Theories of Intelligence

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Introduction

A prominent definition of intelligence describes the construct as follows:

Intelligence is a very general mental capacity that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—“catching on,” “making sense” of things, or “figuring out” what to do (Gottfredson, 1997a, p. 13).

This working definition has been broadly endorsed and repeated by numerous scholars in the field (Haier, 2016; Nisbett et al., 2012; Protzko, 2017) and captures many of the traits and capabilities that scientists and lay people alike would consider important parts of intelligence. Notably though, while it does a good job of describing various things that intelligent people tend to do, and distinguishes the construct from others (e.g., book knowledge), it also recapitulates a key tension at the heart of the intelligence literature. Namely, how is it that intelligence is on the one hand a very *general* capacity and yet attempts to define it very often invoke a host of apparently discrete behaviors and tendencies? For intelligence theorists, this question can be translated into the issue of whether intelligence truly represents a singular or *unitary* capacity, as much of the psychometric literature has suggested, or whether the appearance of a unitary structure is merely a statistical or measurement artifact, such that intelligence actually represents an aggregate of many capacities.

As detailed below, the issue of whether intelligence is a unitary capacity arguably represents the most important issue concerning theories of intelligence and can serve as an organizing theme for the models discussed in this chapter. Beyond that, any theory of intelligence can then be grouped according to (1) whether it is better construed as a historical or a contemporary theory; (2) whether its evidence base is primarily *psychometric* (based on statistical modeling of the correlations among various types of mental tasks), *experimental* (derived from analyses of laboratory-based measures, rather than norm-referenced standardized tests), *conceptual* (derived from literature reviews and rational considerations), or even *physiological* (arrived at through correlations of intelligence task performance with EEG or neuroimaging data); and finally (3) whether it emphasizes the importance of more *basic* (i.e., sensory perceptual) or more

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complex tasks in measuring and defining intelligence. Upon exhausting those dimensions, each theory of intelligence can ultimately be characterized in terms of its more distinguishing features and contributions to the literature. Given that psychometric research forms the bulk of the evidence base for these theories in general, the next sections outline the history of psychometric models of intelligence (also termed "structural" models), from Charles Spearman's discovery of psychometric *g* up through the development of multifactor and hierarchical models in the middle and later part of the last century.

Early Psychometric Theories of Intelligence

Spearman, the Birth of Factor Analysis, and Psychometric *g*

The most important historical figure in psychometric intelligence research is undoubtedly Charles Spearman, whose key ideas are still relevant today. As reviewed in his 1904 monograph, prior research in early psychology had produced conflicting findings about the nature of intelligence. On the one hand, Francis Galton (discussed below) and others had advocated for a view of intelligence as a single mental capacity that had its basis in relatively primitive functions such as sensory discrimination (e.g., discriminating fine differences between the weights of objects or the pitches of auditory tones). However, other scholars had either failed to find evidence for this claim or had at times contradicted it showing that more complex mental abilities better reflected the nature of intelligence (Spearman, 1904). Having reviewed the literature on both sides and found it wanting, Spearman sought out to more rigorously investigate the relation between sensory discrimination and intelligence, in an effort to improve the theoretical and empirical foundations on which the debate rested.

For that purpose, Spearman collected measures of sensory discrimination in samples of school children and related them to various tentative estimates of intellectual ability, such as class rankings in various subjects (Classics, English, French, Mathematics, and Music) and teachers' and others' general impressions of the students' abilities. Notably, Spearman also included a precursor to the contemporary IQ score in the form of a mental age measure, where he distinguished between a form of intelligence he called "present efficiency" (absolute academic performance) and "native capacity" (a student's performance in a given subject divided by their age). Overall, these studies produced several important contributions.

First, Spearman recognized the need to control for the unreliability of measurements, which, if achieved, would allow one to obtain a better estimate of the true relationship between two variables (Jensen, 1998a, p. 23). Second, Spearman also identified that by examining the variance that is shared across different types of tasks (e.g., visual and auditory discrimination, proficiency in Greek vs. piano-playing; Spearman, 1904, p. 259), one could determine the extent to which they involve one or more underlying dimensions or faculties. This marked the beginning of factor analysis (Bartholomew, 2004, p. 18), wherein Spearman laid the mathematical foundations to be able to ask whether, for example, auditory and visual discrimination reflect wholly distinct capacities, owing to their basis in different sensory modalities, or whether the variance between people on each reflects a more general sensory discrimination ability. That is, factor analysis allows one to assess how many dimensions contribute to variance in performance on a group of psychological tasks. For that reason, it has come to be the primary tool in psychometric intelligence research, including many of the following models discussed in this chapter. It also brings us to Spearman's third and most important contribution, where he showed that, indeed, there was evidence for "general discrimination" and "general intelligence" factors that were common to all of the respective measures and, further, that the two factors were related to such a large degree that they seemed to both draw on a single mental capacity (Spearman, 1904, p. 272).

While contemporary estimates of the correlation between intellectual ability and sensory discrimination suggest that the relationship is considerably smaller than Spearman's initial claim (Acton & Schroeder, 2001), the basic finding has nevertheless proved reliable (Sheppard & Vernon, 2008) and provides meaningful support for the reductive program in intelligence research, as outlined further below. More importantly, however, Spearman's broader suggestion that a single capacity might be common to all cognitive tasks has proved to be even more central.

In particular, it has now been shown that across hundreds of datasets (Carroll, 1993), whenever a sufficiently diverse set of mental tasks is administered to a sufficiently large and representative group of people, the tasks will invariably positively intercorrelate, producing the so-called *positive manifold* phenomenon. Crucially, this is an empirical phenomenon and not a logical necessity, in the sense that there is nothing inherent to the statistical procedures that require that grades in Mathematics, Classics, and French must be positively correlated. Rather, their correlation reflects an empirical truth. Not only did Spearman observe the now-ubiquitous positive manifold among the academic and sensory measures, but he further saw that the correlations between the various subjects exhibited a clear hierarchy, such that grades in English and French related more strongly to grades in Classics than either did to Math. He then showed that upon extracting what he called the common "general intelligence" factor, all of the measures—sensory and academic alike—seemed to derive their variance from only this general factor and a second, idiosyncratic test-specific factor (see Fig. 2.1). This in turn made it possible to determine how "saturated" each task was with the general factor (i.e., its "*g*-loading" in contemporary parlance) and could ultimately allow for identifying which tasks would provide the best of measures of overall intelligence (Spearman, 1904, p. 277).

Altogether, these results provided the basis for Spearman's "two-factor" theory[1] of mental ability, which argues that the variance between people on any given task appears to be a function of only two factors: that which is *specific* to each task (termed "*s*") and that which is *general* or shared, now known as psychometric *g* (Spearman, 1927).

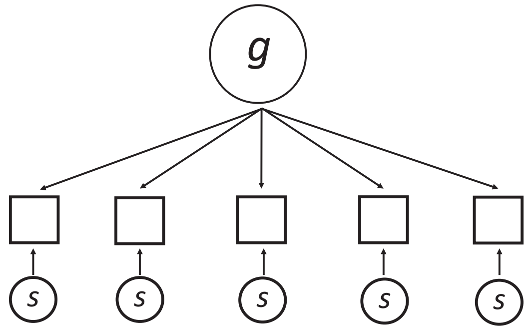

Fig. 2.1 Spearman's two-factor theory. Spearman's two-factor theory of intelligence asserts that the variation between people on all cognitive tasks is a function of two factors: general intelligence (*g*) and test-specific variance (*s*). A hypothetical battery of five tests is shown, where the variance in each test reflects only the contributions of *g* and test-specific variance. Following typical conventions for depicting structural equation models, latent factors are depicted as circles, and manifest variables (obtained test scores) are depicted as squares

In the time since Spearman's initial observations, it has become essentially universally accepted that a general factor can often account for much of the variance among cognitive tests (typically approaching 50%; Deary, 2012). Yet, as will be seen, the status and significance of this factor remain an important area of debate. On that note, it is appropriate to turn to a discussion of Spearman's primary interlocutors and the alternative models they favored.

Thurstone and Multifactor Theories

Spearman's two-factor theory of intelligence is most often and readily distinguished from Louis L. Thurstone's model of Primary Mental Abilities (Thurstone, 1938). The latter exemplifies an alternative class of models that advocated a multifactor rather than unitary structure for mental abilities (Sattler, 2008, p. 224). As the name implies, Thurstone's model emphasized the idea

[1]The name "two-factor" theory can be somewhat confusing, in the sense that it strongly emphasizes the importance of the single *g* factor. Nevertheless, the name refers to the assertion that any task involves contributions from two factors: *g*, which is common to all tasks, and *s*, which is unique to particular tests.

that, rather than invoking just a single general factor along with test-specific factors in explaining cognitive performance, a group of independent, lower-order processes, with a clearer psychological meaning (e.g., memory, verbal skills, spatial skills, etc.), might better explain the patterns of correlations among cognitive tests. Indeed, a form of this idea can be seen in Spearman's very own hierarchy, where he observed that grades in certain subjects (e.g., Classics, French, and English—all notably linguistic) correlated more highly with one another than they did with other measures.

