Abstract

Beyond General Intelligence:
The Dual-Process Theory of Human Intelligence

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Over 30 years of research in cognitive science reveals that a considerable amount of information processing takes place automatically—without our intent, awareness, or deliberate encoding—and plays a significant role in structuring our skills, perceptions, and behavior. Indeed, it is increasingly recognized that dual-process theories, which posit that humans possess two distinct modes of thought—one controlled, and the other automatic— are required for explaining cognitive, personality, and social phenomenon. However, while intelligence researchers have done a remarkable job measuring individual differences in explicitly controlled cognitive processes, individual differences in automatic cognitive processes have not received nearly as much attention. In this dissertation, I aim to go beyond general intelligence (*g)* by measuring individual differences in implicit cognition and their relations to a wide variety of intelligent behaviors, thereby expanding both the range of methodologies as well as dependent measures studied by intelligence researchers. Toward these goals, I proposed the Dual-Process (DP) theory of human intelligence in which intelligent behavior is jointly influenced both by Controlled and Autonomous forms of cognition. According to the DP theory, intelligence is the ability to balance and flexibly switch between modes of thought depending on task demands. While Controlled Cognition is largely constrained by central executive functioning, Autonomous Cognition is not. Further, both ability and Openness to Engagement in Autonomous forms of Cognition are

expected to predict a wide variety of intelligent outcomes independently of Explicit Cognitive Ability (ECA).

The theory was largely supported in a sample of 177 English Sixth Form College students between the ages of 16-18. Two forms of implicit cognition tested were implicit learning (IL) of a probabilistic sequential pattern and latent inhibition (LI) of stimuli that was previously tagged as irrelevant. IL and LI were both unrelated to measures of ECA (g, working memory, and intentional associative learning) and Intellectual Engagement. Yet IL and LI both displayed meaningful individual differences. IL was positively related to specific components of cognitive ability, Openness to Experience, impulsivity, and language achievement. Reduced LI was positively associated with Openness to Affective Engagement and self-reported creative achievement in the Arts, but not the Sciences. Additionally, Openness to Affective and Aesthetic (Art, Music and Fantasy) Engagement differentially predicted deductive reasoning and self-report measures of the Big Five (Costa & McCrae, 1992), impulsivity, need for uniqueness, and creative achievement in the Arts above and beyond ECA and Intellectual Engagement. ECA and Intellectual Engagement were related to self-reported creative achievement in the Sciences, but not the Arts. Taken together, these results have implications for understanding rationality, evolutionary psychology, interactions between Controlled and Autonomous Cognition, social cognition, creativity, schizophrenia, expertise, and the relationship between personality and cognition. As such, these results illustrate how—by investigating individual differences both in Controlled and Autonomous forms of cognition—the Dual Process theory provides a more complete understanding of human intelligence.

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What is intelligence? Intelligence tests were originally created with the practical goal of identifying students in need of alternative education (Binet & Simon, 1916). Since intelligence tests were originally devised to predict school grades, the items were intentionally devised to measure a general ability to profit from explicit instruction, concentrate on a task, and engage in intellectual material. Indeed, research shows that such a general ability does exist. Over a century ago, Spearman (1904) discovered that when a battery of diverse cognitive tests is administered to a diverse group of people, there is consistent tendency for all the tests to be positively correlated with one another, producing what has been referred to as the "positive manifold". Spearman labelled the factor on which all individual tests loaded g for general intelligence. He also argued for a specific factor, s, which consisted of variance that was unique to each test and also influenced intelligence. Even though Spearman argued that both factors jointly determined intelligence test scores, he clearly believed that the g factor was the single factor that captured the importance source of variance common to all tests of intelligence. Many studies since then have replicated the statistical regularity that is g (Carroll, 1993; Jensen, 1998; Johnson, Bouchard, Krueger, McGue, & Gottesman, 2004), and have shown that g predicts many practical outcomes in addition to academic achievement (Gottfredson, 2002). Even though the existence of g in the sense of a statistical feature (a "positive manifold") is a robust finding, an important research question is whether there are other forms of cognition that display meaningful individual

differences and predict intelligent behavior above and beyond *g* and the cognitive mechanisms that support *g*.

This dissertation attempts to go beyond *g* by considering human intelligence from a dual-process perspective. Dual-process theories conceptualize human cognition as consisting of controlled, explicit, and effortful processes as well as automatic, spontaneous, and rapid processes. The main thesis of this dissertation is that *g* is largely constrained by a central pool of limited capacity resources but that there are forms of cognition that are autonomous of a central pool of resources, have meaningful individual differences, and independently predict intelligent behavior. Therefore, intelligent behavior is conceptualized in this dissertation as jointly influenced both by Controlled and Autonomous forms of Cognition. Since both modes of thought are important contributors to intelligent behavior, intelligence is defined in this dissertation as the ability, desire, and Openness to Engagement in both modes of thought, as well as the ability to balance and flexibly switch modes of thought depending on task demands.

In support of the Dual-Process theory of human intelligence, evidence will be presented that individual differences in the ability to autonomously acquire information as well as the desire and Openness to Engagement in Autonomous Cognition predict intelligent behavior above and beyond Explicit Cognitive Ability. *Chapter 2: Methodology* describes the sample and the tasks that are analyzed in the dissertation. The presentation of the findings is then comprised of two main sections. The first part takes up ability, separating the variance in Controlled

Cognition from the variance in Autonomous Cognition. After the cognitive

mechanisms supporting Explicit Cognitive Ability are examined (*Chapter 3: Explicit*

Cognitive Ability), the relation between Explicit Cognitive Ability and two

Autonomous Information Acquisition Abilities—Implicit Learning (*Chapter 4:*

Implicit Learning) and Latent Inhibition (*Chapter 5: Latent Inhibition*)—are

investigated.

Implicit learning is an important part of intelligence and involves the ability

to automatically and nonconsciously detect complex regularities, contingencies, and

covariances in the environment. So much information enters our senses that if we

had to rely on Controlled Cognitive processes to process all this information, we

would quickly become overwhelmed. This ability is an important contributor to

various forms of intelligent behaviour, as nearly every aspect of human cognition

requires the ability to learn probabilistic information (i.e., information with noise)

that isn't explicitly stated but must be extracted through experience. As an example,

implicit learning is particularly important in social situations, in which an individual

must automatically infer emotionality from facial expressions, as well as extract

information from nonverbal cues. Those who are lacking in this ability may be

perceived as unintelligent in such social situations regardless of their Controlled

Cognitive functioning. At the same time, a certain degree of flexibility and Openness

to new information is also an important component of intelligence. Another

important contributor to intelligent behaviour is latent inhibition. Latent inhibition

is a pre-conscious gating mechanism that automatically inhibits stimuli that have

been previously experienced as irrelevant from entering awareness. Those with reduced latent inhibition are more likely to find information that was previously tagged as irrelevant novel and interesting. Reduced latent inhibition, in combination with at least a reasonable level of Controlled Cognitive functioning can lead to the highest levels of creativity (in which both novelty and usefulness are important) by allowing the individual to make connections that others may have automatically inhibited.

Section two explores the implications of self-reported Engagement in Controlled and Autonomous forms of Cognition. Many thoughts, feelings, and sensations come to us spontaneously and unexpectedly, but nonetheless may be adaptive and therefore can be an important contributor to intelligent behavior. Those with a desire and an Openness to Engaging in these cognitions may therefore be at an advantage for some forms of intelligent behavior. Controlled forms of Engagement include *Intellectual Engagement*, such as when an individual enjoys solving effortful puzzles and engaging in abstract thought. Autonomous forms of Engagement consist of *Affective Engagement*, such as when an individual uses his or her gut feelings to influence decision making or when he or she gets caught up in the experience of a live music concert, *Engagement in Aesthetics* such as when an individual is absorbed in a piece of artwork or poetry, or *Engagement in Fantasy*, such as when an individual is daydreaming or uses fantasy to imagine future selves. It is predicted that Openness to Engaging in these various forms of Controlled and Autonomous Cognition predict intelligent behavior above and beyond Explicit

Cognitive Ability. In *Chapter 6: Four-Factor Model*, a four-factor model consisting of *Explicit Cognitive Ability*, *Intellectual Engagement*, *Affective Engagement*, and *Aesthetic Engagement* is presented. Each form of Engagement is differentially associated with Controlled vs. Autonomous Cognition. In *Chapter 7: Personality*, *Chapter 8: Creative Achievement*, and *Chapter 9: Deductive Reasoning*, implications of the four-factor model are investigated for understanding personality, self-reported creative achievement, and deductive reasoning. In *Chapter 9: Deductive Reasoning*, Fantasy Engagement is also considered an important form of Autonomous Engagement contributing to intelligent behavior, as individuals reporting having an active fantasy life as well as an active imagination are more accurate and faster at contextualized deductive reasoning even after controlling for Explicit Cognitive Ability. *Chapter 10: General Discussion* then concludes by suggesting new avenues of research for intelligence researchers.

By investigating relations among these variables, and differential patterns of relations with other important psychological variables such as academic achievement, domain-specific cognitive abilities, personality, self-reported creative achievement, and deductive reasoning, this dissertation aims to expand the range of intelligent behaviors that intelligence researchers predict. Another aim of the current dissertation is to expand the study of human intelligence from a focus on Explicit Cognitive Ability to include the study of Autonomous Cognitive processes and the desire and Openness to Engagement that are associated with such processes, thereby coming to a more complete scientific understanding of human

intelligence. In particular, this dissertation combines two research traditions that have traditionally been investigated separately from one other—the study of human intelligence and the study of the adaptive unconscious.

Integrating two research traditions

The 20th century witnessed at least two major paradigm shifts within psychological science. One major shift was from behaviorism to the "cognitive revolution", which brought along it a shift in focus from learning and conditioning to investigating the mental processes involved in conscious thought, including memory, thinking, and problem-solving (Miller, 2003). This shift has had an enduring effect on conceptualizations of human intelligence as well as research methodology. Indeed, one of the earliest investigators of the development of intelligence in children was Jean Piaget (1952), whose focus was on conscious higher-order reasoning and how children at different ages think. This emphasis on age differences in thought as well as the notion that intelligence involves conscious, deliberate reasoning also underlies the logic behind the first widely administered intelligence test, the Binet-Simon Scale (Binet & Simon, 1916). Furthermore, the discovery that performance on diverse tests of explicit cognitive ability tend to correlate with one another, Spearman's (1904) so-called 'positive manifold' further supported the idea that intelligence tests are tapping into a 'general cognitive ability'.

Around the same time that the shift from behaviorism to the cognitive revolution was taking place, another dramatic shift in psychology was occurring.

The conceptualization of the unconscious that was predominant with

psychodynamic theories of personality was slowly being transformed into an

unconscious recognized to serve many adaptive functions both amongst modern

day humans as well as our evolutionary ancestry (Hassin, Uleman, & Bargh, 2005).

Over 30 years of research in cognitive science reveals that a considerable amount of

information processing takes place on a daily basis automatically—without our

intent, awareness, and deliberate encoding—and plays a significant role in

structuring our skills, perceptions, and behavior (Hassin, et al., 2005; Kihlstrom,

1987; Lewicki & Hill, 1987; Lewicki, Czyzewska, & Hoffman, 1987; Reber, 1967;

1993, Stadler & Frensch, 1997).

