gs*(P)** + *Ga*(PC) + *Glr*(VAL) or *Gsm*-MS

(RAPT and WLAPT nearly overlapped in figure. Given their high degree of overlap, they were combined into a single GRWAPT in the figure.)

<u>MAPT</u> = ***Gc*(LD/VL) + *Gs*(P)** + *Gf*(I) + *Gf*(RG)

-WJ-R SAPTs each composed of 4 tests with equal weightings (.25)

-**Bold font** designates shared test CHC ability content in GRWAPT and MAPT

WJ-R CHC factor clusters

WJ-R broad achievement clusters

WJ-R Broad Cognitive Ability & Scholastic Aptitude clusters

<u>Note:</u> Measures closer to the center are more *cognitively complex.* The distance between points represents the inter-relations between variables. Highly-related variables are spatially closer-have less distance between their circles.

Figure 9. Guttman Radex MDS Analysis Summary of WJ-R Cognitive, Aptitude, and Achievement Measures Across All Ages in WJ-R Norm Sample

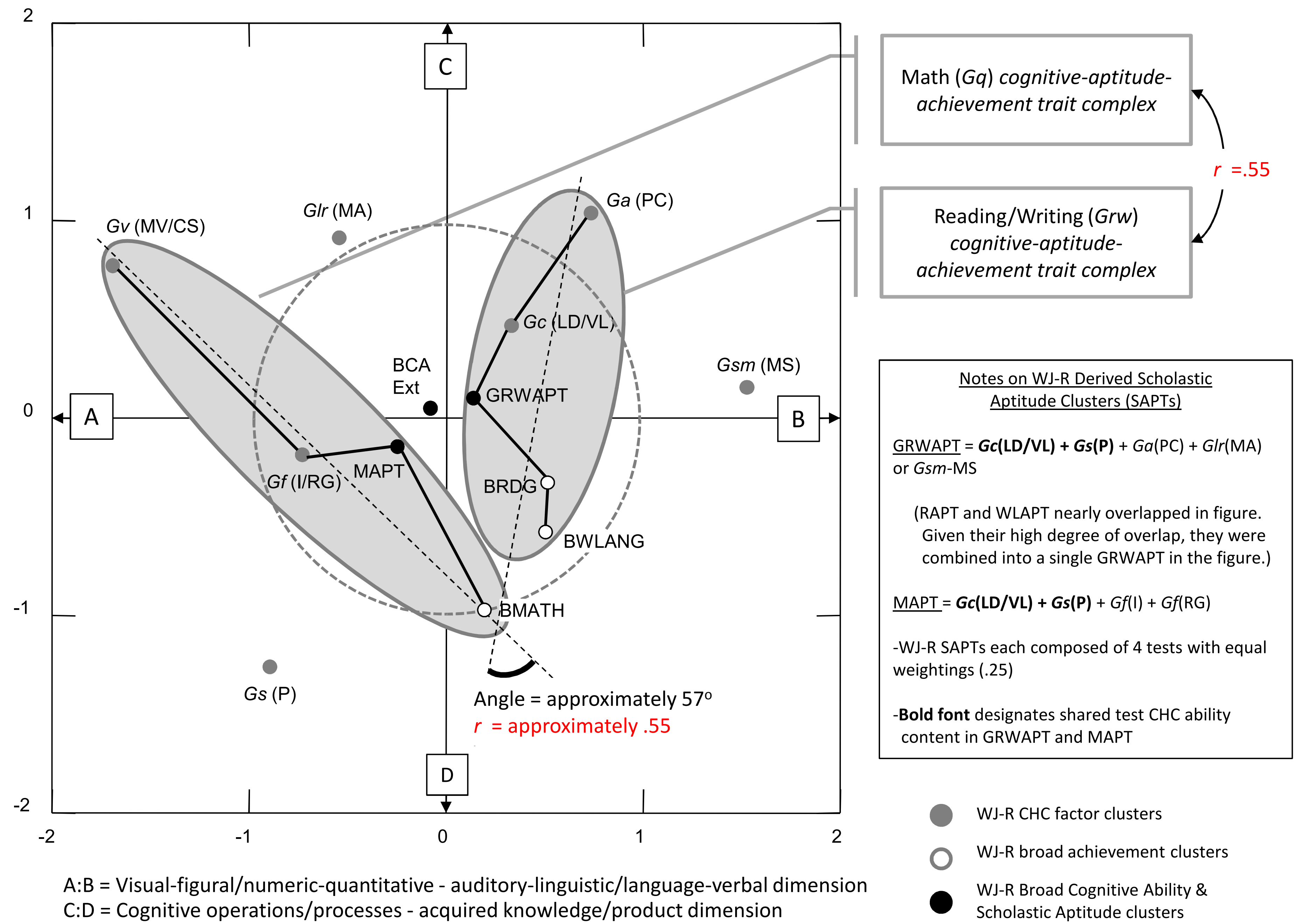
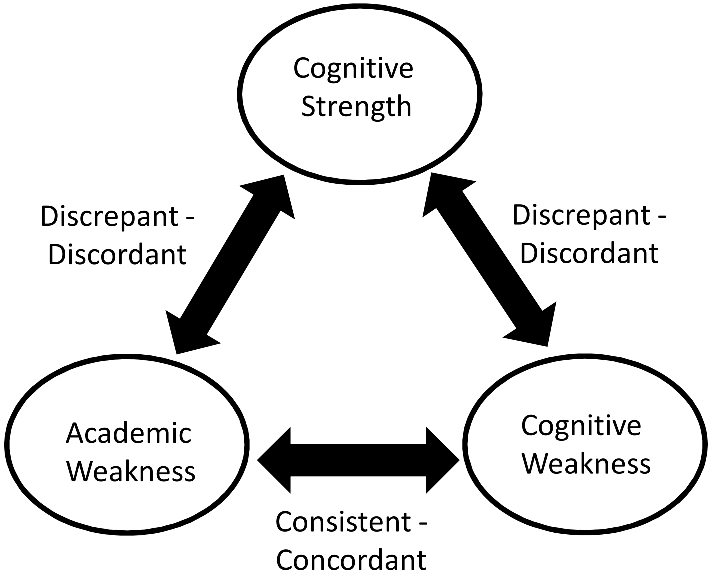
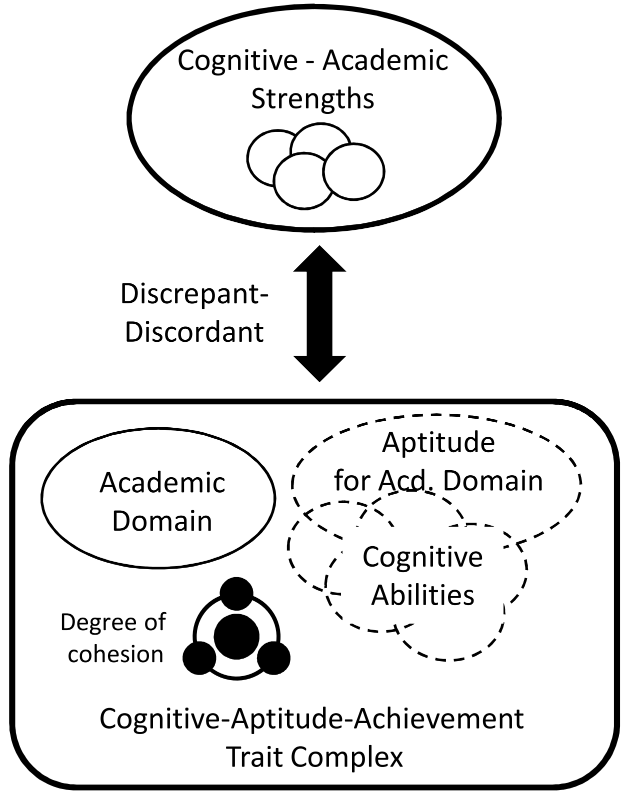


Figure 10. WJ III-Based Reading and Math Cognitive-Aptitude-Achievement Trait Complexes (CAATCs)



Common components of third-method approaches to SLD identification

(Adapted from Flanagan & Alfonso, 2011)



Dashed shapes designate academic domain <u>related</u> cognitive abilities.