Inspired by that premise, Thurstone devised a large set of cognitive tasks that were designed to be maximally pure in their reliance on what were presumed to be independent capacities. Using an alternative factor-analytic technique that forces the extraction of maximally independent factors (Jensen, 1998a, pp. 75–76), he was then able to derive a model that consisted in seven, seemingly independent, primary abilities (see Fig. 2.2). Among these were capacities like memory, perceptual speed, and spatial visualization (Sattler, 2008), which exhibit an intuitive degree of conceptual separation, as well as others like verbal comprehension and word fluency that might be expected to have more variance in common. As it happens, this turns out to be the case, as Thurstone himself later recognized. That is, although it is possible to achieve maximally independent factors by (1) carefully selecting tests on that basis and then (2) mathematically constraining the relations between resulting factors, in truth, when the latter constraints are relaxed, the primary factors will positively intercorrelate. As explained by Jensen (Jensen, 1998a, Chapter 4), this is due to the fact that although some tests may load only on one primary ability, they all will still invariably load on *g*.[2] Moreover, the latter will often account for considerably more variance in performance than do the primary abilities. In turn, the *g* factor can then be modeled at a level above the primary abilities, or even alongside them, to account for their intercorrelations, as in the contemporary hierarchical and bi-factor models described below. As will be seen, these latter models provide something of a compromise position (Deary, 2000, Chapter 1).

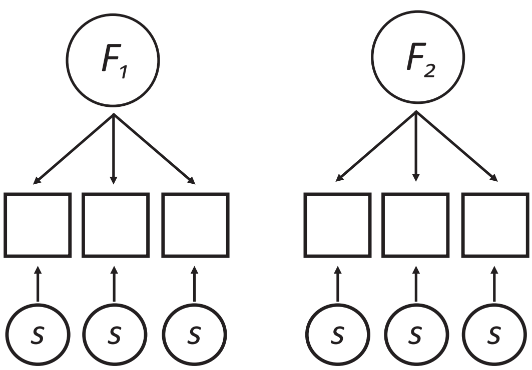

Fig. 2.2 Schematic factor model depicting two orthogonal primary abilities. A simplified version of Thurstone's primary ability model is shown here with only two factors, derived from three tests each. The key distinguishing features of Thurstone's initial model are the presence of uncorrelated (mathematically "orthogonal") primary abilities and the absence of a general factor. F_1 and F_2 designate hypothetical primary abilities (e.g., verbal and spatial skills)

Sampling Theory and Thomson's "Bonds" Model

While it is instructive to distinguish between the extremes represented by Spearman's two-factor theory and Thurstone's initial model based on Primary Mental Abilities, in recent years, a third alternative outlined by their contemporary, Godfrey Thomson, has been rediscovered. As recently described by Bartholomew and colleagues, Thomson's work is unique, in that it does not necessarily dispute the mathematical adequacy of two-factor theory, but somewhat like Thurstone's early model, it objects on conceptual grounds (Bartholomew, Deary, & Lawn, 2009). Specifically, whereas Thurstone emphasized the need for psychological and conceptual coherence in psychometric models of intelligence, Thomson was concerned with biological plausibility in terms of neural organization.

[2]It should be noted that Thurstone himself came to recognize these issues and acknowledged the possibility of a high-order *g* (Carroll 1993, p. 56; Major et al. 2012, p. 544).

As an intuitive, if high-level example, consider the well-known neurological findings that specific, higher-order faculties (e.g., language comprehension) can be disrupted by focal lesions, while leaving other cognitive skills intact. This of course suggests that cognitive functions are subserved by at least partly dissociable neural systems and that individual differences therein might not be the result of a single underlying factor. Yet, unlike Thurstone, Thomson did not argue that the underlying neural processes should be wholly independent, in the sense that they would never interact. Rather, just as we now know that language production and comprehension are both largely housed in the dominant hemisphere (Lezak, Howieson, Bigler, & Tranel, 2012) and even interact (Papathanassiou et al., 2000), one might expect these abilities to positively correlate based on their overlapping substrates.

In essence, Thomson extended this basic logic to develop a broader account of how diverse neural processes could give rise to the appearance of a single underlying factor in mental abilities. He reasoned that this could occur any time the items or tests in a given battery each "sampled" the same set of discrete but connected neural processes (which he termed "bonds"). In turn, as the number of bonds shared among tasks increases, so too should the correlation between them. Thus, Thomson argued, and more recent work has confirmed (Bartholomew, Allerhand, & Deary, 2013) that it is possible to develop a statistical model that replicates the *g* factor, despite actually being comprised of numerous underlying processes. Further, although not recognized at the time, Thomson's proposal makes even more sense when one considers the finding that the tasks with the highest *g*-loadings are nearly always the most complex. Given that complexity has been explicitly defined as the number of processes involved in a task (Guttman, 1954; Marshalek, Lohman, & Snow, 1983; Stankov & Raykov, 1995), it is quite suggestive that the most complex (and hence most *g*-loaded) tasks might in fact involve the most overlapping processes. Interestingly, like much of this literature, this idea, presented here in a psychometric context, would come to be echoed later on in more conceptual theories.

Cattell's Legacy: Fluid and Crystallized Intelligence and Investment Theory

Working in the middle and later part of the twentieth century, Raymond B. Cattell made a major contribution to this literature in developing the concepts of fluid and crystallized intelligence (respectively, denoted as Gf and Gc). In a seminal paper, Cattell (1963) described his effort to synthesize factor-analytic methods with developmental considerations as they pertain to the growth of intelligence. One of his key assertions was that "there is not *one* "general ability" second-order factor…but more," with each having a semi-independent basis and developmental trajectory (Cattell, 1963; emphasis in original). Specifically, he argued that it is possible to separate the *g* factor into Gf and Gc, where the former represents the capacity to respond adaptively in novel situations, while the latter is drawn upon by tasks that require learned skills and knowledge. Concretely, Gf would be expected to play more of a role in solving tasks involving unfamiliar relationships or components, such as in the well-known Raven's matrices (Raven & Court, 1998). These tasks are broadly nonlinguistic and require examines to identify the shared features among abstract figures arranged in a matrix. Gc, on the other hand, loads heavily on linguistic, academic, and other skill-based knowledge and should be more important for tasks involving things like verbal reasoning and one's general fund of information.

In line with these distinctions, Gf was hypothesized to more closely reflect one's inborn, momentary cognitive processing capacity, which is then *invested* in developing crystallized skills (thereby forming the crux of "investment theory"; Cattell, 1987). In addition, the trajectory of Gf and Gc should follow a particular developmental course, with Gf increasing as children reach adulthood but declining in middle and older age, whereas Gc would in principle continue expanding as individuals accrue further experience. Indeed, this general trajectory has been roundly confirmed (Salthouse & Davis, 2006) and represents a key consideration in developing norms for cognitive tests. Notably, although the Gc-Gf model may sound very similar to that of Primary Mental Abilities, it is distinguished from this and other "multifactor" models in that its components are allowed to intercorrelate (a so-called oblique model; Kovacs & Conway, 2016). Last, although the original Gf-Gc model contained only two factors (see Fig. 2.3), Cattell and his coworker John Horn later extended it to include ten broad abilities (McGrew, 2009).

Ultimately, while the Gf-Gc distinction has been retained in some more recent psychometric models (notably CHC theory, see below), it is not without its challenges. Most significantly, it is now well-established that although it is possible to separate Gf and Gc statistically, if one allows for a *g* factor at a third level in a higher-order model (see next section), Gf and *g* then correlate at or close to unity (Kan, Kievit, Dolan, & van der Maas, 2011; and Lichtenberger & Kaufman, 2013, p. 32–33). This of course makes them statistically and potentially substantively indistinguishable. Second, as noted by Cattell (1963), the theoretical distinction between Gf and Gc has important implications for determining which sorts of tests would be the most likely to show bias due to educational or cultural factors. Yet, although it is clearly the case that tests which presume certain linguistic and cultural information are not appropriate for some examinees, it unfortunately does not follow that the so-called "nonverbal" measures are in fact culture fair or "culture free." To the contrary, recent work examining age differences in performance on the Raven's progressive matrices suggests that such tasks are in fact highly sensitive to broader cultural knowledge, such as that which changes over successive generations (Fox & Mitchum, 2012).

Other aspects of the Gf-Gc model have received mixed support as well. On the one hand, there is meaningful support for investment theory's claim that investing in developing a certain type of skill may limit the growth of others (e.g., resulting in strong verbal and weaker math skills or vice versa; Coyle, Purcell, Snyder, & Kochunov, 2013; Coyle, Snyder, Richmond, & Little, 2015). However, at the same time, other research has undermined some of its other claims (e.g., Kievit et al., 2017). Thus, while the Gf-Gc distinction still finds support in facets of the literature, the overall challenges faced by the model have given sufficient reason to consider alternatives.

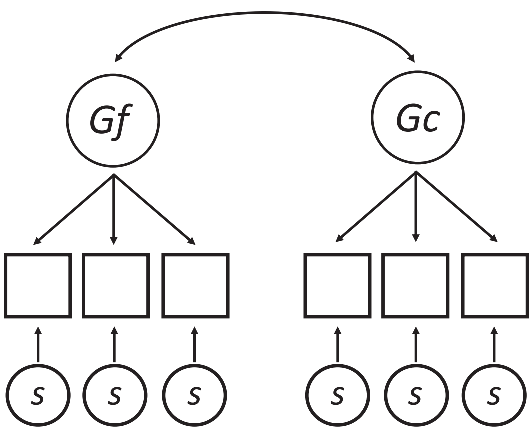

Fig. 2.3 Oblique fluid and crystallized intelligence model. Oblique factor structure depicting a schematic version of the initial Gc-Gf model. Unlike Thurstone's Primary Mental Abilities model, the two factors are allowed to intercorrelate

Carroll and Vernon's Hierarchical Models

The last group of notable historical models is the hierarchical models developed by Phillip Vernon (2014) and John Carroll (1993).[3] Like Spearman, these theorists posited a *g* factor that was common to all cognitive tasks, but like Thurstone and Cattell, they also acknowledged and incorporated other factors that had a clearer psychological meaning. They accomplished this through the process of successive factorization (developed by

[3]Although many authors have considered Carroll's model to be a quintessential example of a hierarchical model (Deary 2000; Lubinski 2004), it has also been argued that Carroll's view was in fact closer to the bi-factor model discussed in the next section (Beaujean 2015).