Even though some of these nonconscious representations were once

conscious and have become automatized (e.g., tying a shoe, driving a car, etc.),

research shows that quite complex nonconscious mental processes can operate on

knowledge structures that are in themselves preconscious. John Kihlstrom (1987)

has coined these mental structures the "Cognitive Unconscious". Over the past 30

years or so, there's been a plethora of research demonstrating the sophisticated and

intelligent nature of the cognitive unconscious (Lewicki, Hill, & Czyzewska, 1992;

Loftus & Klinger, 1992). In fact, after reviewing the literature on the nonconscious

acquisition of information, Lewicki, Hill, and Czyzewska (1992) ask "Is the

nonconscious information-processing system 'intelligent'?" to which they conclude:

"The answer to the question about intelligence would be affirmative if intelligence is

understood as 'equipped to efficiently process complex information.' In this sense,

our nonconscious information-processing system appears to be incomparably more able to process formally complex knowledge structures, faster and 'smarter' overall than our ability to think and identify meanings of stimuli in a consciously controlled manner (p. 801)".

Today there is a strong consensus amongst contemporary researchers in cognitive science, philosophy, cognitive psychology, social psychology, reasoning, and morality that humans possess these quite distinct modes of thought—one controlled, and the other automatic (Posner & Snyder, 1975; 2004; Schneider & Shiffrin, 1977). Indeed, it is increasingly recognized that dual-process theories of cognition are required for explaining cognitive, personality, and social phenomenon (Evans & Frankish, 2009). However, while intelligence researchers have done a remarkable job developing tests that measure individual differences in intentional, deliberate, reflective cognitive processes, an investigation of individual differences in domain-general automatic, associative, nonconscious processes has not received nearly as much attention. Furthermore, while researchers of the cognitive unconscious have investigated the nature of the unconscious using the experimental approach, they have tended to treat individual differences as "noise" (error variance), or have posited that whatever individual differences in implicit cognition do exist are minimal (Reber, 1993; Stanovich, 2009b).

This situation of mutual neglect has had the unfortunate consequence of limiting our picture of both the nature of human intelligence and the cognitive unconscious, thus potentially limiting our understanding of the role of individual

differences in information processing in complex cognition more generally. The study of individual differences in the cognitive unconscious can increase understanding of the nature of intelligence by helping to find boundary conditions for so-called general intelligence and by doing discovering where g breaks down. Similarly, the study of individual differences in general intelligence and its associated cognitive mechanisms can elucidate the nature of the cognitive unconscious by helping to clarify and delineate automatic, spontaneous, and rapid information processing mechanisms. In the next section, I will discuss extant dual-process theories and the nature of the two systems of thought.

Dual-process Theories

The idea that humans have two information processing routes that influence human behavior—one controlled, slow, and deliberative and the other automatic, rapid, and high capacity—goes back at least as far as William James (1890) and Freud (Freud, 1900/1976), whose ideas were greatly influenced by brain researchers such as the Neurologist John Hughlings Jackson (1958) and the British Physician A.L. Wigan (1844). Dual-process theory has also been prominently featured in a variety of research programs over the past 30 years [see Table 1-1 for a list of various dual-process theories, only one of which (M. Anderson, 1992) is explicitly a theory of human intelligence]. System 1 is thought to be evolutionarily older (Reber, 1993) and comprise a set of autonomous subsystems (Stanovich, 2004) that include both innate input modules (Fodor, 1983) and domain-specific knowledge acquired by domain-general learning mechanisms that operate

automatically and efficiently (Reber, 1993; Evans, 2003). This system processes

information fast (relative to System 2), is heavily influenced by context, biology, and

past experience, and aids humans in mapping and assimilating newly acquired

stimuli into pre-existing knowledge structures.

Table 1-1
Dual-process theories

Researcher	System 1	System 2
M. Anderson (1992)	Route 2 / Knowledge	Route 1 / Thought
Baumeister (2005)	Automatic	Conscious
Bruner (1986)	Narrative	Paradigmatic
Chaiken (1980)	Heuristic	Systematic
Epstein (1994)	Experiential system	Rational system
Evans (1984; 1989)	Heuristic processing	Analytic processing
Evans & Over (1996)	Tacit thought processes	Explicit thought processes
Fodor (1983, 2001)	Input modules	Central systems
Freud (1900/1976)	Superego	Id
Hammond (1996)	Intuitive cognition	Analytical cognition
James (1890)	Associative	True
Johnson-Laird (1983)	Implicit inferences	Explicit inferences
Kahneman (2003)	Intuition	Reasoning
Klein (1999)	Recognition-primed decisions	Rational choice strategy
Levinson (1995)	Interactional intelligence	Analytic intelligence
Lieberman (2007)	Reflexive	Reflective
Metcalfe & Mischel (1999)	Hot	Cool
Nisbett et al. (2001)	Holistic	Analytic
Paivio (2007)	Nonverbal system	Verbal system
Pollock (1991)	Quick and inflexible modules	Intellection
Posner & Snyder (1975; 2004)	Automatic activation	Conscious processing
Reber (1993)	Implicit cognition	Explicit learning
Shiffrin & Schneider (1977)	Automatic processing	Controlled processing
Sloman (1996); Smith & DeCoster (2000)	Associative system	Rule-based system
Stanovich (2004; 2009b)	Autonomous (TASS)	Algorithmic and Reflective
Strack & Deustch (2004)	Impulsive	Reflective

Toates (2006)	Stimulus-bound	Higher-order
Wegner (Wegner, 1994)	Ironic monitoring process	Intentional operating process
Wilson (2002)	Adaptive unconscious	Conscious
Zajonc (1980)	Feeling	Thinking

Note: The labels "System 1" and "System 2" adopted here can be traced back to Kahneman & Frederick, 2002 and Stanovich, 1999.

An advantage of this system over System 2 is that it requires little conscious cognitive effort, and frees attentional resources for computationally complex reasoning. Indeed, according to Lewicki, Hill, and Czyzewska (1992), "Data indicate that as compared with consciously controlled cognition, the nonconscious information-acquisition processes are not only much faster but are also structurally more sophisticated, in that they are capable of efficient processing of multidimensional and interactive relations between variables. Those mechanisms of non-conscious acquisition of information provide a major channel for the development of procedural knowledge that is indispensable for such important aspects of cognitive functioning as encoding and interpretation of stimuli and the triggering of emotional reactions (p. 796)".

Indeed, in the social cognition literature, there is an emerging consensus that most of our behaviors and judgments are in fact made automatically, without intention, effort, or awareness (Bargh, 1994, 2006; Bargh & Chartrand, 1999; Greenwald & Banaji, 1995). Research on automatic evaluation (Bargh, Chaiken, Raymond, & Hymes, 1996; Fazio, Sanbonmatsu, Powell, & Kardes, 1986), impression formation (Albright, Kenny, & Malloy, 1988), and automatic characterization (Devine, 1989) all demonstrate the prevalence of automaticity in social life. It is

generally thought now that mere perception of a stimulus can lead instantly and automatically to a judgment without any conscious reflection or reasoning (Bargh, 1994). Along similar lines, Dijksterhuis & Nordgren (2006) conceptualize the cognitive unconscious as more powerful and prevalent than conscious thought and pre-meditation. They have applied their Unconscious-thought theory (UTT) to a broad range of phenomenon, such as decision making, impression formation, attitude formation and change, problem solving, and creativity. Dijksterhuis & Nordgren's (2006) theory is one of the most nuanced theories, in that they argue that both conscious and unconscious thought is preferable under different task demands and circumstances, with conscious thought better suited for "simple" issues, and unconscious thought left to complex matters.

The advantages of System 1 can also serve as disadvantages under certain circumstances. When thinking is dominated by System 1, task representations are highly contextualized. This can lead to the thoughtless application of judgment and decision heuristics. According to Stanovich & West (2000), this mode of thought is in fact "default" in humans. They refer to this tendency toward automatic contextualization of problems as the "fundamental computational bias" in human cognition (Stanovich, 1999; Stanovich & West, 2000). A similar idea can be found in Chaiken's (1987) heuristic systematic model of persuasion, where people are guided in part by a "principle of least effort." Because people have limited cognitive resources, and because heuristic processing is easy and adequate for most tasks, heuristic processing from System 1 is generally used unless there is a special need

to engage in systematic processing (see also Simon, 1979). In line with this idea, Klaczynski & Cottrell (2004) have argued that "metacognitive intercession" often occurs, where responses derived from intuition are available in working memory, where reflection is possible. However, according to Klaczynski, most people do not take advantage of the opportunity to reflect on the contents of working memory, taking the contents from the experiential system as self-evidently valid. Finally, the view of System 1 as the default mode of human cognition is also present in Haidt's (2001) social intuitionist model of moral reasoning, where it is posited that intuitive processing is the default process, with deliberate reasoning called upon only when intuitions conflict with reason (see also Stanovich & West, 2000).

In contrast, System 2 is often characterized by deliberately controlled, effortful, and intentional cognition. According to Stanovich & West (Stanovich & West, 1997), a hallmark of this type of thought is the ability to decontextualize task representations. It can deal with abstract content, and is not dominated by the goal of attributing intentionality nor by the search for conversational relevance (Margolis, 1987). It has been posited that System 2 is evolutionarily more recent and uniquely developed in humans (Evans, 2008; Gabora & Kaufman, 2009). It makes evolutionary sense that two systems of thought would persist in the human mind today, constantly interacting and competing with each other to aid humans in making sense and reasoning through our environment. Just because humans evolved what is often referred to as a "higher consciousness" does not mean that the learning system that was already in place in our ancestors and had already been

operating for millions of years in many related species would suddenly disappear (Reber, 1993; Dennett, 1992, 1996, 1997). After all, there is a long line of psychological research showing that many animals that do not have a "consciousness" still can be conditioned to perceive causal relationships and form complex hierarchical associations (Mackintosh, 1998).

It should be noted that while there are some aspects which are common across most dual-process theories, there are also distinct differences (Evans, 2008; see Table 1-2 for a list of attributes that have been proposed to underlie the two systems). Most dual-process theorists agree on the automatic/controlled distinction between the two systems, as well as the idea that one system is constrained by a central working memory system whereas the other system is unconstrained by a central pool of resources. Dual-process theorists differ, however, in terms of other features they attribute to the two systems. For instance, some dual-process theorists emphasize the affective nature of System 1 (Epstein, 1994; Metcalfe & Mischel, 1999; Zajonc, 1980) whereas emotions aren't a key component of other models of the implicit cognition system (e.g., Reber, 1993). Also, as Evans (2008) rightly points out, some of the distinctions between the two systems (e.g., abstract vs. contextualized, associative vs. rule-based, shared with other animals vs. unique to humans) are not as neat and clear cut when one considers the fact that System 1 isn't a unitary system, but includes a set of autonomous systems, some which are innately specified and some which come about through learning and practice (Stanovich, 2004). Evans (2008) also points out that even System 2 is most likely

not a unitary system, suggesting that not all System 2 processes are consciously

controlled.

