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Cognitive Approaches to Intelligence

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You learned in Chapter 4 that the psychometric approach to studying intelligence involves identifying cognitive abilities and the relationships between them. Psychometricians administer test batteries to participants, and infer an ability structure by factor analyzing the results. At its core, the psychometric approach is a descriptive one. It describes how people tend to differ in their performance on various mental tests, but it cannot explain *why* these differences occur.

Cognitive psychology tackles the question of intelligence from a different angle. The cognitive approach to psychology in general is focused on understanding the processes involved in cognition by reducing cognitive tasks to one or more measurable component processes. Cognitive psychologists who are interested in individual differences in intelligence ask whether the ability to perform these component processes varies between people, and if so, whether this variability can explain differences in intelligence (Hunt, Lunneborg, & Lewis, 1975). This is a fundamentally different question from the one that drives the psychometric approach: the psychometric approach is focused on *whether* people answer items correctly, while the cognitive approach is focused on *how* people answer the items, and *why* some people are better than others at answering items of various types (Anderson, 2015).

Precursors to the Cognitive Approach to Intelligence

Although cognitive psychology as a field came into being in the mid-1900s (Anderson, 2015), some of the earliest research on human intelligence had a distinctly cognitive flavor. While some early psychologists (e.g., Thorndike, 1898) took a strong "nurture" view of intelligence as the sum total of acquired knowledge,[1] others (e.g., Galton, 1883) sought to explain differences in intelligence by way of basic mental processes. Galton suggested that mental ability should be

[1] This idea is still common today, reflected in computer-inspired computational models of cognition such as Anderson's ACT-R model (Anderson, 1996).

related to measures that he believed reflected these basic processes, such as reaction time and sensory discrimination tasks. Establishing an empirical relationship between intelligence and basic processes proved difficult, however. In 1901, Clark Wissler, a student with James McKeen Cattell, reported a failed attempt to find a link between mental speed, as measured by five trials of a reaction time task, and academic achievement among students at Columbia University. Following Wissler's disappointing result, intelligence research in general shifted away from trying to identify such primitive causes of between-person differences in intelligence. Instead, psychologists focused on measuring these differences, whether in the context of education (as exemplified by Binet; Hunt, 2011) or in the interest of developing theories about the structure of cognitive abilities (as exemplified by the factor-analytic/differential methods of Spearman, 1927, and Thurstone, 1948). Meanwhile, in psychology more broadly, the rise of behaviorism in the 1920s led to a strong focus on observable behavior and experimental methods, especially in the United States. Mental processes, along with everything else taking place within the "black box" of the mind, were not considered appropriate objects of inquiry if psychology was to establish itself as a serious science (J. B. Watson, 1913). Over the next few decades, the two branches of intelligence research (educational and differential) proceeded separately from the behaviorist approach to psychology, and largely separately from each other.

In the 1960s, the field of psychology as a whole pivoted again, as theorists realized the limitations of behaviorism for explaining complex human behavior. As computers worked their way into the popular imagination, psychologists began to think of the mind as something like a computer, in that it took in information, processed the information, and generated output based on the information (Neisser, 1967). Psychologists began to develop cognitive models, which generated testable hypotheses about the cognitive architecture and the processes involved in various mental activities. Relying heavily on the experimental method that was refined during the heyday of behaviorism, researchers in the new subdiscipline of cognitive psychology devised tightly controlled laboratory studies in order to test predictions about how the human mind works. In just a few decades, cognitive psychologists made tremendous progress in understanding human attention (Broadbent, 1958; Treisman, 1964), memory (Atkinson & Shiffrin, 1968), knowledge representation (Collins & Quillian, 1969), problem-solving (Newell & Simon, 1972), and reasoning (Wason, 1968). All of these topics are relevant to intelligence, insofar as they play a role in intelligent behavior. According to colloquial definitions of intelligence, a person who has a better memory, who learns faster, and who solves problems and makes decisions more effectively, typically will be seen as more intelligent than another person who is not as able in these domains, all else being equal. But, if a student interested in intelligence reads a cognitive psychology textbook, he or she may be disappointed to find that it barely, if at all, covers research on intelligence. How can this be?

Two Branches of Psychology: Experimental and Differential

There are two general branches of psychology: experimental and differential (also called correlational; Cronbach, 1957). The cognitive research mentioned in the paragraph above was a product of the first branch of psychology, the *experimental tradition*, meaning that most of the research was designed to test mean differences between two or more *experimental groups* that receive different treatments in an experiment. (In cognitive psychology, "different treatments" often means different versions of one or more cognitive tasks used in an experiment.) Such differences in performance across treatments can allow psychologists to infer things such as the organization of concepts in the mind (Collins & Quillian, 1969) or the structure of memory (Atkinson & Shiffrin, 1968). The goal of **experimental research** is to identify processes that are common to all people – that is, to explain how human cognition operates in general.

The second branch of psychology, the *differential tradition*, is focused on describing differences between *individuals*, especially in the degree to which they can adapt to their environment (Cronbach, 1957). **Differential research** focuses on constructs such as intelligence and personality, which cannot readily be manipulated in a laboratory and which are inherently between-person constructs. It is difficult to talk about a given person's level of intelligence or extraversion, for example, without at least an implicit reference to where that person stands in relation to others. Intelligence is not a binary characteristic that a person either does or does not possess; it exists along a continuum. Differential researchers are concerned with the variance of these constructs and their covariance with other constructs.

The experimental and differential traditions of psychology evolved separately from each other. Cronbach (1957) called for a unification of the two branches of psychology, arguing that each approach could be strengthened by incorporating methods that were commonplace in one but not the other. By the 1970s, the advantages of a unified field were especially salient for intelligence research. Differential psychologists drew from nearly a century of research measuring how people differ in intelligence, while theories about how the mind works had been offered by cognitive psychologists engaging in experimental work. Seeking to bring these two traditions together, Hunt and colleagues (Hunt et al., 1975) asked whether individual differences in intelligence (as measured by scores on intelligence tests, developed from the differential tradition) could be explained by individual differences in the ability to carry out basic cognitive processes (as measured by laboratory tasks, developed from the experimental tradition). In the 40 years since then, a robust literature of cognitive-oriented research on intelligence has developed, and is still vibrantly active today.

Psychometric *g* versus Psychological *g*

More than a century of intelligence research in the differential tradition (dating to Spearman, 1904) has left no doubt that there is a positive correlation (also called "positive manifold") between scores on a wide variety of mental tests (i.e., **psychometric *g***; Conway & Kovacs, 2015). However, the existence of a single *factor* does not necessarily imply the existence of a single *process* underlying it. This was first demonstrated mathematically by Thomson (1916), but the idea did not gain much traction at the time. Even decades later, when cognitively oriented psychologists redeveloped an interest in explaining psychometric *g*, they attempted to identify a single underlying explanatory mechanism (i.e., **psychological *g***; Conway & Kovacs, 2015), such as mental speed (Eysenck, 1982; Jensen, 1998), or attention control (Shipstead et al., 2016).

These attempts to identify a single mechanism have met with little success, despite decades of effort and hundreds of studies. The threshold for identifying such a mechanism is high: Detterman (2002) suggested that in order for something to qualify as *the* mechanism underlying *g*, tasks designed to assess that mechanism should correlate at least $r = .80$ with intelligence test performance. Although this threshold is somewhat arbitrary, Detterman argued that a correlation of this magnitude would indicate that the mechanism accounts for most of the reliable variance in intelligence tests. In other words, if a single cognitive process is in fact responsible for the positive manifold, then it should be possible to find a relatively simple test that measures this process, and this test should provide an accurate indication of intelligence as measured by traditional intelligence tests (Mackintosh, 2011). Although this may be an impossibly high threshold – intelligence tests only correlate about $r = .80$ with each other – no measures of mental processes (such as mental speed or attention control) yet reported have come anywhere close. This has led some observers (Conway & Kovacs, 2013; Detterman, 2000; Mackintosh, 2011) to conclude that psychology's failure to identify such a task, despite a century of work, suggests that such a process does not exist. That is, *g* does not seem to correspond to a single mental process or biological factor. Although psychometric *g* clearly exists, few modern cognitive psychologists believe that there is a unitary psychological *g* (Conway & Kovacs, 2015).

Understanding the Cognitive Approach

The psychometric approach to studying intelligence involves obtaining scores from many people on a variety of tests. The results are factor analyzed in order to describe the pattern of correlations between the tests, and the factors are named according to the tests that load on them. Theories regarding the structure of cognitive abilities have been developed based on the results of these studies, but the psychometric approach is primarily centered on observing relationships between test scores. In other words, the psychometric approach is data-driven.