Thurstone, 1947; cited in Carroll, 1993, p. 637), where, after extracting first-order factors that corresponded to broad abilities, the remaining correlations between those factors were then factor analyzed themselves, giving rise to a single higher-order *g* factor and thereby creating a hierarchy.

Vernon's model (depicted schematically in Fig. 2.4) posited two major group factors below the level of *g*. These are v:ed, which refers to verbal or educational skills, and k:m, or kinesthetic and mechanical skills (Johnson & Bouchard, 2005b). Below those two major factors, the model then contained the six minor factors of creative abilities, numerical skills, and verbal fluency, which loaded on v:ed, and spatial, psychomotor, and mechanical ability factors which loaded on k:m (Sattler, 2008, p. 227). Although Vernon's verbal-educational and kinesthetic-mechanical factors share some similarities with Gf and Gc, in contrast to Cattell, he argued that v:ed and k:m were both susceptible to cultural influences (educational and noneducational, respectively). Further, he chose to omit Gf, due to its considerable statistical overlap with *g* (Johnson & Bouchard, 2005b).

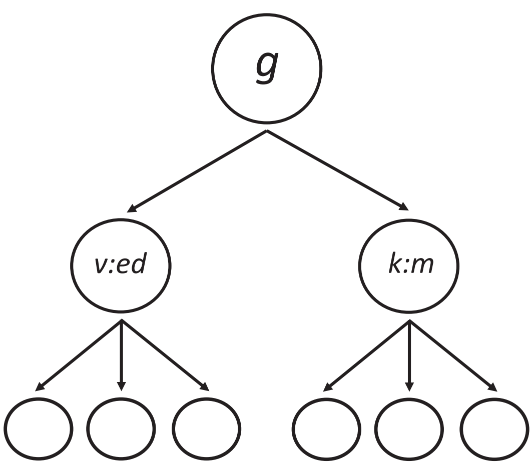

Fig. 2.4 Vernon's hierarchical model. Schematic depiction of Vernon's hierarchical model with a second-order *g* factor that explains the correlations between the verbal-educational and kinesthetic-mechanical group factors. Test-specific factors and manifest variables are omitted for simplicity

As recounted by many authors (Beaujean, 2015), Carroll's work and the resulting model are among the most celebrated achievements in psychometric intelligence research. He arrived at his framework through a meticulous reanalysis of over 450 previous datasets, from which he synthesized the then-extant literature to arrive at his "three-stratum" theory of cognitive ability. In the model, the strata, or level, at which a given ability was placed partly reflected the number of successive factorizations that were performed in deriving it but more directly corresponded to the factor's *generality* in terms of the types of lower-order factors that loaded on it (Carroll, 1993, p. 577). At the lowest level were *narrow* (Stratum I) abilities, or those that are specific to particular tasks (e.g., visualization and sequential reasoning in matrices tasks). Broad (Stratum II) factors then constituted group factors, like those employed by Thurstone and Cattell and Horn, that were common to a given class of tasks. Finally, *g* formed the single Stratum III factor representing general cognitive ability (Carroll, 1993, Chapter 16).

In summarizing his results, Carroll derived four primary conclusions: (1) that there was "abundant" evidence for a general factor of intelligence that would emerge at the highest order of factorization in any given dataset, (2) that eight broad abilities could be distinguished at Stratum II (fluid intelligence, crystallized intelligence, general memory and learning, broad auditory perception, broad retrieval ability, broad cognitive speediness, and processing speed or reaction time decision speed), (3) that additional second-order factors could further be identified in domains such as learning and memory and language (among others), and (4) that the general program of analyzing abilities into strata provided valid insights into the structure of human cognitive ability and could form the basis for such a theory.

Aside from the significance of Carroll's overall achievement, his model was also noteworthy in that, in addition to providing a relatively definitive account of the broad ability factors known at that time, he also arranged them according to their approximate *g*-loadings (Fig. 2.5).

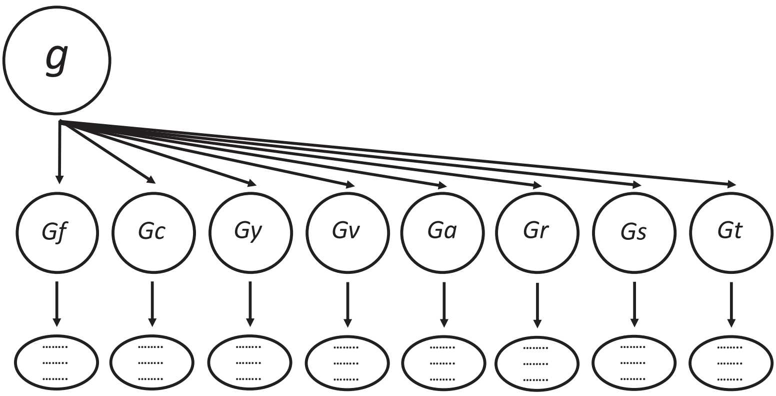

Fig. 2.5 Carroll's three-stratum model of cognitive abilities. Adaptation of Carroll's (1993) hierarchical model, with *g* at Stratum III and broad abilities ordered by their approximate *g*-loadings from left to right. Stratum II factors use contemporary abbreviations, following McGrew (2009). *Gf* fluid intelligence, *Gc* crystallized intelligence, *Gy* general memory and learning, *Gv* broad visual perception, *Ga* broad auditory perception, *Gr* broad retrieval ability, *Gs* broad cognitive speediness, *Gt* reaction time decision speed. Ovals containing ellipses depict narrow Stratum I variables, which varied in number across Stratum II factors

This is useful, because in principle, such an ordering should help to clarify which sorts of measures best predict overall intelligence and hence might inform the "true" nature of construct (e.g., does intelligence have more to do with on-the-spot reasoning or with one's depth and breadth of general knowledge?). Carroll's model is also remarkable for the fact that it truly represented a comprehensive synthesis of the available literature (Johnson & Bouchard, 2005b, p. 395). For example, although he included Gf and Gc in his model, the proximity of the former to *g* also acknowledges the debate (both then and since; Gustafsson, 1984; Colom, Rebollo, Palacios, Juan-Espinosa, & Kyllonen, 2004; Oberauer, Schulze, Wilhelm, & Süß, 2005) about whether Gf or other lower-order factors best define the limits on intelligence. Thus, it is perhaps due to the success of this synthesis that Carroll's model forms one half of the prominent, contemporary Cattell-Horn-Carroll integrated model, or simply CHC (McGrew, 2009).

Contemporary Psychometric Theories of Intelligence

Having incorporated the lessons of the prior century, the current phase of psychometric intelligence research is generally characterized by a clearer acknowledgment of the statistical validity of the *g* factor and a move toward discussing how best to represent it in model structures, what its substantive implications might be, and on determining the number and status of the broad ability factors. At present, there are arguably four major models under discussion.

Cattell-Horn-Carroll (CHC) Theory

The CHC model is likely the most prominent contemporary psychometric theory. Its elements have long been incorporated into the Woodcock-Johnson Cognitive Assessment Battery (initially as Gf-Gc theory; Woodcock, 1990; and later as CHC itself; Woodcock, McGrew, & Mather, 2001), it has received prominent treatments both in the scholarly literature and in practical assessment guides (Lichtenberger & Kaufman, 2013; Newton & McGrew, 2010), and at the time of this writing, a major review of CHC (McGrew, 2009) lists more than 700 citations in the Google Scholar database.

According to a recent chapter detailing the tenets of CHC, the theory consists in two primary components. First, it provides a "taxonomy" or classification of human cognitive abilities, and second, it provides "a set of theoretical explanations for how and why people differ" in those respects (Schneider & McGrew, 2012). As the name indicates, CHC represents a synthesis of the Cattell-Horn extended theory and John Carroll's three-stratum model. Although *g* is included, owing to the disagreement between its namesakes regarding its status (McGrew, 2009, p. 4), the substantive emphasis of CHC is decidedly on the broad and narrow factors. Not only is the casual status of *g* left undetermined, but practitioners who adopt CHC are explicitly encouraged to ignore it if they question its theoretical value and particularly for practical aspects of assessment (Schneider & McGrew, 2012, p. 111). A schematic depiction of CHC would thus be similar to Fig. 2.5 above but lacking a causal arrow from *g* to the broad factors or the emphasis on *g*-loadings.

Although the most well-known treatment of CHC lists ten broad (Stratum II) abilities along with six tentative factors, McGrew and colleagues have since reorganized aspects of the framework to clarify the conceptual groupings among the factors at that level (Schneider & McGrew, 2012). The present section draws heavily from their excellent exposition, which interested readers should consult for a deeper treatment, as well as practice guidelines. The first conceptual grouping corresponds to Domain-Free General Capacities and includes Fluid Reasoning (Gf), two memory factors (Short-Term Memory, Gsm, and Long-Term Storage and Retrieval, Glr), and three cognitive speed factors (Processing Speed, Gs; Reaction and Decision Speed, Gt; and Psychomotor Speed, Gps). These factors group together because they all emphasize more process-related aspects of cognition (e.g., how fluently can one perform a task, how readily can one recall information) as opposed to particular content.