Suggested reconceptualization of academic and cognitive weaknesses (and possible SLD identification model) based *on cognitive-aptitude-achievement trait complexes* (CAATC)

Figure 11. Comparison of Current Third-Method and Cognitive-Aptitude-Achievement Trait Complex (CAATC) Models of SLD Identification

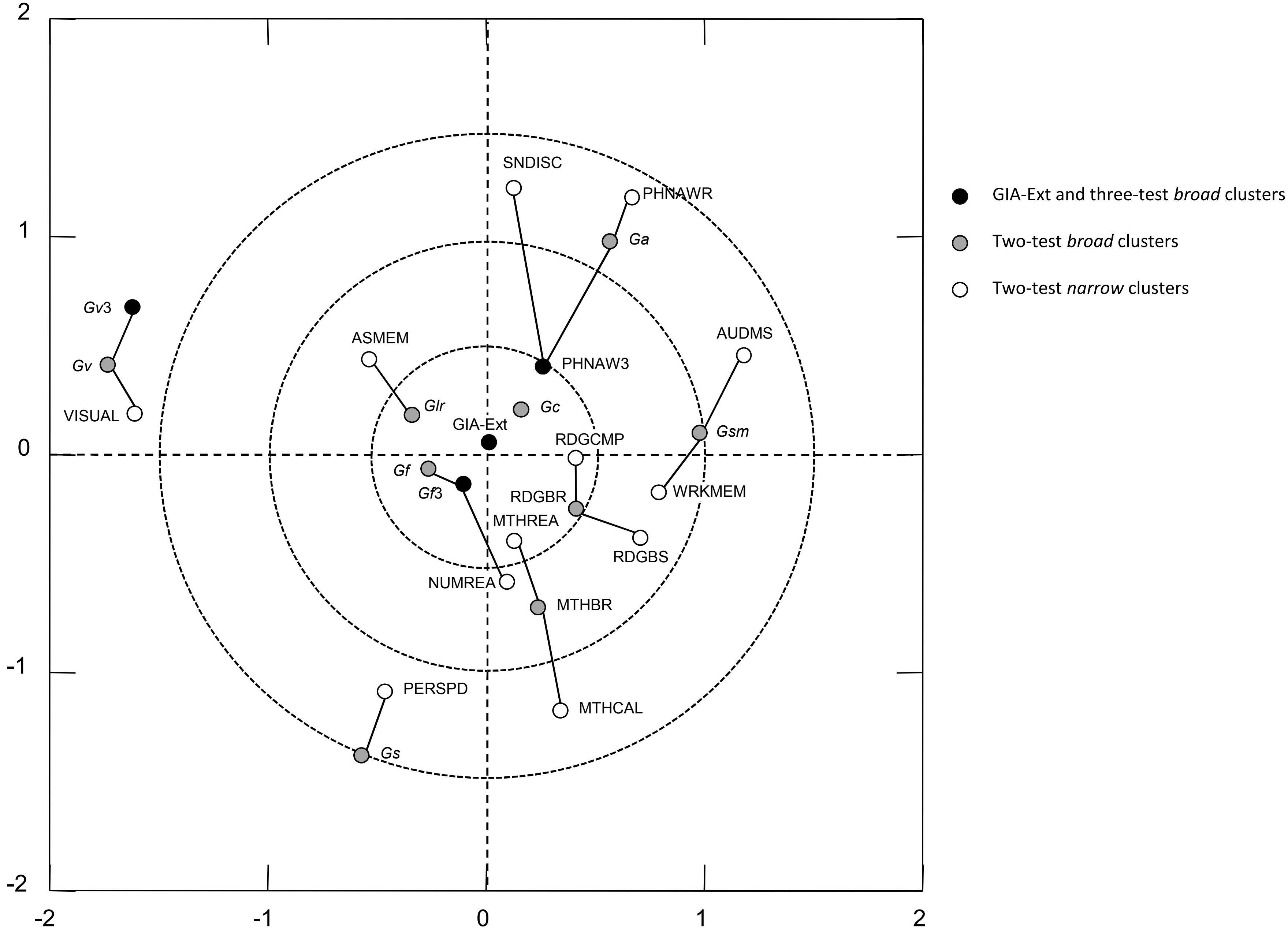


Figure 12. MDS Radex Model-Based Cognitive Complexity Analysis of Primary WJ III Clusters