Table 1-2
Properties of the Two Systems

System 1	System 2
Automatic	Controlled
Spontaneous	Directed
Unintentional	Intentional
Parallel distributed processing	Serial processing
Fast	Slow and effortful
Does not demand control of attention	Demands control of attention
Acquisition by biology, mere exposure, or personal experience	Acquisition by conscious, deliberate mechanisms
Default	Inhibitory
Context dependent	Can operate on abstract material
Pattern matching; Holistic processing	Symbol manipulation; analytical thought
Implicit	Explicit
Common to all mammals	Uniquely developed in humans
Associative	Rule-based

Indeed, Evans argues that "We might be better off talking about type 1 and

type 2 processes since all theories seem to contrast fast, automatic, or unconscious

processes with those that are slow, effortful, and conscious…My suggestion is that

type 2 processes are those that require access to a single, capacity-limited central working memory resource, while type 1 processes do not require such access (p.270)". In the current dissertation, I follow Evans criteria and refer to processes that are either Controlled or Autonomous. In the next section I present a dual-process theory of human intelligence that consists of these two main cognitive components.

The Dual-Process Theory of Human Intelligence

The dominant approach to understanding individual differences in human intelligence, dating back at least 100 years, has been a psychometric one. The underlying assumption of the psychometric approach is that patterns of correlations can be simplified with sophisticated factor analyses techniques to discover the structure of human mental abilities. Even today, "the wide-eyed optimism that 'if-only-we-get-our-measures-right-and-derive-reliable-replicable-associations-then-we-can-eschew-hot-air-speculations-about-the-nature-of-intelligence-and-get-on-with-the-job-of-normal-sciences-of-collecting-sensible-data-bit-by-bit' is still with us (M. Anderson, 2005, p. 283)."

While the psychometric approach has certainly increased our understanding of the structure of some forms of mental abilities, a major limitation of the psychometric approach is that you only get out of the factor analysis what you put into the factor analysis. I believe that an exclusive focus on the factor analysis of explicit cognitive tasks that require cognitive control and Central Executive processes has unintentionally impeded progress toward a more complete

understanding of the determinants of intelligent behavior. As Anderson rightly points out, theory can be useful by giving facts their meaning and stimulating new research. According to Anderson, "In short, generating theories is not some superfluous affectation but what science is all about... Theories simply represent our current best understanding of the world, and understanding the world is what science is all about—not unearthing 'facts', no matter how replicable...It is the failure of individual-differences researchers to take theories seriously that has impeded scientific progress in the field (p. 283)".

To my mind, our current understanding of human cognition is that it involves two information-processing routes—one controlled and another more automatic. A theory is needed that incorporates individual differences in automatic information-processing mechanisms to balance out the predominant focus of intelligence researchers on individual differences in explicit cognitive ability, effortful reasoning, and cognitive control. I believe that such an exclusive focus on abstract reasoning processes, measured by tests that are intentionally designed to strip away the activation of automatic processes, has impeded progress toward coming to a more complete understanding of the determinants of human intelligent behavior.

Indeed, such a theory will require nothing less than sensitivity and consideration of the entire current body of knowledge researchers have acquired about both controlled and automatic processes, being open to the research conducted by cognitive psychology, social psychology, evolutionary psychology and other sub-disciplines and disciplines. At the same time, I do not want to discount the

important research conducted on Explicit Cognitive Ability. Indeed, a major criticism leveled against theories of multiple intelligences is that they discount the role of Central Executive Functions that are important across a wide range of intelligent behavior (Lohman, 2001). In closing this section, I once again quote Anderson from the same book chapter, since he puts it so elegantly:

"What constrains a theory of intelligence is neither a methodological approach nor any a priori belief that intelligence is a property of genes, neurophysiology, education, or culture but rather it is the research agenda for that theory- or more prosaically what it is that such a theory wants to explain. It is the research agenda that determines the level of description and explanation for that theory. For the psychology of intelligence and its development, that research agenda clearly requires a cognitive theory (p. 284-285)."

It is with this worthy ideal in mind that I propose the Dual-Process (DP) Theory of Human Intelligence.

Basic Tenets

The idea that there are both controlled-reflective and automatic-impulsive determinants of social behavior is not controversial (see Strack & Deutsch, 2004 for a reflective-impulsive model of social behavior). Indeed, in social psychology there is currently a flurry of research and books on the topic of the automaticity of social behavior and on the interactions between controlled processes and the "new" adaptive unconscious in explaining everyday social life (Bargh, 1997; Bargh & Williams, 2006; Hassin, et al., 2005; Bargh, 1997; Wyer, 1997).

The central tenet of the DP theory of human intelligence is that intelligent behavior is also a product of controlled and automatic processes. Not all intelligent behaviors are alike though—intelligent behaviors differ in the ratio of controlled and automatic processes required for successful performance. Performance on the very best measures of *g* will maximize control processes and minimize automatic processes (although automatic processes in the form of enculturation still will play a role), whereas abilities such as automatically and nonconsciously detecting complex covariations in the environment will draw more on the successful operation of automatic information acquisition mechanisms.

According to the DP model, measures of *g* index an important aspect of human intelligence that is "general" in the sense that the processes tapped by *g* are important (albeit in varying degrees) across nearly every aspect of human cognitive life. The model goes beyond *g* though and proposes that there are also domain general information acquisition mechanisms that are automatic and not constrained by a central pool of resources, and also make a significant contribution to nearly every aspect of cognitive life. A very similar idea was proposed by Mackintosh (1998) when he argued for the existence of two domain general learning systems in humans—a domain general cognitive learning system and a domain-general associative learning system. Therefore, according to the DP theory, by limiting our understanding of human intelligence to performance on tests that were intentionally designed to maximize controlled processes, we may be limiting our measurement of individual differences in other important cognitive processes.

Indeed, David Wechsler, developer of one of the most commonly administered IQ tests, argued that a complete theory of human intelligence would have to take into account non-intellective aspects of human cognition (Wechsler, 1943). So in the spirit of Wechsler, as well as staying true to the differential tradition of intelligence research dating back to Spearman (1904), the DP theory is a model of individual differences in both Controlled and Autonomous Cognitive processes. This focus on individual differences in both systems of thought is what makes the theory unique among extant theories of human intelligence.

The DP theory consists of two major cognitive components: Controlled Cognition and Autonomous Cognition. Each component is thought to have a separate evolutionary ancestry (Gabora & Kaufman, 2009) and involves the ability, desire and Openness for engaging in the respective components. A key assumption of the DP model is that ability and engagement are correlated with each other because people tend to engage in things that they are good at, and avoid engaging in things they are not good at (Achter, Lubinski, Benbow, & Eftekhari-Sanjani, 1999; Humphreys, Lubinski, & Yao, 1993). Ability and engagement influence each other, however. The more one engages in a mode of thought, the more that individual will develop skill and ability in that mode of thinking, which can then increase a desire for engagement in that skill. Many research results suggest that at least 10 years of concentrated effort and engagement in a domain is required before an individual has accumulated enough knowledge to move the boundaries of a field forward (Ericsson, 1996; Gardner, 1993a; Kaufman & Kaufman, 2007; Simonton, 1988, 1994;

Zuckerman, 1977). Further, the more knowledge that is acquired, the more information the Autonomous System has to process, and the less Controlled Cognition has to play a role in processing new information. Therefore, Engagement can override Central Executive deficits and predict performance above and beyond Explicit Cognitive Ability. Mindset also plays a significant role in the Engagement aspect regardless of Explicit Cognitive Ability. For instance, Carol Dweck (2006) has argued that incremental theorists who believe that intelligence is malleable are more likely to engage in things they are not good at than are entity theorists who believe that intelligence is fixed. Therefore, incremental theorists may engage in a mode of thought regardless of ability, which then influences their ability, which in turn influences their engagement. Future research might benefit from investigating the prediction of engagement and self-theories on important outcomes above and beyond the effects of Explicit Cognitive Ability.

The proper functioning of each component is supported by different brain regions. As an approximate guide to what these brain regions might be, Lieberman's (2007) "C-system" can be approximately mapped onto the Controlled Cognition component, and Lieberman's "X-system" can be approximately mapped onto the Autonomous Cognition component. While Lieberman's two systems are specifically tied to social processes, his brain systems also play a role in reasoning and decision making. According to Lieberman, at the heart of the C-System is the Lateral Prefrontal Cortex (LPFC), as it is involved in tasks that are controlled, intentional, and effortful. Other brain regions associated with the C-System are the Medial

Temporal Lobe (MTL), Posterior Parietal Cortex (PPC), Rostral ACC (rACC), Medial

Prefrontal Cortex (MPFC), and the Dorsomedial PFC (DMPFC).

In contrast, Lieberman argues that brain regions underlying the X-System are

activated under conditions that promote automatic, implicit, or nonconscious

processes. According to Lieberman, these brain regions consist of the amygdala,

basal ganglia, lateral temporal cortex (LTC), ventromedial prefrontal cortex

(VMPFC), and dorsal anterior cingulate cortex (dACC). In the words of Lieberman,

"Whereas X-system processes may be linked to our ongoing experience of the world,

coloring in the semantic and affective aspects of the stream of consciousness, the C-

system, and LPFC in particular, appears to be linked to our experiences of

responding to the world and our own impulses with our freely exerted 'will'" (p.

296)". While these brain regions roughly underlie the two main components, each of

the subcomponents of Controlled Cognition and Autonomous Cognition most

certainly have their own unique network of brain area activations, the default

network being a particularly promising candidate for explaining the functioning of

certain sub-components of Autonomous Cognition, especially forms of engagement

relating to Aesthetics and Fantasy (Buckner, Andrews-Hanna, & Schacter, 2008).

In the DP model, the key distinction between the two components is that

individual differences in Controlled Cognition are constrained by a central pool of

resources, whereas Autonomous Cognition operates independently of a limited-

capacity Central Executive. Therefore, the word Autonomous is used here to indicate

independence from the information processing limitations that the Controlled

Cognition component is dependent upon. The term "Autonomous" in reference to cognitive processing can also be found in the writings of Dennett (1997) when he refers to the "Autonomous Mind". The Autonomous Mind is also part of Stanovich's (2009a, 2009b) tri-process model, in which he explicitly borrows Dennett's term. In Stanovich's model, however, there are no continuous individual differences in the Autonomous Mind, whereas in the DP model individual differences in Autonomous Cognition are an important contributor to our understanding of variation in intelligent behavior.

In line with these two components is Alfred Binet's definition of intelligence: "[It] consists of two chief processes: First to perceive the external world, and then to reinstate the perceptions in memory, to rework them, and to think about them" (translation by Carroll, 1993, p. 35). Borrowing this idea, a major tenet of the DP model is that there are individual differences in the ability, desire, and Openness to perceive and experience the external world, as well as to control thought. Further, the major tenet of the theory is that neither component is more important than the other, but what's important is the functional integration of both components in a yin-yang complementary fashion (Frisch, 2000). Therefore, it is the appropriate (to the situation) balance of the two components that is the key to intelligence. Further, an important aspect of intelligence, according to the DP model, is the ability to focus attention and use Controlled Cognitive processes or defocus attention and use Autonomous Cognitive processes depending on the task requirements (for

applications of this idea to creativity, see Gabora, 2003, in press; Gabora & Kaufman, 2009; Howard-Jones & Murray, 2003; Martindale, 1995).