Next, CHC emphasizes four broad, content-related factors under the heading of Acquired Knowledge. These are Comprehension-Knowledge (Gc), Domain-Specific Knowledge (Gkn), Reading and Writing (Grw), and Quantitative Knowledge (Gq). Naturally, these factors depend at least in part on educational and cultural exposure, and on that basis Schneider and McGrew (2012) emphasize their conceptual alignment with Cattell's crystallized intelligence factor. While the expression of these skills clearly depends on specific content and hence cultural exposure, it remains the case that many narrow capacities in this domain nevertheless have process aspects as well. For example, while this domain includes the narrow capacities of General Verbal Information and Lexical Knowledge (loading on Gc), it also includes skills such as Reading Comprehension and Writing Speed (including under Grw). As an interesting side note related to this domain, despite its seemingly straightforward character, Gc arguably represents one of the more controversial factors in intelligence research, both in the CHC model and in the field as a whole. For example, in contrast to early theory which predicted stronger genetic influences on fluid rather than crystallized skills (Cattell, 1963), there is now evidence that more culture-loaded factors may actually be the *most* heritable abilities (Kan, Wicherts, Dolan, & van der Maas, 2013). Indeed, even the status of Gc as a true cognitive capacity is currently under debate (for further reading, see Kan et al., 2011).

In the last conceptual grouping, CHC emphasizes a set of more modality-specific capacities, in the form of Sensory-/Motor-Linked Abilities. Each of these factors is tied to its respective sensory modality, where the list includes Visual Processing (Gv), Auditory Processing (Ga), Olfactory Abilities (Go), Tactile Abilities (Gh), Kinesthetic Abilities (Gk), and Psychomotor Abilities (Gp). Note that these factors are not thought to be mere perceptual capacities but more complex mental operations that depend upon a given modality. For example, Gv entails visualization skills such as those required for mental rotation tasks or for imagining obscured portions of objects, while Ga includes phonemic decoding (implicated in some forms of dyslexia; Coslett, 2003) and memory for sound patterns. However, these examples notwithstanding, it remains the case that assessing some of these skills often entails mere acuity tests (e.g., olfaction, tactile skills; Schneider & McGrew, 2012). Overall, while this grouping undoubtedly includes valid dimensions of individual differences, it nevertheless also seems clear that additional research in this area is needed (Stankov, 2017).

Finally, with regard to CHC's theoretical implications, the current framework is perhaps closest to Cattell and Horn's views which emphasized the diversity of abilities, as opposed to the relative primacy of any given factor in defining intelligence. This is perhaps also consistent with CHC's very practical emphasis, in that it aims to bridge the "theory-to-practice gap" in cognitive and educational assessment (McGrew, 2009, p. 4). That is, because CHC emphasizes broad and narrow abilities, it provides a very practical framework from which to guide assessment of individual people, with their unique and diverse needs. Thus, whereas the ambiguous status of *g*, or some of the less-well established Sensory-/Motor-Linked Abilities, is somewhat unsatisfying from a theoretical perspective, CHC nevertheless has the unique virtue of eschewing those sometime esoteric debates in favor of very explicitly seeking to inform practical considerations.

Verbal-Perceptual-Image Rotation (VPR)

An equally valid, but somewhat underappreciated, model is the VPR theory, which was first articulated by Johnson and Bouchard (Johnson & Bouchard, 2005b). Using a dataset comprised of 42 cognitive ability tests that had been administered to 436 adults, those authors set out to examine whether the Cattell-Horn two-factor Gf-Gc model, Vernon's v:ed-k:m model, or Carroll's three-stratum model best fit the data. Although they concluded that each model fit reasonably well, they also noted a number of issues. For example, the Gf-Gc model demonstrated a high correlation between those two factors, suggesting the presence of a *g* at a third stratum. In addition, the same model contained two lower-order abilities below the primary level that reflected fluid and crystallized skills, but these proved to be statistically indistinguishable from their respective higher-order factors. The Vernon model performed well, but did not meet the authors' a priori criteria for model fit, failed to represent memory, and also showed a very high correlation between its lower-order verbal factor and v:ed. In the three-stratum model, the fluid intelligence factor was indistinguishable from *g*.

On that basis, the authors sought to evaluate a new model, using Vernon's model as a guide but adding another factor to better account for the data. Ultimately, they arrived at what they termed the VPR model (Fig. 2.6), which, as the name indicates, identifies three broad factors below the level of *g*: verbal ability, which includes things like linguistic and scholastic skills (e.g., memorization); perceptual ability, which includes skills like the ability and speed with which one detects patterns; and image rotation, which more uniquely captures perceptual tasks that emphasize rotation per se (note that some tests load on multiple factors; Johnson & Bouchard, 2005b).

In discussing the advantages of the VPR model, the authors noted that whereas Gf-Gc includes both verbal and perceptual content as part of crystallized intelligence (e.g., mechanical ability is both learned and spatial), both Vernon's model and the VPR model distinguish these as loading on factors that reflect their respective content. Indeed, such a division of verbal and spatial skills has been repeatedly borne out in replications of VPR, where it has been shown that various tests which should theoretically reflect crystallized intelligence (e.g., naming pictures, identifying tools) have actually had *negative* loadings on the crystallized factor (Johnson & Bouchard, 2005a; Johnson, te Nijenhuis, & Bouchard, 2007). Over the course

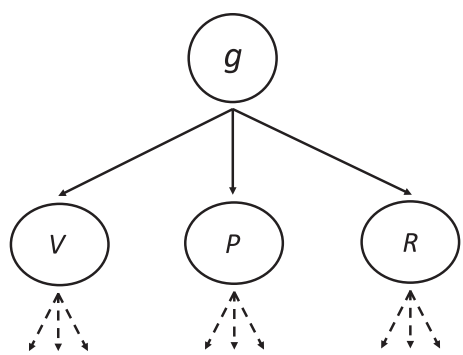

Fig. 2.6 Verbal-perceptual-image rotation model. Schematic depiction of the VPR model. Dashed arrows reflect the fact that first-order factors are unspecified (see text). *V* verbal, *P* perceptual, *R* image rotation

of those and subsequent studies, Johnson and colleagues have now consistently demonstrated the relative superiority Vernon's model over that of Gf-Gc, for both statistical and substantive reasons, as well as the superiority of VPR in turn (Johnson et al., 2007; Johnson & Bouchard, 2005a). VPR has since been shown to fit better than either the extended Gf-Gc model or a three-stratum version of CHC (Major, Johnson, & Deary, 2012).

From a theoretical standpoint, VPR is unique in emphasizing a *dimensional* view of intelligence, such that verbal and rotational skills are thought to represent two poles on a continuum (Major, Johnson, & Deary, 2012). Notably, this may conceptually align it with the well-known (relative) specializations of each cerebral hemisphere (i.e., the left hemisphere is typically dominant for language and sequential processing; the right hemisphere is typically dominant for spatial and configural processing; Lezak et al., 2012), giving it a strong degree of neurological plausibility (Johnson & Bouchard, 2005b). Relatedly, the VPR model also explicitly avoids pre-specifying the number and content of lower-order factors (Major et al., 2012, p. 544), arguing that these instead will depend on the test batteries at hand. Thus, when constructing a model based on a given sample and battery, the obtained perceptual factor may correlate more highly with verbal ability, depending on the exact tests from which it is derived (e.g., if the stimuli tend to induce verbalization), while in another battery with a greater proportion of highly spatial tasks, the perceptual factor might relate more strongly to image rotation.

Overall then, VPR represents a departure from the tradition of precisely specifying models down to all of their constituents. Rather, it aims for a more parsimonious view of intelligence, wherein a *g* factor influences task performance by virtue of its relation to just a few higher-order factors, which are aligned on a single verbal-spatial dimension. While it may be possible to enumerate all of the lower-order capacities in the manner of CHC, VPR instead prioritizes parsimony in its account of intelligence. Although its practical applications are less-developed than that of CHC, its strong base of empirical and substantive support nonetheless makes it a viable alternative to its more prominent counterpart.

Bi-factor Models of Intelligence

Another important class of models to briefly consider is the bi-factor models, which are unique in the way that they represent the relationship between *g* and the group factors. In all of the hierarchical models discussed up to this point, *g* influences individual test scores solely by virtue of its relation to the group factors (Cucina & Byle, 2017). This means that the latter account for all the shared variance among the tests that load on them (e.g., the shared variance among a group of working memory tasks would be fully explained by a working memory factor), with *g* then being modeled at a higher level to account for the correlations between the group factors. Under this scenario, any change in an individual's level of *g* can only impact their test performance through the resulting impact on the relevant group factor(s) (Beaujean, 2015).

In contrast, bi-factor models also allow one to represent *g*, but they instead place it in a nonhierarchical relation. Here, rather than first extracting primary factors and then modeling *g* based on their relations, *g* is extracted first, and primary factors are extracted separately from the remaining shared variance among the tests (Jensen, 1998a, p. 78). This means that the resulting factors are independent of variance due to *g*, with all the latent factors existing at the same level of the model (Gignac, 2016b; Morgan, Hodge, Wells, & Watkins, 2015; and see Fig. 2.7). The result is that variation in test performance across individuals can reflect *either* variance due to *g* or that due to the primary factors, with the two being completely independent (Beaujean, 2015; Morgan et al., 2015).