Cognitive psychologists who study the processes underlying intelligence seek to understand why psychometric *g* exists, rather than describe the relationships between various mental tests. Believing that intelligence will be best understood and measured when it can be connected to models of how cognition operates (Hunt et al., 1975), cognitive psychologists work to identify individual differences on relatively well-understood cognitive processing tasks that may be related to (and may help to explain) individual differences on traditional psychometric tests of intelligence. The idea is that if one or more basic cognitive mechanisms are used to carry out many different types of intelligent behavior (such as the myriad tests used in the psychometric approach), then the positive correlations between these intelligent behaviors can be explained by the fact that they rely on the same basic mechanisms. The cognitive approach is theory-driven: It begins with a model of how cognition works, and seeks to explain individual differences in intelligence via individual differences in the ability to perform the processes specified in the model.

Defining Intelligence for Research

Any research program studying intelligence must decide on a way to operationally define intelligence. Although intelligence tests were designed to predict academic or job success, not serve as the operational definition of intelligence itself (i.e., they were meant to be *predictor variables*, not *criterion variables*), they have long been used as indicators of intelligence for research purposes (see Hunt et al., 1975, for the original justification for taking this approach). Real-world intelligent behavior is difficult to define and measure, so cognitive psychologists often use intelligence test performance as a quantifiable proxy. The assumption is that because intelligence test scores correlate with real-world intelligent behavior, uncovering the cognitive processes that are related to intelligence test performance is theoretically meaningful and interesting.[2]

Practical considerations, such as the need for tests that can be administered in a group setting and the need to reduce the time burden on participants and researchers alike, mean that the use of full-scale IQ tests is relatively uncommon in cognitive research. More frequently, researchers obtain an estimate of general intelligence using one or a few highly *g*-loaded tests (that is, tests with a strong correlation to psychometric *g*), such as Raven's Advanced Progressive Matrices[3] (Raven, 1965). You may recall from Chapter 4 that psychometric *g* is derived from fluid intelligence

[2] There are, of course, many accounts of intelligence that are not centered exclusively (or at all) on intelligence tests – for example, Gardner's (1983) theory of multiple intelligences, R. J. Sternberg's (1999) theory of successful intelligence, Stanovich's (2009) description of rational thought, and investment theories of intelligence (Ackerman, 1996; Chamorro-Premuzic, 2005). However, intelligence as defined by these theories is often difficult to measure. Researchers need an operational definition of intelligence to serve as the criterion measure in their studies. Despite their limitations, intelligence tests fill this need.

[3] In the literature, tests like Raven's matrices are sometimes referred to as Gf measures and sometimes as *g* measures. In reality, Gf and *g* are strongly related to each other (after all, *g* is derived

(Gf; the ability to perceive complex patterns and relationships in unfamiliar situations) and crystallized intelligence (Gc; acquired knowledge), as well as other factors. Tests of Gf are more commonly used in cognitive research than tests of Gc. This is because cognitive processes are hypothesized to underlie information-processing, which corresponds to Gf. Cognitive processes would be expected to relate to Gc only indirectly, through the investment of Gf in acquiring knowledge over time (Cattell, 1943). For these reasons, when we refer to intelligence in this chapter, we mean Gf unless otherwise specified.

In the rest of this chapter, we will give a brief overview of some methods that are commonly employed by cognitive psychologists studying intelligence. Then, we will review research related to the relationship between measures of speed (such as reaction time) and intelligence. For many researchers, this work represents the earliest modern efforts that sought to explain individual differences in intelligence from a cognitive perspective, although, as we will see, it is debatable whether this research should be classified as part of the cognitive approach. From there, we will consider how variability in performance on simple tasks led researchers to propose explanations based on cognitive processes such as attention. We finish with a review of the current state of research on the relationship between intelligence and working memory capacity (which we abbreviate in this chapter as WMC). This is the area which much of the field is focused on today.

Methods in the Cognitive Approach to Intelligence

Cognitive psychologists have used several different methods in order to study the relationship between cognitive processing and intelligence (R. J. Sternberg, 1985). Some of the more common methods are described in this section.

Cognitive Correlates Method

Cognitive psychologists have developed many laboratory tasks in order to study how humans process information. As mentioned above, in the 1970s, Hunt and colleagues (e.g., Hunt et al., 1975) had the insight that tasks that had been used to study cognition in general, could also be used to study individual differences in cognition. They reasoned that performance differences on complex tasks, such as a verbal ability test, might be explained by primitive cognitive elements reflected by performance on basic tasks, such as a short-term memory scanning task (S. Sternberg, 1966). Identifying one or a few cognitive processes that correlate with intelligence test performance would clarify what intelligence tests measure from an

from Gf and other factors), making the distinction something of a moot point from the perspective of a cognitive researcher.

information-processing perspective, and explain why some people perform better than others (Hunt et al., 1975).

The cognitive correlates approach can be divided further into two general types of research designs: microanalytic and macroanalytic. In the **microanalytic approach**, researchers examine the effect of experimental manipulations on the correlation between an intelligence test and another test that measures a cognitive process of interest (Hambrick, Kane, & Engle, 2005). For example, researchers might examine changes in the relationship between response time and intelligence by comparing the correlations between intelligence and two conditions of a Stroop task: one in which a color word is written in the same color text as its name (e.g., the word "red" written in red) and another in which a color word is written in a different color text (e.g., "red" is written in blue). In both conditions, the participant must say the color of the text (not the word that is written). This is very easy when the word and the text are the same color, but difficult when they are different because reading is automatic in literate adults. If there is a correlation between response time and intelligence in one condition and not in the other, then the researcher concludes that the manipulation affects a process that contributes to variance on intelligence test performance. In this case, there is not a correlation between response time and intelligence when the word and text are the same color, but there is a correlation when they do not match. This suggests that the cognitive processes involved in suppressing the automatic response of reading the word itself, and instead saying the color of the text, is related to intelligence more generally.

Many research studies in the microanalytic approach have used an *extreme groups design*, in which the top and bottom quartiles of performers on a test of a cognitive trait of interest are compared on another trait. For example, working memory capacity (WMC) might be compared to intelligence. This design has several limitations, including overestimation of effect sizes, exclusion of the middle 50 percent of the population for the trait under investigation, and often relatively small sample sizes. The extreme-groups design has become somewhat less common in recent years as researchers have come to acknowledge these limitations, but many of these studies are still cited frequently, and their results should be interpreted with some caution, including those published by one of the authors of this chapter (RWE; e.g., Conway & Engle, 1994; Unsworth & Engle, 2005).

The **macroanalytic approach** (Hambrick et al., 2005) involves examining relationships between **latent factor**s, which are representations of variables that cannot be directly measured. For example, intelligence cannot be measured directly; there are many tests that are designed to reflect intelligence, but no test measures it perfectly or captures the entire construct of intelligence. As a result, a score on a single intelligence test is only an estimate of a person's intelligence – the score is influenced both by the person's actual intelligence, and also by other factors, such as the exact content of the test. Individual tests of intelligence correlate with each other, but do not correlate perfectly because of these extraneous factors. Researchers can obtain a more stable estimate of intelligence by administering multiple intelligence tests, and then using advanced statistical techniques to create a latent factor from the variance that is common to all of the tests. Researchers can then examine relationships between this latent factor and others created in the same way for other constructs (for example, attention control). We discuss this approach, and how cognitive psychologists use it in order to test hypotheses, in more detail in the section "Working toward Reliable Estimates of WMC."

Componential Analysis Method

Another method used by cognitive psychologists is componential analysis. This method can be used to develop and validate information-processing models of the cognitive steps (components) involved in solving complex test items, such as analogies (R. J. Sternberg, 1977) or matrix reasoning tests (Carpenter, Just, & Shell, 1990). These models can then be used to identify the sources of individual differences in performance on the task overall.

The general process is as follows. The researcher identifies the steps that are presumed to be involved in solving a given type of item. Take verbal analogies as an example. The stems of these items take the form "Food : Eat :: Beverage : ???" with the answer choices (A) drink; (B) inhale." R. J. Sternberg (1977) suggested that solving these problems requires (1) *encoding* the three given terms and two answer choices; (2) *inferring* the relationship between the first two terms; (3) *mapping* the relationship between the first and third terms (in this case, realizing that food and beverages are things that can be consumed); (4) *applying* the relationship identified in Step 2 to the third term and the two answer choices (here, recognizing that food is consumed by eating it, meaning that the answer choice should indicate the way that beverages are consumed); and (5) *responding* by indicating the correct answer choice. In order to test this five-step model, a precueing procedure is used to isolate the component processes (R. J. Sternberg, 1977). In precueing, part of the analogy is presented. For example, only the first two terms might be presented, allowing the participant to complete the first two steps (encoding the first two terms, and inferring the relationship between them). The participant presses a button to indicate that he or she is ready to see the rest of the terms, and then solves the analogy. The time elapsed for each of these two parts is recorded. Other trials present only the first term or the first three terms before presenting the full analogy, corresponding to one or three of the steps involved in solving the item. The amount of time to complete each individual processing step is then estimated using the *subtraction method* (Donders, 1868/1969). For example, to obtain the amount of time required for applying the relationship from the first two terms of the analogy to the last two terms (Step 4), the researcher subtracts the response time for items that only required Steps 1 through 3, from the response time for items that required Steps 1 through 4.