It should be noted that every input that comes through our senses requires some combination of both Controlled and Autonomous processes. I am not claiming that the two components are entirely separable. Tasks differ to the extent that they measure Controlled or Autonomous Cognitive processes. In fact, a currently active area of research is the attempt to parse controlled and automatic influences on behavior, using the process-dissociation technique (see Jacoby, 1991; Payne & Stewart, 2007; Reber, Ruch-Monachon, & Perrig, 2007). Further, for most people, most of the time the two systems may operate independently but they certainly work together to determine behavior. A major aim of this dissertation is to investigate sources of variance that are not common between the two types of cognition yet independently predict other important variables, using tasks that are carefully designed and constructed to evoke Controlled and Autonomous processes.

Figure 10-1 shows a hierarchical graphical representation of the theory. In each rectangle is a construct that I argue represents unique sources of individual differences that are worthy of investigation in their own right. (It should be noted that the size of the rectangles do not have meaning, they are different sizes strictly for organizational purposes.) At the top of the hierarchy are general constructs and at the bottom of the hierarchy are the most specific constructs. Not all tests that are purported to measure the construct in each rectangle necessarily correlate with each other. It will be up to future research to investigate the particular factor

structure of each construct. Bi-directional arrows in the model represent additional correlations between variables that were discovered in the current dissertation. (The exception is the bi-directional arrow between the Updating component of Central Executive Functioning and Working Memory, which was added to stress the idea that these two constructs are highly related to each other). Hopefully this model will stimulate intelligence researchers to investigate sources of variance that haven't been previously considered, as well as interactions between the sources of variance. Below I will describe the two main components of the theory in more detail, starting with Controlled Cognition.

Figure 1-1
The Dual-Process (DP) Theory of Human Intelligence
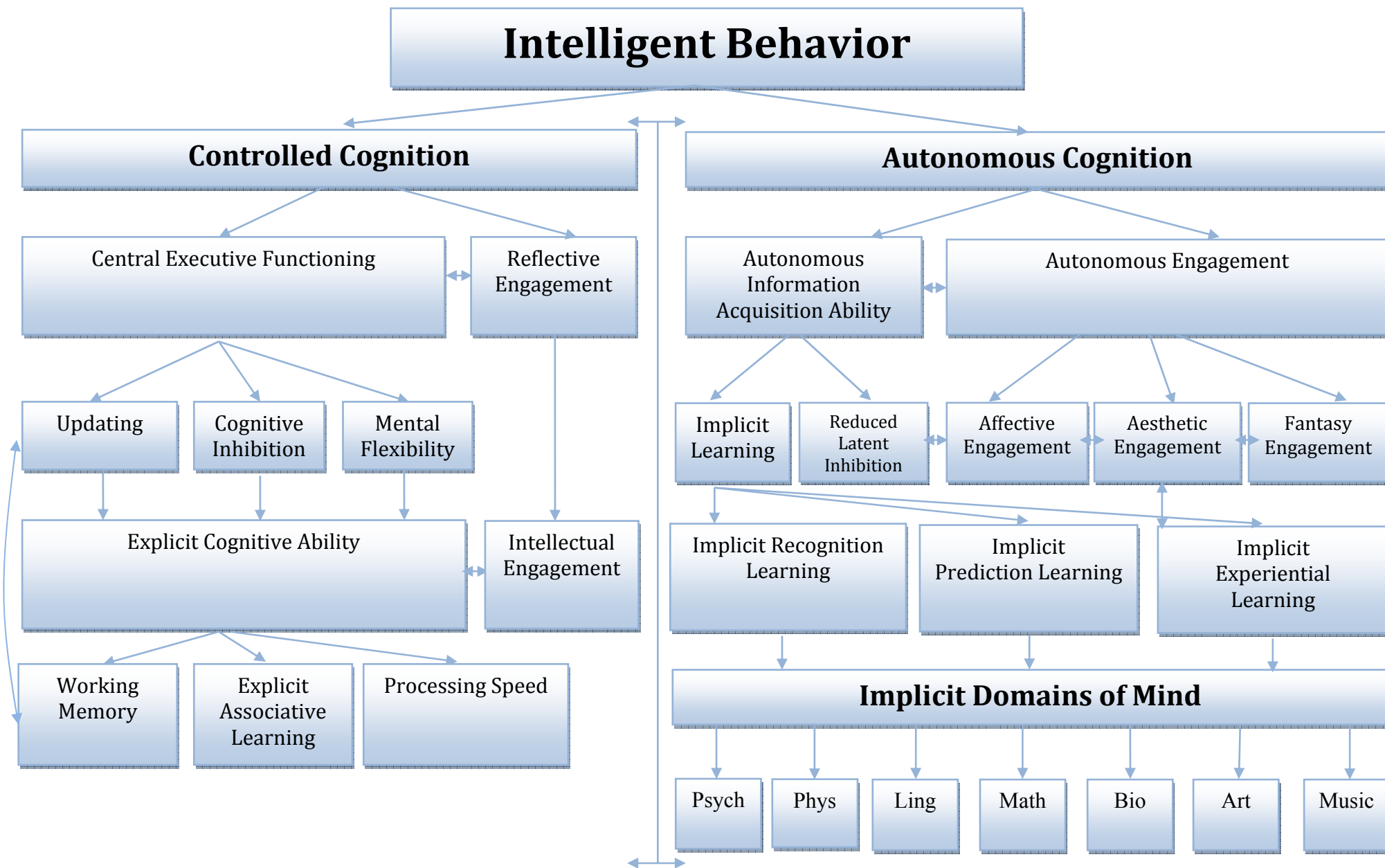
Controlled Cognition

Louis Thurstone (1924), another seminal intelligence researcher, defined

intelligence as the ability to exhibit self-control over instinctive impulses, arguing

that inhibiting such impulses allows one to rationally consider options. Echoes of

this idea can be found in Stanovich's (2009a, 2009b) tri-process theory, in which he

considers rationality a construct that comprises both *g* and a rational thinking

disposition. Similarly, Sternberg (1988) has argued that "mental self-management"

(p.72) is an important aspect of human intelligence that allows an individual to

adapt, select, and shape the environment. Indeed, a key set of processes in

Sternberg's (1988) triarchic theory of human intelligence are Central Executive

processes such as goal setting, goal management, and monitoring. Appreciating that

the capacity for control is an important component of human intelligence (although

arguing it's not the only aspect of intelligence), the construct *Controlled Cognition* is

at the top of the hierarchy in the DP model, alongside *Autonomous Cognition*.

Consistent with prior theorizing, I am conceptualizing Controlled Cognition as the

ability and desire across situations to control thinking about thinking (Dennett,

1992), reflect on prior behavior, and use that information to modify behavior and

plan for the future.

At the level underneath Controlled Cognition are two distinct sources of

variance: *Central Executive Functioning* and *Reflective Engagement*. Controlled

Cognition is intimately tied to the functioning of the Central Executive in the frontal

lobes, particularly the dorsolateral prefontal cortex. The various Central Executive

functions cohere well together, inter-correlating with each other and influenced by a highly heritable (99%) common factor (Friedman, et al., 2006, 2008). Indeed, Friedman et al. 2008 argue that Central Executive functions are among the most heritable psychological traits. Even though Central Executive functions are heritable, they certainly can be improved (see Jaeggi, Buschkuehl, Jonides, & Perrig, 2008; Klingberg, 2008; Klingberg, et al., 2005; Klingberg, Forssberg, & Westerberg, 2002; Olesen, Westerberg, & Klingberg, 2004; Thorell, Lindqvist, Nutley, Bohlin, & Klingberg, 2009; Westerberg, et al., 2007; Westerberg & Klingberg, 2007).

This level of the hierarchy also consists of *Reflective Engagement*, which reflects a tendency to engage in reflection and deliberation. This construct is similar to the UPPS impulsivity dimension premeditation (Whiteside & Lynam, 2001; see *Chapter 7: Personality*), as well as Baron's (1985) Actively Open-Minded Thinking construct (e.g., "The disposition to spend a great deal of time (or very little) on a problem before giving up, or the disposition to weigh heavily the opinions of others in forming one's own (p. 15)." Many items relating to Reflective Engagement can be found on Stanovich and West's (1997) measure of Active Open-Minded Thinking, such as items relating to epistemological absolutism, willingness to perspective-switch, willingness to decontextualize, and the tendency to consider alternative opinions and evidence. Indeed, the "Reflective Mind" is a prominent part of Stanovich's (2009a, 2009b) rational system in his tri-process model of rationality. My prediction is that this form of engagement is correlated with Central Executive functioning, since many of the item types just mentioned bear a striking

resemblance to the types of abilities tapped into by various measure of Central Executive Functioning (e.g., Friedman, et al., 2006). However, separating out these two sources of variance (*Central Executive Functioning* and *Reflective Engagement*), hopefully will spur research investigating linkages and interactions between the two constructs.

The Central Executive, however, is not unitary. The next level of the hierarchy represents at least three distinct sources of variance in relation to Central Executive Functioning that have been identified: the ability to update working memory representations (labeled *Updating*), the ability to inhibit prepotent responses (labeled *Cognitive Inhibition*), and the ability to shift mental sets (labeled *Mental Flexibility*) (Friedman, et al., 2006, 2008). While related to Explicit Cognitive Ability, each of these set of measures are distinct and worthy of investigation in their own right. Further, while all of these functions do cohere well together (thus the more general construct at the higher level of the hierarchy), each Central Executive Function is also separable, having unique sources of genetic variance associated with each function (Friedman, et al., 2008). It should be noted that there may even be separable processes within each type of Central Executive Function that have their distinct sources of variance. For instance, Friedman & Miyake, 2004 found that three cognitive inhibition-related functions (Prepotent Response Inhibition, Resistance to Distractor Interference, and Resistance to Proactive Interference) were not all related to each other and to other real world outcomes such as thought intrusions.

At the next level of the hierarchy is *Explicit Cognitive Ability* (ECA), the ability formerly known as "*g*" (see *Chapter 3: Explicit Cognitive Ability*). The choice to include Explicit Cognitive Ability at a separate level in the hierarchy from Central Executive Functioning has empirical justification: Friedman et al. (2008) found that the common variance across various Central Executive Functions are influenced by a highly heritable (99%) common factor that goes beyond *g* and processing speed. Nonetheless, Explicit Cognitive Ability is heavily influenced by the proper functioning of Central Executive processes, particularly the Updating component. In fact, Friedman et al., (2006, 2008) demonstrated that the updating function of working memory is the only Central Executive process that is correlated with *g*. This provides further justification for not equating Explicit Cognitive Ability with a unitary Central Executive System, and suggests that the study of individual differences in various Central Executive Functions are worthy of study in their own right, apart from the investigation of Explicit Cognitive Ability. Additionally, in my view, framing things in this way puts Spearman's *g* into perspective, and more clearly defines the cognitive mechanisms that support *g*. According to the DP model of intelligence, *g* is certainly an important construct and does represent an important aspect of human cognition, but it is only part of a larger construct *Central Executive Functioning*, which is in turn part of the larger construct *Controlled Cognition*.