Following from the previous example, in a bi-factor model, one's score on a given working memory test would be a function of *both* one's level of "general intelligence" and their independent, more specific working memory ability. Setting aside the various technical considerations

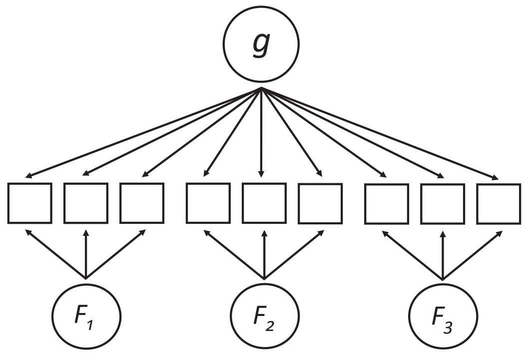

Fig. 2.7 Example bi-factor model. Schematic bi-factor model with three group factors. Boxes represent measured variables (specific tests), and circles represent latent factors as above. Each arrow going from a latent factor to a measured variable reflects the former's unique contribution to variance in the latter

related to the challenges and virtues of the bi-factor model (see Gignac, 2016b; Morgan et al., 2015; Murray & Johnson, 2013), these models are of substantive interest because they provide an alternative way to think about *g*. Namely, because both the general and group factors independently account for test performance in these models, they seem to allow a greater reconciliation between the empirical evidence for *g*, on the one hand, and the notion that more specialized skills might have additional explanatory utility on the other (e.g., Benson, Hulac, & Kranzler, 2010).

The Mutualism Model

The final psychometric model is somewhat akin to Thomson's sampling theory in also offering a very different perspective on psychometric *g*. Specifically, whereas sampling theory argues that the positive manifold arises from a situation where cognitive tests recruit overlapping sets of neural connections, the mutualism model holds that initially uncorrelated processes, such as group factors like memory and perceptual ability, come to be correlated through reciprocal positive interactions that occur during development (van der Maas et al., 2006). In essence, what are initially independent processes come to support the growth of one another, thereby increasing their interrelations. Some related examples from the empirical literature come from the work of Demetriou and colleagues, who have shown that various lower-order factors appear to play different roles in intelligence at different developmental phases (Demetriou et al., 2013; Makris, Tachmatzidis, Demetriou, & Spanoudis, 2017).

Using simulation studies,[4] van der Maas et al. (2006) demonstrated that given a model containing no relationships among limiting resources but with positive correlations between otherwise independent processes, factor analyses of the simulated data are nonetheless consistent with a single major latent factor such as psychometric *g*. As a result, because the model is comprised of multiple, separate but *correlated* processes, the resulting statistical pattern cannot be said to result from a single underlying cause. Thus, although fully hypothetical, the mutualism model suggests an alternative route by which *g* could statistically arise, but without a unitary cognitive or neurological basis. In turn, van der Maas and colleagues further demonstrated that the mutualism model could also explain several other important phenomena in the intelligence literature. These include the more complex cognitive hierarchies like the models described above, as well as patterns of intellectual development, intra-subject variability, and cohort effects on IQ test performance (see discussion and details in van der Maas et al., 2006).

In the time since mutualism was first proposed, the theory has received mixed support. For example, although mutualism suggests that *g* should account for more variance in test performance as children grow older, a study that examined this in a cross-sectional sample ranging from 2 to 90 years old failed to support this (Gignac, 2014). A second study also argued against mutualism when it failed to find expected patterns in factor-analytic results (Gignac, 2016a). However, proponents of mutualism debated the prior

[4]Primary simulations were based on 16 hypothetical neurocognitive processes, which were each independently sampled from pre-specified distributions to define 1000 simulated subjects. Different models specified various constraints and relationships among model parameters.

study's premise (van der Maas & Kan, 2016). These issues notwithstanding, in the most recent and direct test of mutualism to date, a longitudinal study did find evidence for reciprocal positive interactions between two broad abilities over the span of almost 2 years (Kievit et al., 2017).

Finally, the mutualism model provides a good venue to raise an additional point related to modern conceptions of psychometric ability models. Specifically, while most of the models considered here are said to be *reflective* in nature, mutualism (along with sampling theory and possibly VPR; Deary, Cox, & Ritchie, 2016; Major et al., 2012, p. 544) instead represents what is known as a *formative* model (van der Maas, Kan, & Borsboom, 2014). In a reflective model, the latent factors are understood to be the cause of the observed variation in the individuals' test scores, in the sense that factors are taken to represent real entities (Borsboom, Mellenbergh, & Van Heerden, 2003; Kievit et al., 2011), without which the observed results would not be obtained. As an example, whenever one attributes a global quality to an individual, e.g., he or she broke the law because they are simply a "bad person," one is implicitly making a reflective explanation—an underlying attribute of the person was the cause of their behavior. Under this scenario, because of the specified causal direction, changing the subtests that are used to measure the variable (intelligence in this case) would change the accuracy of the measurement, but could not logically affect the variable itself (Kievit et al., 2011).

In contrast, although formative models also relate latent factors to observed data, here, the factors are merely understood to be weighted composite scores, such that the data are responsible for the composition of the factor, as opposed to vice versa (van der Maas et al,. 2014). Common examples of formative variables include constructs like socioeconomic status and "overall health," where it can be readily seen that many diverse factors come together to define them. Researchers might disagree about whether cardiovascular efficiency or strength and flexibility are more important aspects of health, but they likely would not argue that an underlying "health factor" was the cause of variation in both. The two are of course often related in healthy people, but it is possible to have one without the other. In turn, to the extent that one chose to measure one dimension at the exclusion of the other, these choices could produce very different pictures of a person's overall health. In this instance, the choice of indicators determines the attributes of the factor, rather than the reverse (see Fig. 2.8). Finally then, returning back to intelligence, it can be seen how the formative/reflective distinction provides a useful way for thinking about *g*. Although reflective models *imply* a unitary cause for variation in intelligence, the mutualism model (along with sampling theory) shows that this is not necessarily the case. Rather, *g* could in fact be legitimately unitary in a statistical sense, while still ultimately resulting from many underlying processes (Deary et al., 2016).

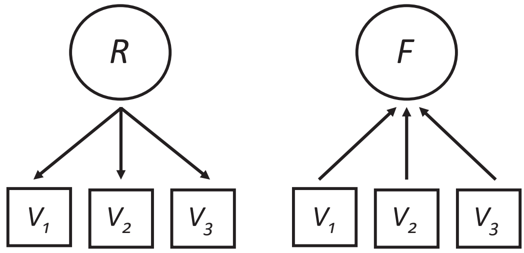

Fig. 2.8 Reflective vs. formative models. In a reflective model (left), including most models of intelligence, the latent factors are to understood as causing the variation in the obtained scores (V_1–V_3). In a formative model (right), the casual direction is reversed such that the composition, and thus the nature, of the latent factor entirely depends on the variables used to measure it. Error and residual terms and other parameters are omitted for simplicity.

Summary of Psychometric Theories

To summarize this section, psychometric theories of intelligence have addressed the "structure" of the construct, considering the role of various specific and broad factors (e.g., Gf and Gc) and of course the role of *g*. While early historical accounts debated whether intelligence is better reflected by a single general factor (*g*) or a series of independent skills, more recent theories have generally endorsed a hybrid of the two. That is, intelligence likely has a hierarchical structure, with *g* at the top, and broad factors operating between *g* and performance on particular types of tests. Practically, this suggests that a single general capacity influences all tasks, regardless of their content, although more specific abilities govern the relation between *g* and specific tasks. More recent theories have also debated the nature of these broad factors, with CHC perhaps being the most comprehensive, though VPR offers a conceptually simpler account centered around a verbal-spatial continuum. These two theories emphasize continuity with different theoretical traditions, but they differ in their emphasis on practical utility vs. theoretical consistency. Still other psychometric theories acknowledge the empirical phenomenon of *g* but propose alternative ways that it might come about, in terms of the interrelations between lower-level cognitive and neural processes. Overall, while psychometric theories are useful for thinking about the structure of intelligence (i.e., is it a single capacity or many?), they say less about its "nature." These latter issues, such as whether intelligence relates to more basic or complex processes, and its more-detailed information processing basis, are better addressed by conceptual theories of intelligence, as reviewed in the next section.

Conceptual Theories of Intelligence

Because psychometric theories involve a high degree of mathematical rigor, they have perhaps justifiably dominated discussions about intelligence. Nevertheless, a number of more conceptually oriented theories still have their place in filling out the scope of these debates. These models run the gamut from being primarily theoretical and rationally derived, to those that are backed by a substantial body of empirical results. In the latter category, some models (especially those that emphasize working memory and processing speed) could also claim substantial psychometric support. Yet, insofar as they advocate for *particular* processes in defining intelligence and also bring experimental methods to bear on their views, they are somewhat more similar to conceptual models than the primarily statistical frameworks outlined above. In every case, though, the models and theorists highlighted below have been selected for review because of the ways in which they exemplify other key or controversial ideas in theories of intelligence.

Francis Galton: The Reductive Tradition in Intelligence Research

Sir Francis Galton is generally regarded as the most important early figure in the modern era of intelligence research.[5] His work took place in the context of Victorian England with evolutionary theory in the intellectual milieu (Jensen, 1998a), including its emphasis on the role of genes in determining the traits of organisms. Whereas many at the time held that intelligence could "act independently of natural laws," Galton held the contrary, evolutionary view that genes and the biological processes they govern should be important determinants of intellectual ability (Galton, 1883). In turn, by examining the implications of just that single assertion, one can derive what are perhaps Galton's three most important intellectual contributions.