In other words, the time taken to process Steps 1 through 3 is removed, leaving only the time required to complete Step 4. A variant on this approach, often used with spatial stimuli, allows researchers to examine accuracy at each step in addition to response time (Mumaw & Pellegrino, 1984).

Using this method, researchers can test models of the component processes involved in solving items of a particular type. An overarching goal of this method is to identify the components that give rise to individual differences in task performance and, by extension, differences in general intelligence (R. J. Sternberg 1983). Components that correlate substantially with overall intelligence test performance may be relevant to cognition in general, especially if they are part of the model for many different cognitive tasks. R. J. Sternberg (1977) found that the time that elapsed during all steps after Step 1 (encoding) was negatively related to general intelligence, indicating that more intelligent people complete the steps after encoding more quickly than less intelligent people. To the extent that the components that are involved in analogical reasoning are also involved in other types of mental tasks, this suggests that more intelligent people execute these components more efficiently than people who are less intelligent.

Speed of Mental Processing

Although mental speed is not a *process*, it has been invoked as an explanatory mechanism for individual differences in intelligence (Deary & Stough, 1996; Eysenck, 1982; Jensen, 1998), and speed-related research is often included in cognitive-oriented reviews of intelligence research (e.g., Hunt, 2011; Mackintosh, 2011). Therefore, we include a review of speed-related theories and evidence here. We will also point out the limitations of these theories.

Like all cognitive approaches to the study of intelligence, the explanation for the relationship between mental speed and intelligence is a reductionist one. That is, it represents an attempt to explain intelligence in terms of a much simpler process – in this case, mental speed. Speed theories of intelligence are based on the long-standing observation that the capacity of the cognitive system is limited (Moray, 1967), both in terms of the amount of information that it can handle at any one time, and the length of time that information remains activated before it begins to decay. Proponents of speed theories claim that faster information processing effectively increases the capacity of the system, allowing more information to be processed before it decays (Jensen, 1998). This increased capacity means that a person with a faster "operating system" is able to incorporate more information per unit of time when solving a problem, making that person better able to answer complex items and attain better scores on ability tests. Meanwhile, people with slower systems become overwhelmed by the information processing demands of complex items, and are unable to solve them correctly.

Measuring Speed: Inspection Time and Reaction Time

Most research on the speed-intelligence relationship has centered on two constructs purported to reflect mental speed: reaction time and inspection time.

Reaction Time

Reaction time (RT) is defined as the amount of time it takes a person to complete some simple action in response to the appearance of a target stimulus. The basic RT tasks that were used by Galton and Wissler over a century ago are still in use today, albeit with more precise measuring equipment. Different varieties of RT tasks exist, but they all require the examinee to respond as quickly as possible (usually by pressing a button) to a stimulus (usually a light that appears on a screen). This is obviously a very simple task, so the main variable of interest is how long it takes the examinee to respond, rather than whether or not he or she responds correctly.

Although reaction time tasks are very simple, they are not direct measures of mental speed. A pure mental-speed measure would isolate the amount of time it takes the examinee to decide that the stimulus is present. RT includes this *decision time*, but also time for other response components, such as the time that the nerve impulse takes to travel from the brain to the finger, and the time that the muscles take to contract in order to press the button. These components may be slower in some populations, especially older adults (Salthouse, 1996). RT measures cannot separate out these components from mental-processing speed.

Inspection Time

In order to address this limitation of RT tasks, researchers devised the even simpler **inspection time** (IT) task. IT is intended to reflect the amount of time it takes a person to merely process a stimulus; it does not include the time required to initiate and complete the response. In a typical IT task, a simple stimulus is flashed on the screen, followed by a visual mask. The stimulus is similar to the shape of a capital Greek letter *pi* (Π) except that the two vertical "legs" are not the same length. The participant must indicate which "leg" is longer. The lengths of the legs are quite different, and identifying the longer one would be a trivially easy task for any participant with normal visual acuity if the stimulus were left on the screen. The task is made difficult by the visual mask, which replaces the stimulus after a variable amount of time has passed (usually less than 100 milliseconds). Across trials, the amount of time before the onset of the mask is varied, in order to establish the length of stimulus exposure a person requires to consistently respond correctly (usually defined as a threshold of, say, 85 percent accuracy). Researchers who use this task claim that it is a nearly pure measure of processing speed because it only requires the participant to view and process the stimulus. The speed of the response itself does not matter, because a person's processing speed is estimated from the exposure time, which is manipulated by the experimenter (Deary & Stough, 1996). Therefore, some researchers have argued that inspection time measures a process that is sufficiently basic to serve as a limiting factor of cognition in general (Vickers & Smith, 1986). However, others (e.g., White, 1993) have argued that the task is so basic that it does not meaningfully involve cognitive processing at all, and that it only reflects sensory processes. Based on the observed relationship between IT and intelligence, the reality seems to be somewhere in the middle, as we will see in the next section.

The Speed–Intelligence Relationship

A large body of research has examined the relationship between speed tasks (RT and IT) and intelligence. Early inspection time studies found very large correlations with intelligence (Nettelbeck & Lally, 1976). However, these early studies used very small sample sizes (e.g., n = 10; Nettelbeck & Lally, 1976), and included people with a very wide range of cognitive abilities, including people with intellectual disabilities. More recent reviews (Deary & Stough, 1996; Nettelbeck, 1987) and meta-analyses (Grudnik & Kranzler, 2001; Kranzler & Jensen, 1989; Sheppard & Vernon, 2008) have consistently reported uncorrected correlations between inspection time and general intelligence in the r = -.30 range in samples that do not include people with intellectual disabilities.[4] However, most samples consist mainly or exclusively of college students, which restricts the range of scores on both IT (because they are young adults) and intelligence tests (because they are college students). This range restriction depresses the correlation between IT and intelligence. After correcting for restriction of range, estimated IT–intelligence correlations increase to the r = -.50 range (Kranzler & Jensen, 1989). Similar results have been obtained for RT. A meta-analysis by Sheppard and Vernon (2008) reported uncorrected correlations between mean RT task performance and intelligence test scores ranging from r = -.22 for simple RT tasks to r = -.40 for more complex, 8-choice RT tasks.

Clearly, IT and RT tasks do not come close to reaching Detterman's (2002) r = .80 threshold correlation with intelligence (remember that this threshold is somewhat arbitrary, however). But do the relatively modest but consistent correlations suggest that mental speed, in itself, is at least somewhat important to intelligence? In the next section, we argue that they do not.

[4] Note that intelligence–speed correlations are negative because higher intelligence is associated with greater speed (lower response time).

Challenges for Intelligence-as-Speed Theories

Despite the existence of well-cited theories that have offered explanations of intelligence in terms of speed (Eysenck, 1982; Jensen, 1998), this stance faces many challenges. From the perspective of cognitive psychology, speed theories do not answer the question, "Speed of *what*?" Both Eysenck (1982) and Jensen (1998) have argued that mental speed reflects neural transmission speed, although there is no evidence that speed of nerve conduction is related to intelligence among individuals in the normal range of intelligence. Furthermore, it is not clear that RT or IT actually reflects the speed of neural conduction. By skipping directly to the cellular level, this extremely reductionist view of intelligence does not offer any insight into the cognitive processes involved in intelligent behavior. For this reason alone, speed-based theories of intelligence are unsatisfying to many cognitive psychologists (Conway, Kane, & Engle, 1999).

Despite the limitations and ambiguities of speed-based theories of intelligence, the fact remains that IT and RT tasks do correlate reliably with intelligence (Deary & Stough, 1996; Jensen, 1998). Why performance on a full-scale intelligence test would be related to performance on the simplest of laboratory tasks, which some (e.g., White, 1993) have argued do not even involve cognitive processing, is a question worth examining. The correlation between speed and intelligence does not mean that speed *causes* intelligence. But correlations *do* have causes. So what causes the speed–intelligence correlation?

Modern psychologists measure RT using many trials, which yields a distribution of response times for each participant.[5] Speed theorists (Eysenck, 1982; Jensen, 1998) often have focused on measures of *central tendency* (usually, mean RT) as the primary speed indicator of interest. However, central tendency is not the only way to quantify a distribution. RT distributions are highly positively skewed, with most RTs clustering near a person's fastest time, and progressively fewer trials having longer RTs. Is it possible that some subset of RTs drive the relationship between mean RT and intelligence? In other words, is the RT–intelligence correlation consistent across the distribution of observed RTs, or does the relationship change at different points on the RT distribution?