To be more precise, *ECA* reflects the ability to apply Central Executive processes (particularly the updating component) to a complex task with explicitly

stated instructions and an explicit goal. This ability involves the capacity to concentrate, block out irrelevant stimuli, store and retrieve relevant associations, and manipulate representations in one's head in order to explicitly discover patterns and produce abstract generalizations. Another important aspect of ECA is the ability to sustain an internal cognitive representation in the presence of distraction by decoupling representations (Stanovich & West, 2000). This ability to manage representations comes into play quite well on tasks that are excellent markers of *g*, such as the Ravens Advanced Progressive Matrices (Carpenter, Just, & Shell, 1990; also see *Chapter 6: Four-Factor Model*), as well as on tasks where individuals must represent a belief as distinct from the current environment they are representing (Stanovich, 2009b). This ability also helps to prevent representations of the real world from being confused with imaginary representation and fantasy (Gendler, 2006; Leslie, 1987; Nichols & Stich, 2003). In this way, ECA may serve as a protective function that inhibits Autonomous Cognition from determining too much of behavior.

This level of the hierarchy also consists of *Intellectual Engagement*, which reflects a desire, enjoyment—indeed some would say '"need" (Cacioppo & Petty, 1982)—to engage in intellectual matters. Those higher in a typical level of Intellectual Engagement are willing to devote more energy and invest more in their intellectual development (Goff & Ackerman, 1992). Note that while related, I am arguing that this construct is separable from *Reflective Engagement*. I am basing this argument on the finding that Intellectual Engagement is not related to the UPPS

dimension Premeditation (see *Chapter 7: Personality*), which I am arguing is a good marker of Reflective Engagement. Therefore, the individual who desires to engage in solving abstract, challenging puzzles isn't necessarily more reflective in their daily lives. The results of *Chapter 7: Personality* suggests that Intellectual Engagement is more related to Perseverance and Conscientiousness, hence "Self-Discipline", not "Reflection". Although the two constructs are most likely related (due to linkages with Central Executive Functioning), I am arguing that both sources of variance are worthy of investigation in their own right. Further, although Explicit Cognitive Ability and Intellectual Engagement are related, Intellectual Engagement does not necessarily *require* high Explicit Cognitive Ability. Indeed, anyone with a normal, healthy functioning brain certainly has the capability, given the right resources (e.g., money for books) and prerequisite expertise, to engage in intellect. Indeed, a desire for Intellectual Engagement is something that can be fostered in schools and by society. Whether those with higher Explicit Cognitive Ability learn material faster than an individually equally matched in terms of engagement but with less functioning is a separate issue. According to the DP model, the two sources of variance will be at least modestly inter-correlated, with the underlying assumption that the two constructs are mutually beneficial to each other—engagement in intellect builds intellectual skills, and improved intellectual skills increase an individual's desire for Engagement in Intellect.

At the lowest level of the hierarchy are Elementary Cognitive Tasks (ECTs; see Jensen, 1998) that support performance on measures of Explicit Cognitive

Ability. The full range of ECTs has yet to be unearthed, and remains an important line of research. Recently, a number of different models of working memory have been put forward (Miyake & Shah, 1999), but all agree that it involves the ability to store and hold information for a brief period of time while other cognitive decisions or operations are taking place, and the ability to manipulate that information or use it to guide action (Baddeley, 1986; Goldman-Rakic, 1987; Kane & Engle, 2002). Explicit Associative Learning involves the ability to deliberately encode associations among stimuli and explicitly recall them at a later point in time, and processing speed is the speed that rather simple operations can be performed. In the current dissertation, all three of these ECTs made independent contributions to the variance in Explicit Cognitive Ability (see *Chapter 3: Explicit Cognitive Ability*). It should be noted, however, that implicit learning was also related to processing speed (see *Chapter 4: Implicit Learning*). Therefore, processing speed may reflect some dimension of information processing that plays a role in both Controlled Cognition and Autonomous Cognition. As such, processing speed isn't included in the latent Explicit Cognitive Ability factor (see *Chapter 6: Four-Factor Model*).

Autonomous Cognition

The second main component of the DP model is *Autonomous Cognition*. At the broadest level, individual differences in Auotonomous Cognition reflect the ability to acquire information automatically and the desire as well as openness to Engage in Autonomous forms of cognition. Autonomous Cognition is the default mode of cognition in humans, and is highly contextualized. Further, this mode of cognition

most likely has strong ties to the default network of the brain, a network that consists of brain regions associated with task unrelated thoughts, fantasy, and imagination (Buckner, et al., 2008). Autonomous Cognition can be either conscious, such as when an individual is consciously aware of their daydreaming, fantasy, or mind wandering, or nonconscious such as when an individual is dreaming, mindwandering without conscious awareness, implicitly learning the underlying rule structure of the environment in order to predict the future or nonconsciously allowing task unrelated information to enter consciousness (while the end result enters consciousness, the latent inhibition mechanism may be nonconscious). To the extent that Controlled Cognition supports Autonomous Cognition (e.g., as in conscious Fantasy Engagment when it is imporant to sustain a particular aspect of an elaborate fantasy in one's working memory while performing elaborate transformations on another aspect of the fantasy), Autonomous Cognition will be correlated with Explicit Cognitive Ability. Vice versa, it is also quite possible for Autonomous Cognition to be active during controlled thinking and support controlled reasoning processes. Of course, Autonomous areas of the brain may also be active during working memory tasks and such thoughts can be completely unrelated to the task at hand (Hampson, Driesen, Skudlarski, Gore, & Constable, 2006; Singer, 1988).

The current dissertation investigated two auotonomous information acquisition mechanisms: Implicit Learning [Probabilistic Serial Reaction Time (P-SRT) Learning, Artificial Grammar Learning (AGL), Invariance Learning (IL),

Contextual Cueing (CC)], and Latent Inhibition (LI). According to Reber (1993), implicit learning is "a fundamental root process…that lies at the very heart of the adaptive behavioral repertoire of every complex organism" and can be characterized as "the acquisition of knowledge that takes place largely independent of conscious attempts to learn and largely in the absence of explicit knowledge about what was acquired (p. 5)." Implicit learning is an important Autonomous Information Acquisition Mechanism in our daily lives. We frequently encounter many complex contingencies and patterns, and this ability to automatically learn these patterns and then use that knowledge to recognize and detect patterns in the future is an important component of intelligence (see Hawkins, 2005).

Although related, the scientific investigation of implicit learning differs from the study of implicit memory. Seger (1994) notes four differences between research on implicit memory and research on implicit learning. First, while most research on implicit memory involves memory for specific stimuli (e.g., Schacter, 1987), implicit learning involves memory for patterns. Second, studies on implicit memory usually involve words, whereas most of the stimuli used in implicit learning studies are nonverbal and involve performing some inductive process on the stimuli. Third, in implicit memory research participants do not necessarily have to be aware of the connection between the learning and test phases, whereas implicit learning might depend on some degree of memory for the previous learning phase for successful performance during the test phase. Fourth, implicit memory is not influenced by attentional manipulations, whereas implicit learning is often affected by attentional

manipulations such as the presentation of stimuli with concurrent tasks, the presentation of ignored stimuli, and the presentation of stimuli under anesthesia. Latent inhibition is another Autonomous Information Acquisition Mechanism and involves the capacity to screen from conscious awareness stimulus previously experienced as irrelevant. LI is a pre-conscious gating mechanism that automatically inhibits stimuli that have been previously experienced as irrelevant from entering awareness. According to the DP theory, reduced latent inhibition can contribute to intelligent behavior.

While statistically significant auotonomous information acquisition was evidenced in all the paradigms at the group level, P-SRT (see *Chapter 4: Implicit Learning*) and LI (see *Chapter 5: Latent Inhibition*) proved to be the most informative at the individual differences level. Individual differences in both of these implicit cognitive mechanisms were uncorrelated with Explicit Cognitive Ability. Further, these mechanisms operated automatically and significantly impacted on information acquisition. For instance, latent inhibition (LI) determines whether an individual will disregard stimuli previously tagged as irrelevant. Those with reduced latent inhibition will be more flexible in face of repeated stimuli, whereas those with high latent inhibition may automatically screen out stimuli previously tagged as irrelevant when that stimuli may end up being beneficial to information acquisition. Research shows that those with schizphrenia have poor Central Executive Functioning as well as reduced latent inhibition (Barch, 2005). The results of Carson et al. (2003) as well as the current dissertation suggests that in a sample of

individuals with normal Central Executive Functioning, reduced LI can be an important contributor to creative acheivement. Therefore, research that investigates interactions between individual differences in Autonomous Cognition and Controlled Cognition can further our understanding of deabilitiating mental disorders such as schizophrenia as well as increase our prediction of divegent thinking and creative acheivement (see *Chapter 5: Latent Inhibition* and *Chapter 8: Creative Achievement*).

Probabilistic Serial Reaction Time (P-SRT) Learning also significantly impacts on an individual's Autonomous Information Acquisition, by assisting individuals in learning complex covariances and environmental regularities in the environment that occur only probabilistically. P-SRT learning and LI are most likely not the only Autonomous Information Acquisition Mechanisms that display meaningful individual differences. Hopefully the DP model will spur research on individual differences in other Autonomous Information Acquisition Mechanisms that may display meaningful individual differences, and display predictive incremental validity using hierarchical regression with conventional intellectual tasks as the first level of variables and the Autonomous Information Acquisition Mechanisms as the second level. There is already some promising research in this direction (see Gebauer & Mackintosh, 2009). Also, it may be useful to adopt methodologies from social psychology to investigate mechanisms that may be particularly informative for predicting intelligent social behavior (see *Chapter 10: General Discussion*).

As a tentative guide to the additional mechanisms that could be investigated at the individual differences level, the next level of the hierarchy underneath *Implicit Learning* includes three main classes of implicit learning tasks—*Implicit Recognition Learning*, *Implicit Prediction Learning*, and *Implicit Experiential Learning*. These categories were adopted from Seger (1994). In reviewing the literature on implicit learning, Seger (1994) identified ten different implicit learning tasks that largely adhere (nine strictly adhere) to her following four principles of implicit learning: a) knowledge gained during the task is not fully accessible to consciousness, b) subjects learn information that is more complex than a single simple association or frequency count, c) the task does not involve processes of conscious hypothesis testing but is an incidental consequence of the type and amount of cognitive processing performed on the stimuli, and d) implicit learning on the tasks are preserved in cases of amnesia, suggesting that learning relies on neural mechanisms other than the hippocampal memory system. These ten tasks include *Artificial Grammar Learning* (e.g., Reber, 1989), *Visuospatial concepts* (e.g., Posner & Keele, 1968; Fried & Holyoak, 1984), *Covariation learning* (e.g., Lewicki, 1986), *Serial Reaction time task* (SRT; e.g., Nissen & Bullemer, 1987), *Contingent response task* (Lewicki & Hill, 1987; Kushner, Cleeremans, & Reber, 1991), *Hebb digit task* (Hebb, 1961), *Puzzle learning* (P.J. Reber & Kotovsky, 1997), *Motor Learning* (e.g., Franks, 1982), *Function Matching* (e.g., Deane, Hammond, & Summers, 1972), and *Dynamic Systems* (e.g., Berry & Broadbent, 1984).