First, if mental capacities are akin to physical traits in being subject to biological principles, this means that, like other phenomena in the natural sciences, intellectual capacity should be amenable to objective quantification. Thus, it should be possible to develop reliable measures of intellectual ability that can quantify differences among individuals. Second, if mental ability is largely determined by genetic variation, then more fundamental attributes of individuals (those which are more closely tied to their genes) might place constraints on higher-order mental skills. For Galton, this meant that the basic efficiency of lower-order, sensory-motor capacities (those that should be more directly tied to basic nervous system functions, like nerve conduction

[5]Though see Deary's (2000, Chap. 2, and p. 68) account of several authors who espoused similar views but predated Galton

speed) should limit "the field upon which our judgment and intelligence can act" (Galton, 1907; cited in Wasserman, 2012). Thus, while Galton did not necessarily hold that intelligence could be *fully* reduced to lower-order capacities, the primacy he placed on them nevertheless exemplifies the reductive tradition. Third, Galton also made a number of statistical contributions, being the first to develop a measure of the relation between two variables (the forerunner to Pearson's correlation coefficient) and to use the normal distribution to rank individuals on an interval scale (Jensen, 1998a, pp. 10–11). Thus, he provided a foundation not only for differential psychology but also for normative principles that are still used today.

In pursuit of these various ideas, Galton established his "anthropometric laboratory" in London, where, for a small fee, members of the public could be measured on mostly low-level traits and capacities, such as height, grip strength, breathing capacity, and visual and auditory acuity (Sattler, 2008; Wasserman, 2012). Although he amassed data on more than 9000 individuals, likely owing in part to methodological limitations, his measures proved only weakly related to indices of intelligence (e.g., occupational attainment; Jensen, 1998a, Chapter 11). As recounted by Deary (2000, Chapter 2), subsequent prominent but likely overemphasized failures to apply Galton's measures to *practical* assessment may in part account for the waning of interest in Galton's approach and the following stagnation in reductive research. In the time since, the approach has rebounded, and a more balanced view has emerged. On the one hand, many recent studies, including meta-analyses and population-based research, clearly support Galton's contention that lower-order processes should relate to intelligence (e.g., Acton & Schroeder, 2001; Deary, Der, & Ford, 2001; Euler, McKinney, Schryver, & Okabe, 2017; Melnick, Harrison, Park, Bennetto, & Tadin, 2013). Nevertheless, to the extent that effect sizes are modest (typically correlating near $r = -0.30$; Sheppard & Vernon, 2008), their conceptual significance remains open to debate.

Alfred Binet and David Wechsler: Theoretical Insights Gleaned from Practical Assessors

In contrast to Galton's decidedly theoretical aims, the work of Alfred Binet and David Wechsler, who respectively developed the Binet-Simon and Wechsler Intelligence Scales, illustrate a number of insights that were gleaned through more practical endeavors. Specifically, while it would be difficult to discount the predominant role of theory and basic research in advancing this field, the systematic research through which these measures were developed nevertheless yielded important principles that have stood the test of time. Indeed, even if there were no principles guiding their development (untrue in either case; Binet & Simon, 1916; Wechsler & Edwards, 1974), the immense practical success of these instruments (and the tests they inspired) would seem to speak to their construct validity. To wit, if an instrument is near-universally accepted as a valid measure of intelligence, then it stands to reason that the principles that govern it may help elucidate the construct.

In the case of Binet, he and his colleague Theodore Simon developed what is now generally recognized as the first useful test of intelligence in the Binet-Simon scale, with the goal of better identifying children with intellectual disabilities (Sattler, 2008). In the course of their studies, Binet articulated what has proved to be a fundamental principle not only of intelligence testing but of intelligence itself. Specifically, he identified that more complex measures involving multiple dimensions are far superior to simple tasks as measures of intelligence—for the reason that complex tasks elicit more variability across individuals (Wasserman, 2012, p. 14). Here then, is a clear contrast between the lessons suggested by Galton and Binet's work. As Binet acknowledged, simpler measures can be more precisely controlled with respect to stimulus characteristics and the like. Yet, because simple measures elicit little variability across individuals, this mitigates their advantage over less precise but more *sensitive* tasks that involve more complex mental operations (Binet & Henri, 1894; quoted in Wasserman, 2012). Thus, although narrow psychophysical capacities may meaningfully relate to, and even constrain, overall intelligence, the construct itself seems to inherently represent a *higher-order* capacity. In addition, Binet also emphasized the necessity of using multiple tasks to arrive at a composite intelligence measure (Binet & Simon, 1916), and he considered individual tasks to be of questionable value (Boake, 2002). Not only has this become a foundational principle of most intelligence tests, but it also reflects the core theoretical notion that intelligence represents a fundamentally general capacity (Gottfredson, 1997a).

Although David Wechsler was more theoretically inclined than Binet (and produced a number of theoretical papers; Wechsler & Edwards, 1974), he was also largely concerned with practical assessment. Here again though, it can be seen how his practical considerations served to clarify a key feature of intelligence. In particular, while serving in the army, Wechsler was tasked with individually examining unschooled recruits or those with limited English proficiency, who had been deemed intellectually disabled based on their performance on the very verbally dependent Stanford-Binet (Boake, 2002). Yet, in many cases it was evident to Wechsler that these recruits had previously held significant social and professional responsibilities, attesting to their average if not higher intelligence. Based on these experiences, Wechsler came to believe that intelligence could be expressed equally well through verbal and "performance-based" measures (i.e., perceptual and visuospatial tasks) and strove to include diverse measures spanning both dimensions in developing his own scales (Matarazzo, 1972, Chapter 8).

On the one hand, this represents a practical and clinical necessity. For certain examinees, such as those with various neurological syndromes or with limited English proficiency, one might indeed expect their intelligence to be better expressed through a particular route. Yet, like Binet, Wechsler's clinical insight around this reflected a deeper fact about intelligence itself. Namely, that although most healthy individuals will not demonstrate such discrepancies, intelligence itself is broader than any single dimension and thus can be expressed through multiple routes. Not only is this evident in the ubiquity of *g* but also in the somewhat lesser-known phenomenon of the "indifference of the indicator." As discovered by Spearman (1927), this refers to the finding that highly diverse measures with no content in common (e.g., vocabulary vs. visuospatial reasoning) can in some instances predict intelligence equally well (see: Wechsler, 2008; Table 5.1). Thus, as in Binet's case, although practical considerations drove Wechsler's approach, the insights he derived reflected important aspects of intelligence.

Arthur Jensen and Lazar Stankov: Contemporary Debates Around Reductive Approaches

On the spectrum of unitary-non-unitary perspectives of intelligence, Arthur Jensen is a strong supporter of an overall *g* factor. Where Jensen differs from psychometric approaches, however, is in his extensive use of mental chronometry (reaction time-based tasks; RT) as a means to assess information processing accounts of intelligence. As a *g*-theorist, Jensen believed that intelligence could be reduced down to one fundamental process, which he tried to capture through patterns of RT performance (Jensen, 1981). He proposed that speed of information processing (SOP; Jensen, 1993) was this fundamental process and tried to link IQ scores to mathematical models of RT task performance (Hick's Law; Hick, 1952). These studies argue that intelligence is about how long it takes one to process a "bit" of information (Jensen, 1981, 1982, 1998a, 1998b), with variation in other processes (e.g., working memory—one's ability to hold and manipulate information held in mind) being the result of variability in SOP (Jensen, 1993). While a correlation between RT and IQ scores is a well-replicated finding (Sheppard & Vernon, 2008), there is much debate about the nature of this relationship (Stankov & Roberts, 1997) and what it means for understanding intelligence.

In an attempt to resolve these questions about RT-IQ correlations, mental chronometry has explored how discrete processes typically examined in cognitive psychology (working memory, etc.) could be related to intelligence. For example, while overall RT correlates with IQ scores, so does the variability of one's RT within a given task (RT standard deviation; RTSD; Doebler & Scheffler, 2016; Jensen, 1992). Likewise, one's slowest individual RT trial often correlates better with intelligence than their fastest RT (Rammsayer & Troche, 2016; Ratcliff, Schmiedek, & McKoon, 2008). This led to theories that higher-ability people may experience less "neural noise" (Jensen, 1993) or have better "evidence accumulation" during decision-making (Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007). Finally, since chronometric tasks lend themselves well to neuroscience methods, the two approaches have begun to merge. Indeed, Jensen argued that explanations for chronometric effects would only be valid insofar as they were biologically plausible (Jensen, 1993). In a way, many contemporary neuroscience-based theories of intelligence (such as Process Overlap Theory, discussed below) could be considered intellectual descendants of Jensen's initial linkage of experimental and differential psychology.

An interesting contrast with Arthur Jensen's reductive approach can be found in the work of Lazar Stankov and colleagues. While Jensen tried to link chronometric performance to a unitary *g*, Stankov instead used experimental approaches to consider how the coordination of several processes, as opposed to a particular one, might define intelligence. Specifically, he argues that intelligence reflects the capacity to engage multiple processes simultaneously to accomplish a task. Indeed, Stankov has provided experimental evidence demonstrating that tasks with increasing numbers of components (i.e., more complex tasks) correlate better with intelligence (Stankov & Crawford, 1993; Stankov & ,Raykov 1995). While Stankov acknowledges *g*, he argues that it is generally overemphasized and that second-stratum factors are more important to understanding intelligence (Stankov, 2017). In line with his emphasis on higher-order coordination of discrete processes, Stankov has also advocated for the integration of non-cognitive process into models of cognitive ability (e.g., emotional intelligence and meta-cognition; Stankov, 2017). Thus, in contrast to Jensen who emphasized the primacy of *g*, and speed of processing as its ultimate basis, Stankov's work illustrates an alternative experimental approach that eschews strong reductionism and emphasizes a more holistic perspective.