There is good evidence for the latter. Researchers have consistently found that the longest RTs in the distribution are more strongly correlated with intelligence than the shortest RTs (see Coyle, 2003, for a review). A common strategy for examining this phenomenon is to divide RTs into "bins." A researcher might create five bins, so that the first bin has the fastest 20 percent of RTs, the second bin has the next fastest 20 percent of RTs, and so on, with the last bin having the slowest 20 percent of RTs.

[5] Performance varies from trial to trial in IT tasks also, but this variability is somewhat more difficult to describe because of the dichotomous (correct/incorrect) nature of the responses. For simplicity, we will focus on RT tasks for the remainder of the section.

The mean RT for each bin is then computed, and the correlation between intelligence and the mean of each bin is examined separately. Correlations with intelligence increase from the fastest bin to the slowest (Larson & Alderton, 1990), meaning that an individual's slowest RTs are the most predictive of intelligence. This effect is known as the **worst performance rule**, and it cannot be fully explained by statistical artifacts such as outliers or variance compression (Coyle, 2003).

There are limitations to the binning method, such as a relatively small number of observations in each bin and the arbitrary division of the distribution (Unsworth, Redick, Lakey, & Young, 2010). Recently, researchers have employed more advanced statistical methods to describe the RT distribution (Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007; Unsworth et al., 2010; van Ravenzwaaij, Brown, & Wagenmakers, 2011). The positively skewed RT distribution approximates an ex-Gaussian distribution, which is a combination of a Gaussian (normal) distribution and an exponential distribution. The exponential component of the distribution reflects the slower RTs. Researchers can extract separate parameters describing the normal and exponential components of the distribution, and examine how they relate to intelligence. Importantly, these parameters do not reflect cognitive processes directly (Unsworth et al., 2010). However, experimental manipulations known to affect certain cognitive processes have been shown to affect some parameters in predictable ways.

Using various experimental methods, multiple research groups have converged on the interpretation that the normal part of the distribution reflects automatic and sensori-motor processes, while the exponential part of the distribution is associated with controlled attentional processes, including the ability to maintain attentional focus on the task (Schmiedek et al., 2007; Unsworth et al., 2010). We will have much more to say about attentional processes later in this chapter, but for the purpose of the present discussion, the main idea is that people who are better able to keep their attention focused on a simple RT task are able to respond more quickly when the stimulus appears. People whose minds wander away from the task – even if their eyes do not – must bring their attention back to the task when the stimulus appears in order to respond to it. This takes time, and results in a long RT for the affected trial. Frequent attentional lapses lead to a greater proportion of long RTs, which increases the exponential component of the distribution.

The exponential component of the RT distribution is negatively correlated with intelligence (r = -.71; Schmiedek et al., 2007). That is, people with a higher proportion of slower responses on RT tasks also perform worse on intelligence tests, compared to people with fewer slow responses. (Note that this is consistent with findings that mean RT is negatively related to intelligence, because a greater proportion of slow responses would increase the overall mean of the distribution.) A speed-based explanation for this relationship may seem tempting on the surface, but does not in fact make much sense. A relationship between the exponential part of the distribution (i.e., the slowest RTs) and intelligence does not provide much support for the idea that faster speeds make a person smarter. The finding that "occasionally much slower equals less intelligent" does not support the idea that "faster equals smarter," because the results and the theory pertain to opposite ends of the RT spectrum (Mackintosh, 2011).

If attentional lapses can disrupt performance on something as simple as an RT task, while the participant (presumably) is trying to concentrate, then such lapses may be regular occurrences that negatively affect cognition. People who experience more attentional lapses during RT tasks may also experience them more often during other laboratory tasks and in real life. Thus, attentional lapses may drive the correlation between longer RTs and other cognitive tasks, including intelligence tests (Schmiedek et al., 2007; Unsworth et al., 2010, but see Kane, Gross, Chun, & Smeekens, 2017, for evidence that the relationship between mind-wandering in the lab and in real life is not as strong as one might assume). With the suggestion that attention lapses might *cause* the relationship between RT task performance and intelligence, we have moved squarely into the realm of cognitive psychology. We have identified a process which is part of a theory of how the mind works, and we have specified a way in which it might be related to intelligence. For the rest of the chapter, we will concentrate on the process that has become the focus on most cognitive intelligence research: executive attention.

Working Memory and Executive Attention

As noted in the introduction to this chapter, the cognitive approach to psychology focuses on models that describe how the cognitive system processes information. Most cognitive psychologists work to develop models of the processes involved in human cognition in general (for example, a model of the memory system), and are not interested in individual differences in the ability to carry out those processes. However, some cognitively oriented psychologists do use laboratory tests measuring cognitive processes to study differences between people. They then attempt to link differences between people in performance on these tasks to differences in intelligence. Much of this research has focused on working memory capacity and executive attention.

Measuring Working Memory Capacity (WMC)

Daneman and Carpenter (1980) were the first to use what would now be called a complex span task for measuring **working memory capacity (WMC)**. Earlier researchers had not found a relationship between simple short-term memory span tasks and complex cognitive indicators such as reading comprehension, leading to speculation that short-term memory was not important to complex cognition.

(An article by Crowder in 1982, ominously titled "The Demise of Short-term Memory," argued exactly this point; see also Estes, 1982.) Daneman and Carpenter were skeptical of this conclusion, given that a relationship was predicted by theoretical models of both reading comprehension and WMC. At the time, WMC had been defined as involving both processing and storage of information, but it was typically measured using tasks that only required storage. So Daneman and Carpenter designed a task that would tax both the processing and storage components of working memory. In their reading span task, participants were asked to read or listen to a sentence and remember the last word of the sentence. After a set of sentences had been presented (set sizes ranged from 2 to 6), participants recalled the last word of each sentence. The number of correctly recalled words was the person's reading span, which operationally defined WMC. Daneman and Carpenter (1980) found strong correlations (ranging from $r = .42$ to $r = .86$) between reading span and various measures of reading comprehension, as well as SAT-Verbal scores. However, a simple word-span task that required participants to recall lists of words (i.e., a task that involved storage but not processing) did not significantly correlate with reading comprehension or SAT-Verbal scores. Although their sample sizes were very small for correlational research ($n = 20$ for Experiment 1, $n = 21$ for Experiment 2), Daneman and Carpenter's work provided important early evidence that WMC is critical to complex cognition.

Today, many different tasks are used to measure WMC, including a wide variety of **complex span tasks**. Like the reading span task, the complex span tasks all involve a processing task and a memory task, and participants must shift their attention between the memory task and the processing task before finally recalling all the memory items for the current trial. Figure 5.1 shows example stimuli from three common complex span tasks and explains how they work.

Span tasks are not the only method of measuring WMC. Two other frequently used tasks are the *n*-back task and the change-detection task. In the ***n*-back task**, a string of items (for example, digits) is presented and the person being tested must press a button whenever an item is identical to the item presented *n* items ago. For instance, in the 3-back version of the task, the examinee must press a button when the digit on the screen was also presented three items ago. In the **change-detection task**, a display showing some number of objects is presented briefly, followed by another similar display. Figure 5.2 shows an example of this task. The left box of the figure shows the initial display, and the right box of the figure shows the second display. The person being tested must indicate whether one of the objects, called the target object, was the same or different in the first and second displays. The probe indicating the target object does not appear until after the screen has changed. This means that, to respond correctly, participants must keep the original array in memory until the probe appears. In this task, a person's WMC is the greatest number of objects in the display for which the person consistently responds correctly.