Seger (1994) argues that each of these tasks fall into three stimulus types (visual patterns, sequences, and functions) and three response modalities (conceptual fluency, efficiency, prediction). On implicit learning tests that involve conceptual fluency, participants make judgments based on their intuition or feelings. On implicit learning tasks that involve efficiency, implicit learning is assessed by increased speed or accuracy in processing the information. Finally, among implicit learning tasks that involve prediction and control, participants are required to accurately predict or control some aspect of the stimuli. In Figure 10-1, the three classes of implicit learning tasks (*Implicit Recognition Learning*, *Implicit Prediction Learning*, and *Implicit Experiential Learning*) correspond to the three response modalities that Seger identified (Conceptual Fluency, Prediction, and Efficiency).

While the current dissertation administered two *Implicit Recognition Learning* tasks (Artificial Grammar Learning and Invariance Learning) and two *Implicit Experiential Learning* tasks (Probabilistic Serial Reaction Time Learning and Contextual Cueing), only the P-SRT task was informative at the individual differences level (see *Chapter 4: Implicit Learning*). This suggests that the variation in performance across implicit learning tasks with the same response modality may not necessarily be correlated. An important line of research will be to identify the particular properties (stimulus type, response modality, underlying rule structure, etc.) of implicit learning tasks that evidence the most meaningful individual differences, predicting the variation in intelligent behavior independently of Explicit

Cognitive Ability. The current dissertation suggests that there may be some characteristics of the autonomous, experiential, probabilistic, and sequential nature of the P-SRT task that makes it unique in this regard.

To help understand the different processes that are being measured by various implicit learning tasks, brain science may provide helpful. While the research is still in its infancy, there is evidence that different implicit learning tasks recruit different brain regions. In terms of the SRT task (see *Chapter 2: Methodology*), the evidence suggests that performance relies on intact basal ganglia (Jackson, Jackson, Harrison, Henderson, & Kennard, 1995; Ferraro, Balota, & Connor, 1993; Willingham & Koroshetz, 1993; Knopman & Nissen, 1991), and that performance on the SRT task recruits the basal ganglia (Berns, Cohen, & Mintun, 1997; Hazeltine, Grafton, & Ivry, 1997; Grafton, Hazeltine, & Ivry, 1995; Rausch, et al., 1995, 1997). [The linkage of SRT with the basal ganglia is especially interesting in light of Mishkin et al.'s (1984) suggestion that the basal ganglia plays a role in what they refer to as habit learning (learning to associate a given stimulus with a reward). Since the current dissertation found that the SRT task (which research shows to recruit the basal ganglia) correlated with lack of deliberation, as well as Aesthetic Engagement (*see Chapter 6: Four-Factor Model* and *Chapter 7: Personality*), future research should look at linkages between Implicit Experiential Learning, impulsivity, and predisposition for addiction].

Brain research suggests that other implicit learning tasks may not be as process-pure as the SRT. Lieberman, Chang, Chiao, Bookheimer, & Knowlton (2004)

used event-related fMRI to identify the neural mechanisms underlying performance on the Artificial Grammar Learning task (AGL; see *Appendix C: Additional Implicit Learning Tasks*). They found that activation in the caudate nucleus played a role in applying the implicitly learned rules, but that activation in the hippocampus and medial temporal lobes played a role in the retrieval of chunks from the training items. Further, they found that these two processes operated in a competitive fashion. The P-SRT task that was administered in the current dissertation was intentionally designed so as to minimize chunk learning (the sequence is probabilistic and second order), so most likely does not recruit the additional brain regions in the hippocampus and medial temporal lobes that were activated in performance of AGL.

Research shows that both the hippocampus and medial temporal lobe are also recruited during contextual cueing tasks (Murray & Richmond, 2001; Wirth, et al., 2003). In a fascinating study, Park, Quinlan, Thornton, & Reder, 2004 (2004; see also Chun, 2005) induced temporary amnesia in healthy participants by administering a neuropharmacological manipulation (midazolam). They had participants complete a contextual cueing task in two sessions, one session under the influence of midazolam and another session receiving a saline control injection. They found that when under the influence of midazolam, participants showed no contextual cueing effect (which the authors regard as a measure of implicit relational learning), but when the same participants received the saline injection, they showed the effect. Interestingly, in both conditions participants displayed

intact procedural learning on the task for both old and new displays (which the authors regard as a measure of implicit non-relational learning). Further, when under the influence of midazolam, participants displayed disrupted explicit memory on a cued-recall task (which the authors regard as a measure of explicit relational learning). Taken together with the findings of Lieberman, Chang, Chiao, Bookheimer, & Knowlton (2004), it seems as though both Artificial Grammar Learning and Contextual Cueing may recruit both explicit and implicit relational and non-relational components. And both the hippocampus and medial temporal lobe may be recruited under relational (both explicit and implicit) conditions. Research using other implicit learning paradigms also shows impairments among amnesiacs (Cermak, Lewis, Butters, & Goodglass, 1973; Corkin, 1965; Nissen, Willingham, & Hartman, 1989).

Seger (1994) reviews evidence that association areas of the brain may be involved in implicit learning of visual patterns measured through the conceptual fluency (recognition) response modality. Also, brain processes that underlie Controlled Cognition may also contribute to performance on some implicit learning tasks. Research shows that frontal patients as well as patients with Parkinson's disease have problems performing recency and frequency judgments (Milner, Petrides, & Smith, 1985; Sagar, Sullivan, Gabrieli, Corkin, & Growdon, 1988; Shallice, 1988; Strauss, Weingartner, & Thompson, 1985; Sullivan & Sagar, 1989 Sullivan, Sagar, Gabrieli, & Corkin, 1989). Interestingly, Amnesiacs with intact frontal lobes are unimpaired on such judgments (Sagar, Gabrielli, Sullivan, & Corkin, 1990) but

Korsakoff amnesiacs are impaired (Strauss, et al., 1985). It has been proposed that impairment in the latter group may be due to the frontal damage associated with the disease, which causes a decline in meta-memory judgments (Shimamura & Squire, 1986). Therefore, implicit learning tasks that tap into frequency learning processes may also recruit frontal lobe functions. There is also evidence that the frontal lobes may play a role in recognition processes that may be important for implicit recognition learning tasks like the Artificial Grammar Learning task (Janowsky, Shimamura, & Squire, 1989), although there is also evidence that recognition related processes aren't unitary—Leonesio & Nelson (1990) found that that judgments of memorability made just before an experiment, made immediately after the experiment, and the ability to recognize the correct answer to a question answered incorrectly did not correlate with each other.

Therefore, an important line of research will be to seek out and devise a wide variety of implicit learning tasks that are process pure (as process pure as can be), reliable, evidence meaningful individual differences, and predict intelligent behavior above and beyond Explicit Cognitive Ability. In devising such tasks, it may be necessary to look beyond the implicit learning literature and adopt methodologies employed in related disciplines such as statistical learning (including visual and auditory modalities; e.g., Aslin, Saffran, & Newport, 1998; Baker, Olson, & Behrmann, 2004; Saffran, Aslin, & Newport, 1996; Turke-Browne, Junge, & Scholl, 2005) and social cognition (see *Chapter 10: General Discussion*). While this dissertation and prior research has demonstrated weak correlations among various

implicit learning paradigms (see *Appendix C: Additional Implicit Learning Tasks*;

Gebauer & Mackintosh, 2007; Pretz, Totz, & Kaufman, 2009; Salthouse, McGuthry, &

Hambrick, 1999), recent work by Gebauer & Mackintosh (2009) suggests that with a

larger test battery of implicit learning tasks, a distinguishable factor from g, at least

at the second-order level, does emerge. Therefore, even though various implicit

learning paradigms may differ in their mix of processes that are being measured,

even among a wide range of existing implicit learning paradigms in the literature

there may be a source of variance across the tasks that contribute to variation in

cognition independent of g.

At the same level of the hierarchy as Implicit Learning and Latent Inhibition

is *Autonomous Engagement*. Autonomous Engagement indexes the extent to which

the individual desires and has Openness to Engagement in Autonomous Cognition.

Those who desire Autonomous Engagement tend to be impulsive, are open to

experience, enjoy varied experiences and sensations, seek novelty, show less

conformity, and have a general orientation for exploration of experiences (see

Chapter 7: Personality). In a sense, people who score high in Autonomous forms of

Engagement tend to often think independently of Controlled Cognition as well as

independently of external societal influence often displaying nonconformist

behaviors (see *Chapter 7: Personality*). Further, Autonomous forms of Engagement

are more related to creative achievement in the Arts than in the Sciences (see

Chapter 8: Creative Achievement), most likely due to various factors, including the

link between nonconformity and the Arts as well as the cognitive task requirements

of Arts achievement. Autonomous forms of Engagement are most likely linked to functioning of the dopaminergic system (DeYoung, Peterson, & Higgins, 2002).

At the level just below Autonomous Engagement are three specific types of Autonomous Engagement: *Affective Engagement, Aesthetic Engagement*, and *Fantasy Engagement*. Affective, Aesthetic, and Fantasy forms of Engagement are represented in the Openness to Experience scale of the NEO-PI R (Costa & McCrae, 1992). Further, these three types of Engagement are associated with the Big Five aspect Openness to Experience, which research has found is at least partially separable from the aspect Intellect (DeYoung, Quility, & Peterson, 2007; see *Chapter 6: Four-Factor Model*). In the current dissertation, factors representing Affective Engagement and Aesthetic Engagement are associated with the higher-order factor "Openness to Experience" whereas Intellectual Engagement is associated with the higher-order factor "Intellect" (see *Chapter 6: Four-Factor Model*). Additionally, DeYoung, Quilty, & Peterson, 2007 have found that the Aesthetics, Fantasy, Feelings, and Actions facets are good markers of the Openness to Experience domain, whereas the Ideas facet is a good marker of Intellect. Engagement in Actions was not included as a specific form of Autonomous Engagement since Engagement in Actions does not involve Engagement in a specific type of Autonomous Cognition, but is more related to Engagement in varied experienced and general sensation seeking. While Fantasy Engagement loaded onto the Aesthetic Engagement factor (see *Chapter 6: Four-Factor Model*), Fantasy Engagement has its own box in the DP model since Fantasy Engagement provided improved prediction of contextualized

deductive reasoning above and beyond Aesthetic Engagement (see *Chapter 9:*

Deductive Reasoning). Future research may suggest that there are additional types of

Engagement that are differentially associated with the two components of the

theory.

Affective Engagement reflects a desire for engaging in Affect. This construct is

closely related to Seymour Epstein's "Experiential System" (Epstein, 1994).