The Role of Executive Abilities: Working Memory Capacity and Process Overlap Theory

The negative correlation between intraindividual variability in RT and IQ scores (meta-analysis: Doebler & Scheffler, 2016) suggests that attention may be an important component of intelligence, for the reason that higher variability may reflect attentional lapses. The execution of the top-down attention (commonly called executive functioning; EF) is thought to reduce RT variability and promote higher Working Memory Capacity (WMC; Bellgrove, Hester, & Garavan, 2004; Miyake, Friedman, Rettinger, Shah, & Hegarty, 2001). Given these findings, it is perhaps not surprising that structural models often find strong relationships between intelligence and WMC. Research examining the known neurophysiological correlates of these constructs has highlighted the importance of the prefrontal cortex (Kane & Engle, 2002, 2003) as a common neural substrate of both EF and Gf (a robust correlate of *g*). These authors argue that fluid reasoning is achieved through the manipulation of information held in working memory and that WMC (and thus EF as well) acts like a "bottleneck" on reasoning and the expression of intelligence (Kane & Engle, 2002). In the time since, process overlap theory (POT; Kovacs & Conway, 2016) has been developed from this original WMC model. POT integrates experimental (e.g., RT variability, complexity effects) and psychometric (e.g., IQ-WMC correlation) findings to propose frontal-parietal networks as the ultimate neural basis of the aforementioned bottleneck, consistent with the known neuroimaging correlates of intelligence (Basten, Hilger, & Fiebach, 2015; Jung & Haier, 2007). While POT is a relatively new theory, it integrates a number of findings in the intelligence literature and, unlike many theories, proposes fairly concrete neurological correlates. While POT strongly emphasizes WMC, the latter's relation to intelligence is perhaps best thought of as a necessary, but not sufficient explanation (Redick et al., 2013), with intelligence being a broader construct and WMC acting as a limiting factor.

The Planning, Attention, Simultaneous, and Successive Model

The Planning, Attention, Simultaneous, and Successive (PASS) model of intelligence was developed by Naglieri and Das (1990) and was heavily influenced by the work of the esteemed neuropsychologist Alexander Luria. Like POT, PASS also emphasizes the role of EF but also considers lower-level cognitive operations in its conceptualization of intelligence. PASS theory outlines how any complex task involves three different functional units that are differentially involved depending on the task demands. The first unit corresponds to basic attention processes, the second unit corresponds to perceptual processing and multimodal sensory integration, and the third unit corresponds to the planning, maintenance, and correction of behavior. Das and Naglieri argue that these three units are involved in all tasks, whose effective coordination and integration with prior knowledge constitute intelligence. That is, intelligence is the capacity to (1) effectively engage with the environment (2), process information from the environment (3), and plan/execute effective behavior in the environment based on that information. The authors argue that the structured nature of current IQ tests do not adequately capture the first and third functional units (specifically basic attention and planning processes), thus limiting their capacity to make more sophisticated claims about an individual's real-world achievement.

In support of the PASS model, studies have found that neuropsychological tests of executive functioning (corresponding to the third unit) are more predictive of daily functioning (Barkley & Fischer, 2011) and achievement (Clark, Prior, & Kinsella, 2002) than IQ tests alone. A handful of studies suggest that PASS-based measures are at least as sensitive to dysfunction in ADHD and academic achievement as traditional IQ tests (Naglieri & Bornstein, 2003; Naglieri, Goldstein, Delauder, & Schwebach, 2005; Naglieri, Goldstein, Iseman, & Schwebach, 2003), though some argue that PASS is merely a recapitulation of certain CHC factors (Keith, Kranzler, & Flanagan, 2001). While the evidence for PASS is somewhat limited, it highlights the synergistic importance of processes at all levels of the cognitive hierarchy, from basic attention to complex planning and reasoning, when considering real-world success.

Detterman's System Theory of Intelligence

Finally, Detterman's (1987) system theory of intelligence is noteworthy here because in addition to trying to explain the nature of intelligence, it explicitly addresses intellectual disability. As outlined above, a major debate in intelligence research concerns whether intelligence is fundamentally unitary, as at least superficially implied by psychometric *g*, or whether various correlated but ultimately independent factors better represent the construct's true structure. For individuals with cognitive disabilities, this could (hypothetically) translate into either (1) a deficit in overall ability (*g*) or, possibly, (2) a deficit in some but not all cognitive abilities. Detterman's model provides an innovative, partial synthesis of these two ideas, in that it recognizes and explains *g* but in a way that also acknowledges the multiple factors that make up intelligence.

Specifically, Detterman takes a *systems* view, in arguing that intelligence arises through the interactions of "independent but interrelated parts" (Detterman, 1987). In explaining this concept, he likens IQ scores (which aggregate performance over multiple tests) to the ways in which one might rank universities. For example, one might evaluate various different aspects of a university, like the quality of the faculty and the facilities, the size of the endowment, its physical location and layout, etc., and sum them together to derive an overall score. As just described, each aspect could in principle be fully independent, with the resulting score reflecting an aggregate index of the university's overall quality. Note however, that in practice, such factors will likely not only be correlated, but any *central* factors, like the size of the endowment, will set a limit on the level of the others (Detterman, 1987). Thus, in the case of intelligence, various group factors (or still lower-level processes) might seem independent in principle, yet if some are more central than others, they will place limits on the rest. Indeed, the working memory and process overlap theories of intelligence make exactly this case.

Detterman's theory also has specific implications for intellectual disability. He argues that if intelligence reflects the operation of an interconnected neural system, where some parts are more central than others, this implies that inefficiencies in central resources should cause scores among cognitive tests to be more interrelated at lower levels of ability (Detterman, 2002). Conversely, individuals with highly efficient central processing resources will have fewer constraints on the development of their more specific capacities, and hence cognitive test scores should be less highly related at higher ability levels. Indeed, Detterman and Daniel (1989) found evidence for this exact phenomenon (also known as cognitive differentiation), which has been replicated in numerous other studies (Blum & Holling, 2017; Tucker-Drob, 2009). In the case of intellectual disability, Detterman predicted that it "would be shown to be a deficit in one or more basic abilities…with a moderate to high degree of centrality (Detterman, 1987, p. 8)." Notably though, as discussed further on, he was also careful to note that this does not mean that all intellectual disabilities result from a single cause.

Other Prominent Theories

Finally, there are two other prominent theories of intelligence that also deserve brief mention. Both Howard Gardner's theory of multiple intelligences and Robert Sternberg's Triarchic Theory of Successful Intelligence are widely cited accounts, which remain prominent in some fields. Although these theories do not have strong support among most contemporary intelligence researchers (Warne, Astle, & Hill, 2018), their popularity in applied settings warrants a brief review.

Gardner's Theory of Multiple Intelligences

On the spectrum of intelligence theories which include few to many factors, multiple intelligences (MI) is perhaps only less expansive than that of CHC. Published in the book *Frames of Mind* (Gardner, 2006), MI outlines the view that there are eight conceptually distinct intelligences, which are all of equal importance, with no hierarchical structure. Gardner arrived at these ideas through extensive readings in a variety of different fields, but did not generate any data to empirically test his theory. To date, experimental studies trying to validate MI theory have yielded limited empirical support (Almeida et al., 2010; Visser, Ashton, & Vernon, 2006).

Overall, while the notion that there can be multiple distinct forms of intelligence, which are not all cognitive in nature, is appealing in some respects, this idea is better supported by other theories, with a larger empirical base. For example, Stankov (2017) has argued that emotional intelligence should be considered as a second-order factor in CHC, thereby presenting a more empirically grounded alternative to Gardner's interpersonal and intrapersonal intelligences. Likewise, Carroll convincingly argued that capacities such as musical and mathematical ability, which are included in MI in various forms, actually express themselves via different contents at different levels of ability and also involve numerous lower-order skills (e.g., visualization, induction, sequential reasoning, in the case of mathematical ability). Thus, Carroll argued that such constructs should be regarded as "inexact… popular concepts[s]" rather than distinct, scientifically supported cognitive capacities (Carroll, 1993, pp. 626–627). Finally, insofar as there is essentially overwhelming evidence for the *psychometric* reality of *g* (as distinct from its potential neural basis, which remains undetermined), the literature provides little support for the view that all aspects of intelligences are equally influential, with no hierarchical features.