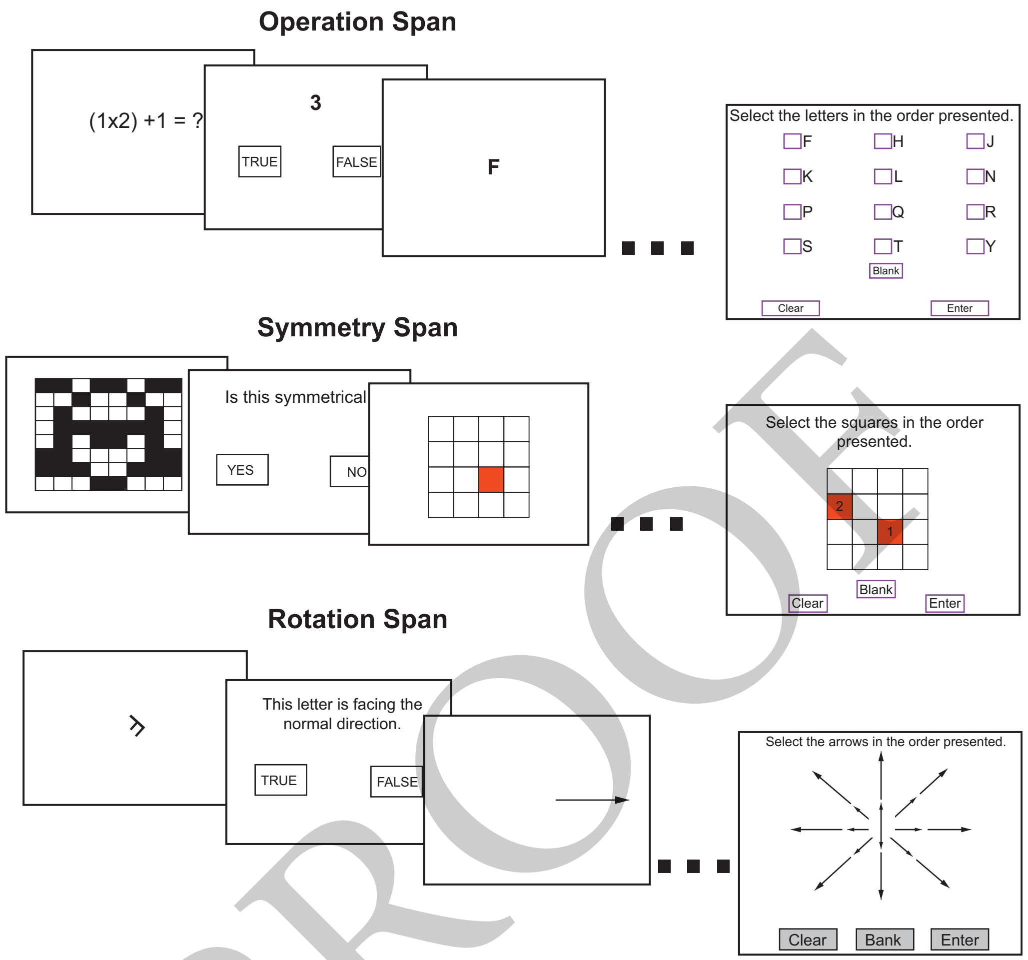

Figure 5.1 Example stimuli from three commonly used span tasks. For each task, the figure shows example stimuli from the symmetry-span task. The boxes represent what the participant sees during a trial, proceeding from left to right. First, the participant is shown a stimulus (arithmetic problem for the operation span task, array of squares for the symmetry span task, and a rotated letter for the rotation span task). Next, the participant must make a judgment about the stimulus (e.g., whether the number shown is the correct solution to the arithmetic problem, or whether the array is symmetrical). These two steps constitute the processing task. The participant is then shown another stimulus, represented in the third box, which is to be held in memory. This is the memory part of the task. This sequence of processing and memory tasks is repeated between two and seven times. Finally, the participant is prompted to recall all of the stimuli presented in the memory component, in the order in which they were presented. This is shown in the boxes on the right side of the figure, starting with the left-most box and ending with the right-most box. The first two boxes show the processing task, in which the participant must judge whether the pattern of black and white squares is symmetrical around its vertical axis. The third box shows the memory task, in which the participant must remember which box in the array is red. This sequence is repeated between two and seven times, until the recall phase (fourth box) in which the participant must recall the information from the memory task. In this example, the participant indicates where the red boxes were, in the correct order.

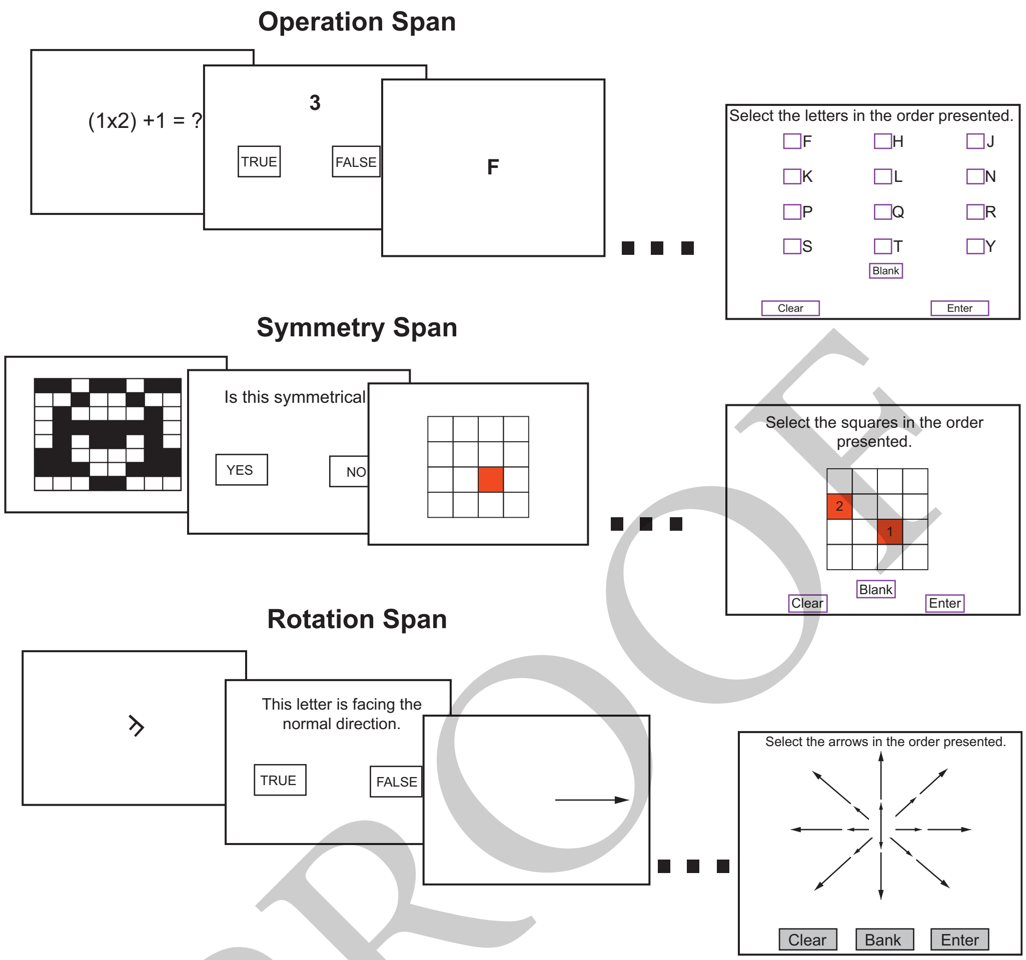

Figure 5.2 Example stimuli for the change detection task. The participant first sees an array like the one on the left. After a brief visual mask, a second array appears, such as the one on the right. After a brief delay, one shape in the array is identified as the target stimulus, and the participant indicates whether the shape changed color in the new array. The number of shapes in the array varies from trial to trial. A person's working memory capacity is the number of shapes in the largest array for which the person can consistently identify changes correctly.

There is growing evidence that although complex span tasks, *n*-back tasks, and change-detection tasks are highly correlated with each other, they emphasize different functions of working memory itself.

Working toward Reliable Estimates of WMC

Before continuing with our discussion of working memory, we must offer a caveat about cognitive tasks: There is no such thing as a process-pure measure of cognition in humans. In even the simplest of tasks, different people will use different strategies, different coding schemes, different rehearsal techniques, and therefore probably different functions in their brains. Further, despite researchers'

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best efforts, no task is content-free. All memory or processing tasks require a person to remember or process *something*. Factors not related to WMC may make some content easier to manipulate for some people than for others, meaning that content plays a role in a person's performance on a WMC task. For example, people differ in their ability to manipulate visuospatial information: People who have lower spatial abilities do not perform as well on WMC tasks with spatial content as on WMC tasks with other types of content (Shah & Miyake, 1996). For these people, domain-general WMC would be underestimated if only WMC tasks with spatial content were used. The same is true for any other type of content. This presents a problem for cognitive researchers: They want to measure general cognitive processes, not the ability to work with specific types of content, but it is impossible to measure a process without using some kind of content. How can they do this?

One solution is to use the macroanalytic approach described earlier. Recall that in this approach, latent factors are created by administering multiple indicators of a construct that cannot be measured directly. If a cognitive researcher wants to measure WMC, for example, he or she may use three WM tasks that use different types of content in order to obtain an estimate of WMC that is not strongly influenced by any particular type of content. Latent factors for other constructs of interest, such as attention control, would be created in the same way. Then, the researcher would use methods such as structural equation modeling to explore relationships between the factors. **Structural equation modeling** is an advanced statistical technique that allows researchers to examine correlations between latent factors. These correlations are often more stable and meaningful than correlations between individual tests, and they offer a clearer picture of the relationship between factors than can be obtained from individual test scores. Structural equation modeling can also provide limited evidence supporting hypothesized causal relationships between variables.