According to Epstein, those higher in experiential processing tend to make decisions

based on their gut feelings (e.g., "intuitions") more so than those lower in

experiential processing. This general construct goes beyond just decision making

however, and suggests that there is a general category of individuals who have

access to a wider range of emotions, are sentimental, and value thinking with their

heart rather than their heads. In this dissertation, Affective Engagement was

correlated with a reduced latent inhibition (see *Chapter 5: Latent Inhibition* and

Chapter 6: Four-Factor Model), creative achievement in the Arts (see *Chapter 8:*

Creative Achievement), and speed of contextualized deductive reasoning (see

Chapter 9: Deductive Reasoning).

Aesthetic Engagement reflects a desire for engagement in aesthetic

experiences and reflects a deep appreciation for art and beauty. Individuals who are

high on this factor tend to get deeply immersed in fiction, literature, music, and

other forms of content that is rich in sensory information, either visually (as in the

visual arts and fiction), auditory (as in music), or taste (as in the culinary arts). In

other words, those high in Aesthetic Engagement tend to "get caught up" in the

experience of sensory information. In the current dissertation, Aesthetic Engagement is positively correlated with implicit learning (see *Chapter 4: Implicit Learning* and *Chapter 6: Four-Factor Model*), and creative achievement in the Arts (see *Chapter 8: Creative Achievement*).

Fantasy Engagement reflects a desire for engagement in fantasy, fiction, and daydreaming. Individuals high in Fantasy Engagement have a vivid imagination and an active fantasy life. While recent research has found that individuals with higher working memory and executive control are better able to focus, maintain on-task thoughts, report less intrusive thoughts in their daily life, and mind-wander less during challenging activities requiring concentration (Friedman & Miyake, 2004, Kane, et al., 2007, McVay & Kane, 2009), higher Openness to Engagement in Fantasy and daydreaming may have adaptive value. Jerome Singer (1966, 1974) has extensively investigated individual differences in the tendency for daydreaming and task unrelated thoughts. Singer, along with other researchers have argued that spontaneous cognition and Engagement in Fantasy and daydreaming is healthy and adaptive, helping individuals anticipate and plan for the future (Antrobus, Singer, & Greenberg, 1966; Klinger, 1971; Mar & Oatley, 2008; Singer, 1966; Smallwood & Schooler, 2006).

Indeed, recent research suggests that lifetime print-exposure to fiction positively predicted measures of social ability and self-reported empathy, while non-fiction print-exposure was a negative predictor. These effects remained controlling for the age of the participant, experience with English, and a measure of

g (Mar, Oatley, Hirsh, dela Paz, & Peterson, 2006). Other research has found a positive correlation between Positive-Constructive Daydreaming (which reflects an acceptance, enjoyment, and practical use of playful and wish-fulfilling fantasies) with Openness to Experience, while both Guilty-Fear-of-Failure Daydreaming (characterized by a preoccupation with fantasies consisting of achievement motivation and failure as well as guilt, hostility, or aggression) and Poor Attentional Control (reflecting the extent of mind-wandering, distractibility, ability to sustain an elaborate fantasy, and susceptibility to boredom) were not related to Openness to Experience (Zhiyan & Singer, 1997). This suggests that a desire and Openness to Engagement in Fantasy can be adaptive and make a significant independent contribution to intelligent behavior. In the current dissertation, Fantasy Engagement positively correlates with deductive reasoning above and beyond Explicit Cognitive Ability (see *Chapter 9: Deductive Reasoning*).

Interestingly, individual differences in the tendency to engage in spontaneous cognitive processes correspond greatly to activity in the default brain network (Buckner, et al., 2008). Therefore, there may be neural mechanisms that contribute to variance in Fantasy Engagement and cause an individual to derive pleasure from engaging in the fantasy world. Also, Jerome Bruner (1986) has argued that when in the narrative mode of thought, the individual engages in detail-driven, contextualized thought, whereas in the paradigmatic mode of thought, individuals engage in thinking that transcends particularities. The results of the dissertation suggest that there are individual differences in the tendency to engage in the

narrative mode that are at least partically distinct from the tendency to Engage in Affect and Intellect and provide incremental validity in predicting important intelligent behaviors.

At the lowest level of the Autonomous Cognition branch are implicit domains of mind. Various researchers have argued for the evolution of distinct "domains of mind" that were selected through natural and sexual selection pressures to solve problems that were crucial for survival and reproductive success (Feist, 2006). These domains are thought to have some degree of brain localization, but are also conceptual or heuristic entities that support reasoning of those entities and link together a given set of principles, the rules of their application, and the entities to which they apply (Gelman & Brenneman, 1994). Researchers have posited between four and ten universally human domains of mind pertaining to knowledge of people, language, number, animals, music, visual images, aesthetics, or the inanimate physical world (Carey & Spelke, 1994; Feist, 2001; Gardner, 1983; 1999; Geary & Huffman, 2002; Gopnik, Meltzoff, & Kuhl, 1999; Karmiloff-Smith, 1992; Mithen, 1996; 2007; Parker & McKinney, 1999; Pinker, 1999; 2002). What makes something a domain involves multiple criteria (Gardner, 1983; Feist, 2006). Feist (2006), for instance, proposes the following seven criteria : archeological, comparative, developmental, universal, precocious talent and giftedness, neuroscientific, and genetic.

In the DP model I list seven domains of mind that have garnered the most evidence: Psychology, Physics, Linguistics, Math, Biology, Art, and Music. Additional

domains of mind may be considered in the future. The assumption of the DP model is that domain-general Autonomous Information Acquisition Mechanisms assist humans in learning repeating covariances that link together different domains. This Implicit learning therefore contributes to domain-specific implicit and explicit knowledge. Individuals may differ, however, in the rate at which they acquire new information within each domain of mind. Indeed, individual differences in specific abilities, such as verbal and spatial, can be used to predict performance in the various domains of mind. Presumably, each domain of mind consists of its own unique constellation of ability-engagement-personality trait complexes (for related ideas, see Ackerman, 1996; Ackerman & Beier, 2003; Ackerman & Heggestad, 1997; Dawis & Lofquist, 1984; Schmidt, Lubinski, & Benbow, 1998; Snow, 1967; 1991; Snow, Corno, & Jackson, 1996).

Domains of mind are similar to group factors in hierarchical models of intelligence. Indeed, research shows that group factors, such as mathematical, spatial, and verbal reasoning abilities provide incremental validity for predicting associated vocations above and beyond general intelligence (Achter, et al., 1999; Benbow, 1992; Humphreys, et al., 1993). Hierarchical models of intelligence came about as a compromise between a predominant focus on g (e.g., Spearman, 1904) and a predominant focus on group factors (Thurstone, 1938). Hierarchical models take into account the importance of both general and group factors. Three hierarchical theories that have had the most influence (and are still used to differing degrees today) are Vernon's Theory, Cattell's Theory, and Carroll's theory.

According to Vernon's theory (1971), *g* lies at the top of the hierarchy with two group factors below it. These two group factors are verbal:educational (*v:ed*), and spatial:mechanical (*k:m*). Early versions of Cattell's theory (Horn & Cattell, 1966) *gf-gc* theory proposed that general intelligence has two major parts: fluid intelligence (*gf*) and crystallized intelligence (*gc*). Fluid intelligence is thought to be dependent on the efficient functioning of the central nervous system, rather than on prior experience and cultural context. Crystallized intelligence, on the other hand is thought to be more dependent on experience and cultural context. The *gf-gc* hierarchical model is a two stratum model in which these two broad second order factors make up the top stratum and over 40 (including Thurstone's primary mental abilities) first-order factors make up the bottom stratum. Horn (1986) organized these second order factors functionally according to their level of information processing. At the highest level of cognitive function is *relation education*, of which both *gf* and *gc* are a part. The next level is *perceptual organization*. This level includes such factors as processing speed, the ability to visualize information, and the ability to process auditory information. The third level is *association processing*. Abilities relating to the retrieval of short-term memory and the fluency of information in long-term memory are part of this level. The lowest level according to Horn is *sensory reception*. Included in this level are basic sensory detection capabilities.

The most recent hierarchical model of intelligence and the one that has arguably been the most widely accepted is Carroll's Three-Stratum theory (Carroll,

1993). Carroll proposed this model after an extensive analysis of more than 460 data sets from the psychometric literature. This model differs from that of the Cattell-Horn model in that it posits the need for a third stratum. Viewing the structure of intelligence as a pyramid, Carroll places g at the top, in stratum III. The middle stratum, consists of eight broad abilities which are similar to the second-order factors in the *gf-gc* theory. They include (in decreasing order of relatedness to g): fluid intelligence, crystallized intelligence, general memory and learning, broad visual perception, broad auditory perception, broad retrieval ability, broad cognitive speediness, and processing speed. Stratum I is situated at the base of the pyramid and consists of highly specific abilities, some of which represent Thurstone's primary mental abilities. Therefore, Stratum I reflects highly specialized skills, Stratum II reflects somewhat specialized abilities that occur in broad domains of intelligence behavior, and Stratum III has only one ability, g, that underlies all aspects of intellectual activity.

The hierarchal models just reviewed went many years without being directly compared and statistically evaluated. The advent of confirmatory factor analytic techniques however has made such a comparison possible. Johnson and Bouchard (Johnson & Bouchard Jr., 2005) administered 42 mental ability tests to 436 participants and evaluated the relative statistical performance of the Cattell-Horn-fluid-crystallized model, Vernon's verbal-perceptual model, and Carroll's three-strata model. They found that Vernon's verbal-perceptual model fit better than the other two, but that the model was significantly improved by adding a higher-order

image rotation factor and a lower-order memory factor. According to Johnson & Bouchard, their results suggest that the best fitting psychometric hierarchical model of intelligence has four stratums with a *g* factor at the top and three third-stratum factors underneath. Their model also highlights the importance of image rotation for human intelligence (see also Kaufman, 2007c). By viewing *g* and domain-specific domains of mind separately, the DP model accommodates both within a dual-process framework of cognition.

Alternative Theories of Intelligence

The DP model is not the only theory of human intelligence that attempts to go beyond *g*. Below I will describe three major contemporary theories of human intelligence along with criticisms of the theories: Howard Gardner's theory of Multiple Intelligences, Robert Sternberg's theory of Successful Intelligence, and Mike Anderson's theory of the Minimal Cognitive Architecture. I will then discuss Peter Salovey and Jack Mayer's model of Emotional Intelligence, which is not a general theory of intelligence, but instead is a theory of a distinct kind of intelligence.

Howard Gardner's model of Multiple Intelligences

Howard Gardner's theory of Multiple Intelligences was first brought to public attention when he published the first edition of *Frames of Mind* in 1983. This and subsequent editions of his book (Gardner, 1983, 1993b, 1999) described the Multiple Intelligences model of intellectual ability, which stresses the need for educators and psychologists to broaden their definitions of human intelligence. In this model, multiple intelligences are not static abilities hierarchically nested under

a general factor, but rather are each an independent cognitive system in its own right. Gardner defined intelligence as "an ability or set of abilities that permit an individual to solve problems or fashion products that are of consequence in a particular cultural setting" (Ramos-Ford & Gardner, 1997).