Sternberg's Triarchic Theory of Successful Intelligence

Finally, Robert J. Sternberg's prominent theory of successful intelligence also deserves a mention here. Overall, Sternberg emphasizes the ecological aspects of intelligence, contrasting between intelligence as typically discussed, and *successful intelligence*, which is argued to be a more comprehensive construct that considers one's sociocultural context and idiographic patterns of strengths, weaknesses, and experience (Sternberg, 1999). His conceptualization of intelligence strongly emphasizes the interactive, transactional nature of an individual within their environment (i.e., the adaption, selection, and shaping of one's environment), focusing on how factors like specific goals, prior experience, and contextual information can change the expression of intelligence (Sternberg, 2012). As such, he argues that the measurement of intelligence should depend on the goals and the environmental context of the individual, as opposed to traditional IQ tests. Sternberg's triarchic theory emphasizes the role of not only analytical skills (his term for what most IQ tests measure) but also creative (i.e., idea generation) and practical skills (i.e., implementation of ideas in real-world settings), so that an individual can be successful as they define it within their environment (Sternberg, 2012). Collectively, these skills are referred to as process skills, which together with meta-components (somewhat like executive functions as described by Suchy, 2015) and knowledge acquisition skills (i.e., learning) are argued to better capture the notion of success in a culturally neutral way. Overall, Sternberg's notion of successful intelligence integrates many often-disparate approaches to studying intelligence (i.e., factor-analytic, experimental, culturally relative, application-based approaches, etc.), and has both some strengths and weaknesses.

Perhaps the most controversial aspect of the triarchic theory relates to the distinctiveness of analytical and practical intelligence and to the extent to which the latter is more predictive of real-world success. Psychometric evaluation of an intelligence test designed specifically to assess the triarchic theory found that a modified *g* model was the best fit for the data (Chooi, Long, & Thompson, 2014). A separate study highlighted that many of Sternberg's findings could potentially be explained by measurement error (Brody, 2003). Additionally, Gottfredson (2003) critically reviewed the studies supporting the triarchic theory and concluded that practical intelligence and traditional IQ scores are statistically related (as opposed to distinct entities), especially when methodological aspects of the studies are considered (e.g., size and diversity of the samples). She further asserted that there is no evidence supporting the idea that a "practical *g*" exists as a separate factor apart from the conventional *g* (an argument supplemented by a separate paper; McDaniel & Whetzel, 2005). In summary, although both the triarchic and MI theories have conceptual merits, relative to the other theories discussed in this chapter, they each have more limited empirical support.

Overall Summary

The preceding sections aimed to give an overview of the historical development of theories of intelligence, with an eye toward articulating the key principles and debates and clarifying current thinking in the area. The overall consensus from psychometric approaches suggests that intelligence consists in an individual's general cognitive capacity, which influences every mental task they might undertake, irrespective of its nature. Although lower-order abilities have a clear and legitimate place in the cognitive hierarchy—consisting in more domain-general, content-related, and modality-specific skills (to borrow from CHC)—their unique significance in determining one's overall intelligence remains a matter of debate. Unlike most contemporary models, which are largely hierarchical, sampling theory

(Bartholomew et al., 2009) and mutualism (van der Maas et al., 2006) both highlight how *g* can arise from a non-unitary basis, giving psychometric credence to the idea that intelligence may result from a collection of interacting processes rather than a single fundamental one.

While psychometric approaches clarify the relationships between cognitive abilities in a detailed way, they are somewhat agnostic as to what *g* and various broad factors reflect in a more functional sense. This is where conceptual theories can help fill in the gap. This latter work has clarified that while lower-order processes play a role in intelligence, it is clearly best characterized as a higher-order capacity and one that is particularly implicated in managing cognitive complexity (Gottfredson, 1997b). Thus, intelligence appears to relate not only to the level of one or more discrete abilities but also to their efficient coordination in support of adaptive behavior. Finally, insofar as the most recent era of experimental and theoretical studies has supported the centrality of particular processes, it appears likely that capacities like WMC and other executive skills (Kovacs & Conway, 2016) or possibly speed of processing (Jensen, 1993; Schubert, Hagemann, & Frischkorn, 2017) may constrain overall intelligence. These constraints are apt to be strongest at lower levels of ability, whereas at higher ability levels, profiles should be more differentiated (Detterman, Petersen, & Frey, 2016). Tables 2.1 and 2.2 summarize the major features of the models discussed in this chapter.

Table 2.1 Overview of historical theories of intelligence

Theory	Major theme	Status of *g*	Emphasizes basic vs. complex processes	Evidence base
Galton	Reductionism	Unitary	Basic	Psychometric, experimental
Spearman	Discoverer of *g*	Unitary	Complex	Psychometric, experimental
Binet	Complex tasks, practical assessment	Ambiguous	Complex	Psychometric
Thurstone	Primary abilities	Non-unitary	Complex	Psychometric
Thomson	Sampling mental bonds	Non-unitary	Basic	Simulation, psychometric
Cattell	Fluid vs. crystallized intelligence	Non-unitary	Complex	Psychometric
Carroll	Hierarchical factor structure	Hierarchical	Complex	Psychometric
Wechsler	Performance-based, practical assessment	Non-unitary	Complex	Psychometric

Table 2.2 Overview of contemporary theories of intelligence

Theory	Major theme	Status of *g*	Emphasizes basic vs. complex processes	Evidence base
Jensen	Speed of processing	Hierarchical	Basic	Psychometric, experimental
Gardner	Multiple intelligences	Non-unitary	N/A	Conceptual
Sternberg	Triarchic/successful intelligence	De-emphasized	Complex	Conceptual, experimental
PASS	Planning, attention, simultaneously, successive	Non-unitary	Complex	Conceptual, psychometric
Detterman	Systems	Non-unitary	Basic	Psychometric, experimental, simulation
Stankov	Role of complexity and group factors	De-emphasized	Complex	Psychometric, experimental

(continued)

Table 2.2 (continued)

Theory	Major theme	Status of *g*	Emphasizes basic vs. complex processes	Evidence base
VPR	Verbal, perceptual, spatial rotation	Hierarchical	Complex	Psychometric
CHC	≥10 broad factors	De-emphasized	Complex	Psychometric
Bi-factor	Simultaneously models *g* and group factors	Unitary	Complex	Psychometric
Mutualism	Developmental, *g* as epiphenomenal	Non-unitary	Basic	Simulation, psychometric
Working memory/process overlap theory	Executive attention	Hierarchical/ hybrid	Complex	Psychometric, experimental, physiological

Implications for Intellectual Disability

In applying these concepts to intellectual disability (ID), perhaps the biggest implication is that intelligence, as it manifests empirically through *g* and in turn through IQ scores, is indeed a very general capacity (and note that IQ scores share >80% of their variance with *g*; Kranzler, Benson, & Floyd, 2015). This is all the more so in ID, given that narrow abilities are more strongly interrelated at lower levels of IQ. In turn, since intellectual functioning is of course one of the two central features in the diagnosis of ID (the other being adaptive functioning; American Psychiatric Association, 2013), the effect and hence the goal of the diagnosis should be to identify individuals whose cognitive challenges span diverse content and situations. Thus, unlike other cognitive disorders which are characterized by some degree of specificity (e.g., specific-learning disorders, ADHD), a diagnosis of ID indicates more pervasive cognitive difficulties.

Notably, the ID diagnosis also helps to clarify what intelligence is not. Because ID also requires adaptive impairments, which further establish diagnostic severity, it highlights the fact that cognitive functioning does not wholly determine one's functional capabilities. This same distinction holds within much of intelligence research, where although earlier theories did emphasize the role of non-cognitive factors (e.g., motivation; Wechsler, 1943), current theories (and particularly psychometric models) tend to restrict themselves to purer cognitive measures. Importantly, this is not to deny the role of such variables in adaptive behavior (e.g., Duckworth, Quinn, Lynam, Loeber, & Stouthamer-Loeber, 2011) but merely to distinguish between cognition and intelligence strictly construed and the other traits and capacities that people bring to bear on life's challenges.

A second implication relevant to the concept of ID is the fact that while psychometric theories seem to make implicit claims about *neural* organization (i.e., they address the relatedness of one cognitive function to another), ID is of course a *behavioral* diagnosis the reflects a diverse group of underlying causes (Lee & Harris, 2006, Chapter 5). Thus, while the ID diagnosis clearly depends upon cognitive capacities that are mediated by the brain, it encompasses a wide group of ultimate neural etiologies. This means that although the diagnosis should correctly identify persons who face broad cognitive challenges, because it does emphasize intelligence, it will tend to obscure more subtle, individual needs. Given that many of the syndromes responsible for ID are now known to be associated with more specific cognitive profiles (Edgin, 2013; Grigsby, 2016), this calls for bringing the neuropsychological approach into individual assessment of ID (see Chap. 27, this volume).

On a final more conceptual note, as Detterman observed (Detterman, 1987), different potential causes for psychometric *g* have different implications for the ways in which ID might arise. In the case of hierarchical theories or those that emphasize one or more central factors in intelligence (e.g., POT, system theory), one might expect the functioning of various core networks to strongly determine one's level of intelligence. Physiologically, this is perhaps most akin to parieto-frontal integration theory (P-FIT; Jung & Haier, 2007) and similar accounts (Duncan, 2010) that emphasize the centrality of those specific regions to overall intelligence. In contrast, mutualism makes a developmental case that initially independent factors become increasingly integrated through time. Finally, as recently pointed out by Deary, Cox, and Ritchie (Deary et al., 2016; citing Burt, 1940), *g* might also arise though a shared adaptive *property* of the brain, as opposed to the features of one or more major structures. That is, while a single neuroanatomical network might account for the appearance of a unitary *g*, individual, lower-level modules (or even single neurons) could also give rise to *g* if they are all homogenous in terms of their lower-level attributes (e.g., dendritic arborization, neural membrane properties; Jensen, 1998a, p. 121). This too could give rise to a *g* factor but for a very different reason. Thus, although there is strong evidence for the *effective* unity of intelligence as it manifests through testing, the ultimate causes of that cohesion could be numerous and multifaceted.

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