The macroanalytic design is common in cognitive intelligence research (e.g., Kane et al., 2004; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002), and studies using it typically report stronger correlations between WMC and intelligence at the latent factor level than studies that examine pairwise correlations between individual WMC and intelligence tests (Oberauer, Schulze, Wilhelm, & Süß, 2005). This would be expected, because latent factors include only the variance that is common to all of the tests measuring that factor, and therefore are considered to reflect the influence of processes that are common to all of the tests measuring the construct. The latent factors do not include variance that arises from idiosyncrasies of particular tests. Thus, latent factors are presumed to represent something approaching the elusive process-pure measure of cognitive processes. Much of the literature that we will review in this section uses latent factors and structural equation modeling to make inferences about WMC and fluid intelligence.

Despite the significant advantages just described, the macroanalytic approach also has some limitations that must be kept in mind when interpreting the results of studies that have used this method. Two limitations are particularly relevant to the current discussion. The first limitation relates to claims of causality (e.g., "Working memory gives rise to Gf"). Researchers can examine whether the data are consistent with their proposed model, but the proposed model is never the only model that could fit the data. Testing a model with structural equation modeling requires a combination of statistics and theory: The statistics indicate the strength of the proposed relationships, but theory has to define the existence and direction of the relationships. Other theories could propose different relationships, and structural equation modeling alone usually cannot definitively support one theory over another. The second limitation relates to the ability to define two factors as the same or different. Statistical tests to determine whether the correlation between two factors, such as WMC and Gf, is $r = 1.0$ (meaning that they are the same) or significantly less than $r = 1.0$ (meaning the they are different) requires a large sample (over 200, but samples sizes closer to 100 are not uncommon in this area of research; Gignac, 2014; Matzke, Dolan, & Molenaar, 2010). It is important to keep this limitation in mind when reviewing evidence of the relationship (or unity) between WMC and Gf, which we will review in a later section.

Theories of Working Memory (WM)

Although there is general agreement about how WMC should be measured, there are different theories about its structure and the processes involved. Early researchers (and some more modern researchers, such as Cowan, 1988) conceptualized WMC as the number of chunks of information that a person's working memory can "hold" at a given time, a position that is very similar to the classical view of short-term memory (Atkinson & Shiffrin, 1968). However, many current researchers (e.g., Engle & Kane, 2004; Engle, Tuholski, Laughlin, & Conway, 1999; Oberauer, 2002) view WMC as reflecting not the "size" of the storage unit, but rather a person's ability to deploy attention in order to control and regulate the flow of information into and through the system. Between-person differences in attention control lead to differences in the ability to maintain multiple pieces of relevant information in a sufficiently activated state (in consciousness, if you will), which is reflected in performance on WMC tasks. Theories differ in terms of how this is accomplished. Two prominent theories are Engle's theory of attention control, and Oberauer's binding theory.

Engle and colleagues (Engle & Kane, 2004; Engle et al., 1999) argue that the main driver of individual differences in WMC is **executive attention** – the ability to control one's attention and prevent having attention captured by distractions, whether internal (such as thoughts and emotions) or external (events in the environment such as people talking or loud noises). In everyday experience, this is reflected in differences in mind wandering and tendency to be distracted. People with good attention control are able to manage their attention in such a way that allows them to complete tasks effectively with minimal disruption. What constitutes effective attention management depends on the task. For some tasks, it means maintaining task-relevant information above a minimal level of activation so that it can be accessed when needed. Maintaining increasing amounts of information requires increasingly tight control over attention, because there are fewer attentional resources that can be spared on task-irrelevant thoughts. For other tasks, effective attention management means actively disengaging from information that is no longer relevant to the task, thereby reducing the risk of interference from outdated information (Shipstead, Harrison, & Engle, 2016). Individual differences in capacity limitations, as measured by WMC tasks, reflect differences in the ability to manage attention during these tasks.

Oberauer and his colleagues (e.g., Oberauer, 2002; Oberauer, Süß, Wilhelm, & Sander, 2007) have taken a somewhat different view of WMC. Oberauer's model conceptualizes WM as an attentional system that is aimed at memory, rather than a memory system in its own right (Oberauer et al., 2007). In this model, WM comprises three regions, which represent different levels of activation. The highest level of activation is at the **focus of attention** (akin to what most people would think of as the contents of consciousness), which can accommodate the one chunk of information that the person is engaging with at a given moment. The **region of direct access** consists of a few chunks of information that are not actively being manipulated, but that are immediately available for processing. The lowest level of activation is the activated region of long-term memory, which can briefly store information in a less-activated state before it fades out of the activated region entirely. (There is also a vast region of long-term memory that is not meaningfully activated at a given time. This region does not play an important role in Oberauer's WM model, because information in this region is, by definition, not in WM.)

For Oberauer (2002; Oberauer et al., 2007), WM keeps chunks of information available by temporarily binding them to positions in a cognitive coordinate system that provides an "address" for the information. Temporary bindings can also be made between activated chunks. These bindings allow people to carry out tasks and solve problems by linking different problem components together. Capacity limitations arise when it becomes difficult to keep the bindings intact, which leads to features of different chunks of information being mixed up (which Oberauer calls *overwriting*) or to different chunks of information competing for the same location in the cognitive coordinate system (which Oberauer calls *crosstalk*). Overwriting and crosstalk both contribute to processing errors by making it difficult or impossible to access the correct information when it is needed.

We have spent a great deal of time describing the processes involved in these theories, because these processes are essential to a cognitive explanation for the relationship between WMC and intelligence. These two theories illustrate both the greatest challenge and the solidly scientific approach of cognitive psychology. The challenge is that there is no way to peer inside the brain and directly observe the processes that are involved in cognition. Both of these models are consistent with data from WMC and many other related tasks. This ambiguity is a major challenge for cognitive psychology. However, these two theories also show the strength of the cognitive approach, which is that well-constructed models of cognitive processes lead to testable hypotheses that can be examined empirically. A great deal of research has been conducted to test the predictions of both theories. A review of this research is beyond the scope of this chapter; for our purposes, the important thing to know is that, regardless of the theoretical orientation of the researchers, WMC tasks consistently are found to correlate with measures of intelligence, particularly Gf. The relevant question here is not which WM model is "correct," but rather why there should be such a consistent relationship between relatively simple cognitive tasks (WMC tasks) and much more complex cognitive tasks (intelligence test items).

The Relationship between WMC and Gf

Much working memory research has directly or indirectly addressed the question of how WMC is related to intelligence. While some researchers (Colom, Rebollo, Palacios, Juan-Espinosa, & Kyllonen, 2004; Kyllonen & Christal, 1990) have found such strong relationships between WMC and Gf that they have concluded that the two are the same construct, this is not the prevailing view. A more common position is that the two are strongly related, but meaningfully different. For example, Kane and colleagues (2004) reported a correlation of $r = .64$ between a latent WMC factor and Gf, as measured by conventional intelligence tests. In general, the relationship between WMC and Gf at the latent factor level is in the range of $r = .60$ to $r = .80$, with the variability in the correlations most likely arising from differences across studies in the range of abilities in the people tested and the exact nature of the tests used. While the strength of the relationship is still subject to some debate, it is clear that a strong relationship exists. The question then becomes *why* WMC and Gf are so strongly related.

As with all correlational research, there are at least three possibilities for the relationship between WMC and Gf. Differences in Gf may cause differences in WMC; differences in WMC may cause differences in Gf; or both Gf and WMC may be caused by a third variable.

Differences in Gf May Cause Differences in WMC

This first option is hypothetically possible – for example, perhaps people with higher Gf are able to devise strategies that help them perform better on WMC tasks – but there is little empirical support for this position (Kane et al., 2004). Moreover, a theoretical justification for a causal path from Gf to WMC must grapple with a key definitional issue. WMC is based on theoretical accounts of mental processes that are grounded in cognitive, clinical, and neuroscientific evidence. Multiple lines of research have converged on similar conclusions about the general nature of the cognitive architecture and functions, and WMC task performance has been linked both to simpler cognitive tasks and to biology (Kane et al., 2004). In contrast, Gf is the common factor derived from exploratory factor analyses of tests that have traditionally been used to measure fluid intelligence. It is a description of relationships between tests, not an explanation for them. From a theoretical perspective, therefore, it is difficult to justify the position that Gf causes WMC. It seems that Gf is not a cause of the correlation between scores on various ability tests, but rather the effect of some underlying process(es) that impact performance on all of the tests. In other words, it is a psychometric phenomenon, not a psychological one (Conway & Kovacs, 2015).

Differences in WMC Cause Differences in Gf

The second possibility, that differences in WMC cause differences in Gf, is more plausible (Kane et al., 2004; Kyllonen & Christal, 1990). A naive position in line with this view is that WM, in itself, is the cognitive process underlying Gf. That is, people differ on Gf because they differ on WMC, and that is the end of the story; the correlation between them is less than r = 1.0 only because of error variance. A possible explanation for the relationship between WMC and performance on an inductive reasoning task, for example, is that WMC is used to keep track of relevant information such as patterns that have been identified and hypotheses that have been tested while attempting to solve the problem. People perform better on Gf tests when they are better able to keep track of these things. This position is likely to be overly simplistic, however. Suggesting a direct one-to-one relationship between WMC and Gf confuses cognitive tasks with the cognitive processes assumed to underlie them (Shipstead et al., 2016). That is, it assumes that WMC tests are pure measures of a single process – that a person's score on a symmetry span task, for example, accurately reflects his or her WMC, and is not influenced by any other factors. We have already asserted that this is unlikely.

Both *g* and WMC May Be Caused by a Third Variable

Recent work indicates that performance on WMC tasks can be decomposed into more basic processes (Shipstead et al., 2016; see also Conway & Kovacs, 2015). This observation leads to the third possibility for interpreting the WMC–Gf correlation: it arises from processes that contribute to both. For example, Shipstead et al. (2016) suggested a model of the WMC–Gf relationship based on two more basic functions: **maintenance** of information in the face of distraction or decay, and **disengagement** from old, potentially interfering information to allow attention to new, potentially

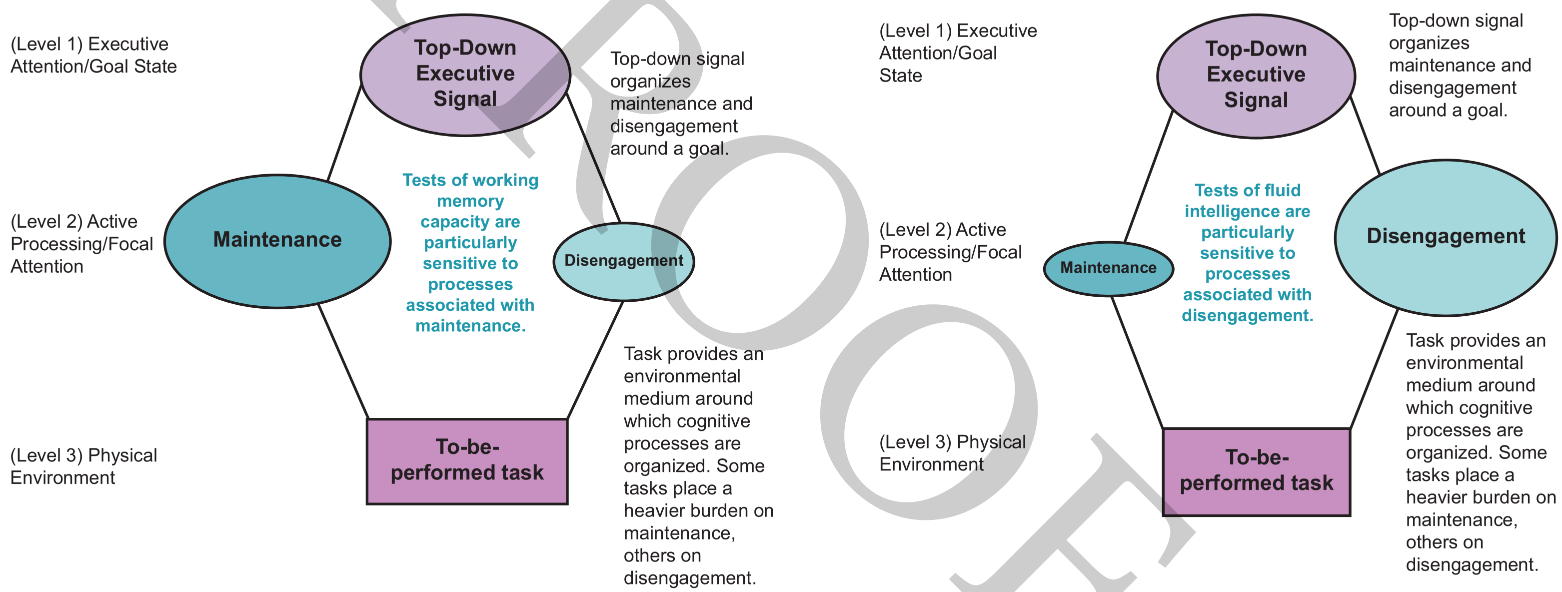


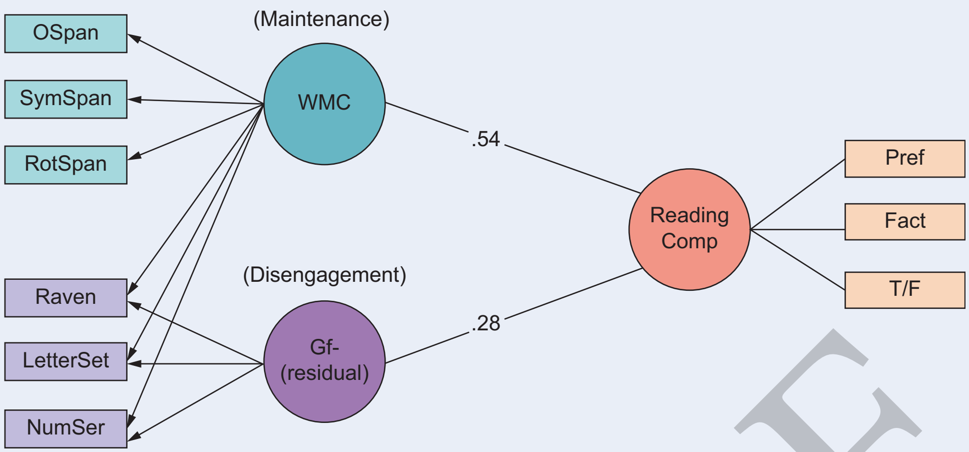
Figure 5.3 Schematic representation of the roles of maintenance and disengagement in WMC and Gf tasks

relevant and useful information. Both of these processes are important for performance both on WMC tasks and Gf tasks, but to different degrees (see Figure 5.3).

Shipstead and colleagues note that WMC tasks appear to mainly tax the ability to maintain information, whereas Gf tests rely more heavily on disengaging from information (for example, in hypothesis testing, during which an examinee must discard previously tested hypotheses in order to move on to new ones). However, both processes are used to some degree in both types of tasks, and both functions are effortful and demanding of limited-capacity attention. The common underlying processes and their reliance on limited-capacity attention cause the correlation between two quite different types of tasks; the difference in the importance of those underlying processes to the two tasks is the reason that they are not correlated more strongly. For a specific example of a recent study from the Randall W. Engle's lab investigating the role of maintenance and disengagement in a complex cognitive task (reading comprehension), see the Focus on Contemporary Research box.

FOCUS ON CONTEMPORARY RESEARCH: RANDALL W. ENGLE'S WORK ON WORKING MEMORY CAPACITY AND READING COMPREHENSION

Individual differences in working memory capacity (WMC) have been shown to be strongly associated with differences in reading comprehension (Daneman & Carpenter, 1980; Turner & Engle, 1989). The mechanism underlying this relationship is not yet known. One possibility is that the relationship is primarily due to individual differences in the ability to maintain information: High WMC individuals can maintain more idea units and more complex language structures in an active state, which results in better comprehension. Another possibility is that the WMC–reading comprehension relationship is primarily due to the ability to disengage from previously attended information (Hasher & Zacks, 1988; Gernsbacher, 1991). Although it may seem counterintuitive that disengaging from information aids comprehension, consider the many ambiguous words that are encountered when reading a passage in English. For example, if you read, "The violinist picked up the bow," you are likely to think of a bow that is used to play the violin. However, if the next sentence is, "She placed the bow in her daughter's hair to keep it in place," you must change the meaning of "bow" to a ribbon. High-ability individuals are better able to block, inhibit, or disengage from the first meaning after reading the second sentence, and to replace it with the new meaning. Low-ability individuals are more likely to keep both meanings active in working memory. Failing to suppress the now-irrelevant meaning of "bow" consumes WM resources that could otherwise be allocated toward understanding the passage.



Box Figure. Structural equation modeling EM analysis from Martin et al. (unpublished), showing the contributions of maintenance and disengagement to reading comprehension. The arrows from WMC to all of the tasks, including the Gf tasks, reflect an attempt to attribute all of the variance due to maintenance to the WMC construct. Putatively, that means the Gf construct reflects largely disengagement. The result is that both WMC or maintenance and Gf or disengagement are shown to be important to reading comprehension. Martin et al., also found a similar result for learning second language vocabulary. The conclusion is that both maintenance and disengagement are important in reading and second language learning but it is likely that different real-world tasks will show differential reliance on these two important functions of intelligence.

A recent study by Martin, Shipstead, Harrison, and colleagues (unpublished) examined the relative importance of maintenance and disengagement in reading comprehension. Although earlier studies found a relationship between WMC and reading comprehension, these studies did not include measures of Gf. (Recall from the chapter that WMC tasks are thought to rely more heavily on maintenance, whereas Gf tasks are thought to rely more heavily on disengagement; this means that previous studies that did not measure Gf may not have adequately measured disengagement.) Using the macroanalytic approach described in the chapter, Martin et al. examined the relationship between maintenance, disengagement, and reading comprehension. They created a latent reading comprehension factor using three measures of reading comprehension for a series of paragraphs. One measure was a set of fact questions based on events described in the paragraph, the second was a set of true/false questions regarding events in the paragraph, and the third was a pronominal reference question in which participants were asked to identify the noun that a pronoun referred to (this was made somewhat difficult by the fact that the noun appeared four to seven sentences before the pronoun). A latent maintenance factor was created using three WM tasks plus the variance in three Gf tasks that was due to maintenance. (Remember that Gf tasks are thought to require *some* maintenance, even though they *primarily* require disengagement.) The latent disengagement factor was created from the remaining variance in the Gf tasks.

The results of the study are summarized graphically in the figure below. The lines connecting the maintenance and disengagement factors with the reading comprehension factor indicate that both maintenance and disengagement are important to reading comprehension. Put differently, both WMC and Gf reflect processes that are important to complex cognitive tasks, and measuring both of these factors explains more of the complex task performance than measuring only one of them. It is likely that different real-world tasks will show differential reliance on these two functions of intelligence, making it even more important to measure both processes when studying complex cognition.

This "third variable" view of the WMC–Gf relationship is arguably both the most plausible, and the most consistent with the cognitive approach to intelligence research. It explains Gf in terms of the basic processes that allow humans to process information, even if the individual processes have not yet been completely identified. One advantage of the theory that the ability to control attention is at least partly responsible for differences in Gf is that a single construct, attention control, can be used to understand a wide variety of phenomena in human psychology, from the ability to inhibit inappropriate behavior in young children (Skogan, Zeiler, Egeland, Rohrer-Baumgartner, & Urnes, 2014), to why depression and schizophrenia cause cognitive deficits (Forbes, Carrick, McIntosh, & Lawrie, 2009; Joormann & Gotlib, 2008; Lee & Park, 2005), to why sleep deprivation hurts performance in skilled pilots (Lopez, Previc, Fischer, Heitz, & Engle, 2012), to why stereotype threat leads some women to do poorly on math tests (Schmader, 2010), to why some point guards in basketball are more strategic in making passes than others (Furley & Wood, 2016), to why some police officers are more likely to shoot in a stressful situation (Kleider-Offutt, Clevinger, & Bond, 2016), to why some people are more likely to be distracted while driving (J. M. Watson et al., 2016), and to why some people are better at multi-tasking than others (Redick, 2016). The evidence suggests that people differ in their ability to control the deployment of attention in all situations where the control of thought, emotion, and behavior is important. In other words, attention control is critical to most of human psychology.

Before closing this chapter, we should address some criticisms that have been leveled against cognitive theories of intelligence, which mirror criticisms of cognitive psychology more broadly. Specifically, critics have argued that (a) real-world intelligent behavior (often, but not always, defined as academic or job success) does not correlate as strongly with tests of narrow cognitive processes as with full-scale IQ tests; and (b) cognitive researchers improperly focus on explaining performance on tests of Gf, which were designed to *predict* intelligent behavior, not to *define* it (Ackerman, 2017; Hunt, 2005). Both of these criticisms somewhat miss the point of the cognitive approach. Although it is true that cognitive researchers have not identified a single test, measuring a single process, that can replace comprehensive intelligence tests, that has not been the aim of most cognitive researchers in the last few decades. Instead, as we hope we have made clear in this chapter, cognitive psychologists strive to develop an understanding of intelligence grounded in models of how the mind works (Hunt, 2005). In other words, they are interested in identifying the *causes* of intelligence, which is different from identifying a set of basic cognitive tests that rival traditional measures of intelligence in their ability to predict intelligent behavior in situations encountered in the real world.

As you will learn in this book, intelligence is a complex concept that is difficult to operationally define. One option is to use intelligence tests as proxies, as cognitive psychologists have done since the early days of the cognitive approach (Hunt et al., 1975), even though the tests were not intended to define intelligence (Ackerman, 2017). Another option is to use specific performance indicators such as the ones mentioned in the previous paragraph. Neither option fully captures the breadth of human intelligence and the many ways it can manifest itself in the world outside the laboratory. However, both options do provide researchers with standardized indicators of intelligence (or intelligent behavior) that can be correlated with basic cognitive characteristics such as ability to control attention. While correlations cannot prove causation, the existence of the relationship indicates that something that affects performance on attention control tasks also affects performance on much more complex tasks. And while psychologists (and psychology students) should always keep in mind that Gf tests provide only a shadow of the complex reality of human intelligence, they nevertheless offer a starting point for understanding the processes that enable and support the many ways that intelligence is manifested.

CONCLUSION

The cognitive approach to studying intelligence is centered on identifying cognitive processes that explain individual differences in intelligence. Hints of the cognitive approach were present in the earliest days of intelligence research, long before the advent of cognitive psychology as a subfield. Although those early efforts (Galton, 1883; Wissler, 1901) were not particularly successful, they laid the groundwork for research programs that emerged many decades later, beginning in the 1970s and continuing today. The unifying theme of all of this work has been a quest to understand *why* some people are more intelligent than others.

We do not yet know the answer to this question. We can be fairly confident that there is not one single process, such as working memory, or characteristic of the cognitive system, such as speed, that fully accounts for between-person differences in intelligence (Detterman, 2002; Mackintosh, 2011). Modern models of intelligence in the cognitive tradition feature multiple processes that are tapped to different degrees by different types of cognitive tests. In these models, Gf is not understood as a psychological entity in itself. Instead, it is a psychometric property that emerges as a result of these various processes, each of which contributes to, but does not completely determine, performance on a subset of cognitive tests (Conway & Kovacs, 2015).

Because cognitive processes cannot be observed directly, there are always likely to be competing theories and room for multiple interpretations. One strength of the cognitive approach is that it is rooted in the experimental tradition, which pits the prediction of one theory against that of another. Experimental methods and tasks will evolve as theories do, leading researchers ever closer to an understanding of intelligence that is based on what is known about how the human cognitive system works.

CHAPTER SUMMARY

Cognitive psychology is the study of the mental processes involved in cognition. In the context of intelligence research, the cognitive approach is focused on identifying the mental processes involved in intelligent behavior and, further, exploring whether between-person differences in intelligence can be explained by differences in the ability to carry out those processes. While early research efforts were aimed at isolating a single process that could explain individual differences in intelligence, most modern cognitive researchers do not seek a single process. Instead, they work to identify a set of processes that together give rise to intelligence.

Cognitive researchers use a combination of experimental and correlational methods in their intelligence research, and we reviewed some of these methods. We reviewed research on the relationship between intelligence and mental processing speed, which is often considered to be an early example of cognitive research, and consider its explanatory power from a cognitive perspective. We then moved to more modern efforts to construct a cognitive account of intelligence, which are centered on attention control and working memory. These cognitive functions have been shown to be related to a wide variety of indicators of intelligence and intelligent behavior, both inside and outside the laboratory.

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We closed by addressing some of the criticisms of the cognitive approach in the context of its particular strengths.

KEY TERMS

change-detection task • cognitive psychology • complex span tasks • differential research • disengagement • executive attention • experimental research • focus of attention • inspection time (IT) • latent factor • macroanalytic approach • maintenance • microanalytic approach • *n*-back task • psychological *g* • psychometric *g* • reaction time (RT) • region of direct access • structural equation modeling • working memory capacity (WMC) • worst performance rule

COMPREHENSION AND REFLECTION QUESTIONS

1. How does the cognitive approach to the study of intelligence differ from the psychometric approach?
2. Explain the two major theories of working memory. How does each one explain the relationship between working memory tasks and intelligence?
3. Why did some theorists believe that speed was related to intelligence? Do you think that speed theories of intelligence are satisfying from a cognitive perspective? Why or why not?
4. Describe the macroanalytic and microanalytic approaches to studying the relationship between intelligence and cognitive processes. What are the advantages and limitations of each?
5. If you were designing an experiment in the cognitive tradition, how would you measure intelligence? How would you defend your choice?

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