Instead of solely relying on factor analysis, Gardner based his conclusions on a selective analysis of the research literature using eight criteria, namely, (a) potential isolation by brain damage, (b) the existence of idiot savants, prodigies, and other exceptional individuals, (c) an identifiable core operation or set of operations, (d) a distinctive development history, (e) an evolutionary history and evolutionary plausibility, (f) support from experimental psychological tasks, (g) support from psychometric findings, and (h) susceptibility to encoding in a symbol system, and concluded that there were eight separate intelligences. The eight intelligences he has proposed are linguistic, logical-mathematical, spatial, musical, bodily kinesthetic, interpersonal, intrapersonal, and naturalist. Additional intelligences are currently being considered, such as existential intelligence.

Although Gardner's theory has had an important influence in the broadening of educators' views of intelligence, various criticisms have been proposed. After presenting the work and theorizing of Gustafsson (1988), Lohman (2001) argues that g is largely synonymous with fluid intelligence (gF), which in turn is a stand-in for Inductive Reasoning ability. Lohman also reviews evidence that a central working memory system underlies inductive reasoning ability. Based on this review, Lohman argues that Gardner's theory of multiple intelligences is misleading because

it ignores the role of a central working memory system and thus a general inductive reasoning ability that cuts across all of his so-called independent intelligences.

Visser, Ashton, & Vernon, 2006 provide evidence that the common element across Gardner's multiple intelligences is a "general intellectual ability" that is expressed especially strongly in explicit reasoning tasks. They selected two tests for each of Gardner's 8 intelligences, based on Gardner's description of the content of each form of intelligence. Through factor analysis they revealed that the two tests with the highest *g*-loadings were the Necessary Arithmetic Operations test (Logical/Mathematical Intelligence) and Diagramming Relationships test (Naturalistic Intelligence), exceeding .70. They found fairly high *g*-loadings (between .40 and 59) for the Opposites (Linguistic), Paper Folding (Spatial), Social Translation (Interpersonal), Vocabulary (Linguistic), Map Planning (Spatial), and Making Groups (Naturalistic) tests, and modest *g*-loadings (between .20 and .39) for tests of Subtraction and Multiplication (Logical/Mathematical), Consistency (Interpersonal), and Cartoon Predictions (Interpersonal). They state, "The overall pattern of *g*-loadings suggests that the purely cognitive tests, except Subtraction and Multiplication, were strongly saturated with a general cognitive ability, and that the reasoning-based tests (Necessary Arithmetic Operations and Diagramming Relationships) were particularly strong indicators of *g* (p. 497)". As to why only modest loadings were found for Subtraction and Multiplication, they argue that "among the purely cognitive tests, the low correlations involving the Subtraction and Multiplication test are probably attributable to the relatively simple cognitive

demands of this task, which required the automatic application of the techniques of arithmetic computation. (p.499). Specially supporting Lohman's hypothesis, they then go on to say that "The common element that saturated the highly g-loaded tests most strongly was their demand on reasoning abilities, not their specifically verbal content (p. 501)."

Additionally, they found low loadings on a g-factor for both tests of Bodily-Kinesthetic intelligence, Tonal and Rhythmic Music ability, and Intrapersonal accuracy. Clearly not considering these "purely cognitive tests", they note that "the relatively modest size of the g factor as computed above was largely attributable to the inclusion of tests with very little cognitive content. When tests from the Bodily-Kinesthetic, Intrapersonal, and Musical domains were removed from the factor analysis, the variance accounted for by g increased to 35.8% (p. 497)." They do concede that "Gardner is likely correct in claiming that Bodily-Kinesthetic ability is quite different from the various cognitive abilities (p. 501)".

Visser et al. conclude that their results "support previous findings that highly diverse tests of purely cognitive abilities share strong loadings on a factor of general intelligence, and that abilities involving sensory, motor, or personality influences are less strongly g-loaded (p. 487)." Furthermore, they state that "the findings of the current study do suggest that Multiple Intelligences theory does not provide any new information beyond that already contributed by hierarchical models of ability, and should not be considered a basis for classroom planning (p. 501)."

Another problem with Gardner's theory is that even though other assessments exist to test Gardner's various intelligences (e.g., Gardner, Feldman, & Krechevsky, 1998), they have not been proven to be of adequate psychometric validity. The evidence is mixed however, in terms of the reliability of each intelligence (Plucker, Callahan, & Tomchin, 1996; Visser, et al., 2006). Without demonstrably reliable and valid tests, however, it is difficult to evaluate the statistical and practical independence of each of Gardner's multiple intelligences from the g factor. It should be noted though that just because a test isn't related to g does not mean that it isn't a measure of "intelligence". It's still an open question the independence of the reasoning processes that are important for successful operation in each domain of intelligence A dual-process framework may be helpful toward making progress on this question, in that individual differences in "abilities involving sensory, motor, or personality influences" (i.e., System 1 processes) may indeed be less g-loaded, but still may make an important contribution to cognition and therefore might still be worthy of the label "intelligent". In the DP model, the implicit domains of mind are akin to Gardner's multiple intelligences.

Robert Sternberg's Theory of Successful Intelligence

The theory of successful intelligence comprises four key elements (Sternberg, 1997a). A first key element is that "success is attained through a balance of analytical, creative, and practical abilities" (pp. 297-298). According to Sternberg, these three abilities, in combination, are important for success in life. *Analytical* intelligence is required to solve problems and to judge the quality of ideas.

According to Sternberg, this is the type of intelligence that is measured by measures of general intelligence. *Creative intelligence* is required to formulate good problems and solutions and *Practical intelligence* is needed to use the ideas and analysis in an effective way in one's everyday life.

A second key element is that "intelligence is defined in terms of the ability to achieve success in life in terms of one's personal standards, within one's sociocultural context (pp. 296-297)." Sternberg argues that intelligence testing has primarily focused on the prediction of success in an academic setting. The theory of successful intelligence emphasizes the importance of going beyond just the academic sphere to account for success in whatever goals individuals (or societies) set for themselves. Indeed, David Wechsler (1958), developer of one of the most widely used adult intelligence tests defined intelligence as ". . . the aggregate or global capacity of the individual to act purposefully, to think rationally and to *deal effectively with his environment*" (italics added). A third key element is that "one's ability to achieve success depends on one's capitalizing on one's strengths and correcting or compensating for one's weaknesses (pp. 297-298)."

A fourth key element is that "balancing of abilities is achieved to adapt to, shape, and select environments" (p. 298). Traditional theories of intelligence have emphasized the importance an individual's adaptation to his or her environment, a setting over which he or she often has little or no control. For instance, performance on IQ tests requires adjustment to the specific questions, but no matter how one performs, these questions (the environment of the test) do not change. To the extent

that you want to obtain a high score, you also do not have a choice as to which questions you want to answer. In the real world, however, the story is often much more complex. We often can choose our environments. Intelligence does not involve simply modifying oneself to suit the milieu (adaptation), it also involves the ability to modify the environment to suit oneself (shaping) and, sometimes, to find a new setting that is a better match to one's skills, values, or desires (selection).

Sternberg has achieved success in interventions designed to increase school success by improving analytical, creative, and practical skills (Sternberg, Grigorenko, Ferrari, & Clinkenbeard, 1999). Additionally, Sternberg has indeed shown a separation between his measures of practical intelligence and his measures of analytical intelligence, even though there is still some overlap between the two abilities (Cianciolo, et al., 2006). Furthermore, his measures of creative and practical intelligence predict real world outcomes and measures of high-order cognition such as the SAT and GPA above and beyond analytical intelligence (Sternberg & The Rainbow Project Collaborators, 2006). Just like Gardner's theory however, it still an open question the extent to which analytical, creative, and practical forms of intelligence are uncorrelated, unloaded on g, or anything other than mid-stratum 'group factors' (Brody, 2004; Gottfredson, 2003).

The theory of the minimal cognitive architecture underlying intelligence and

development

Mike Anderson's (M. Anderson, 1992; M. Anderson, 2005) theory of the minimal cognitive architecture underlying intelligence and development is the

closest extant theory of intelligence that incorporates dual-process theory. Based on

Fodor's (1983) distinction between central processes of thought and dedicated

processing input modules, Anderson's theory synthesizes the idea of general and

specific abilities as well as incorporating the notion of development. Instead of

referring to two systems, Anderson argues that knowledge is acquired through two

different "processing routes", with central processes (Route 1) being tied to

individual differences and input modules being tied to cognitive development

(Route 2). According to Anderson, Route 1 involves "thoughtful problem solving"

and is constrained by the speed of a basic processing mechanism that can be

measured by tasks such as inspection time and reaction time. Anderson (M.

Anderson, 2005) argues that "it is this constraint that is the basis of general

intelligence and the reason why manifest specific abilities are correlated (p. 280)."

In contrast, the second route for acquiring knowledge in Anderson's model is

tied to dedicated information processing modules, such as perception of three-

dimensional space, syntactic parsing, phonological encoding, and theory of mind.

According to Anderson this route is tied to cognitive development in that these

modules undergo developmental changes in cognitive competence and are

underpinned by their maturation and acquisition. Anderson acknowledges that

modular processes can be acquired through extensive practice, arguing that the

common features of both acquired and innate modules are that they "operate

automatically and independently of thought and are consequently unconstrained by

the speed of the basic information processing mechanism." This idea is very much in

line with other dual-process notions of the operation of processes associated with System 1 (what Anderson refers to as "Route 2", see Table 1-2).

It should be noted that in Anderson's model, there is no room for individual differences in route 2 (i.e., System 1). Furthermore, Anderson does not propose any domain general learning mechanisms, such as implicit learning or latent inhibition that are part of route 2, focusing instead on the Fodorian definition of modules. Therefore, while Anderson's model is the closest cognitive theory of intelligence that incorporates the notion of two processing routes of thought (albeit the theory is mostly tied to Fodor's dual route distinction), like Stanovich and Reber, the model explicitly states that individual differences in System 1are minimal. Further, Anderson believes that his addition of a modular component to his cognitive theory of intelligence accommodates Gardner's idea of 'multiple intelligences', as well as acknowledges the importance of a central basic processing mechanism, a criticism that has been repeatedly leveled against theories of multiple intelligences. Anderson believes his theory explains why many low-IQ individuals are capable of remarkable cognitive feats (who are typically referred to as 'savants'), including various practical skills (see Sternberg's theory above), such as the ability to acquire language or see in three-dimensions that are considerably more computationally complex than the abilities that are tapped by IQ tests.

In sum, Anderson should be commended for proposing a new theory of intelligence that incorporates two systems of thought. Nonetheless, there are some limitations to Anderson's theory. One major limitation is that he only incorporates a

restricted range of cognitive mechanisms that underlie each system. By focusing on individual differences in processing speed as underlying one information processing route, and species-typical cognitive modules with minimal individual differences in the other processing route, the plethora of other research that could bring to bear on the cognitive processes underlying these two information processing routes becomes unnecessarily restricted.

Emotional Intelligence

The original idea behind the concept of emotional intelligence (EI) is that there are individual differences in the extent to which individuals can reason about and use emotions to enhance thought (Salovey & Mayer, 1990). Since its inception, EI has been employed to cover a variety of traits and concepts, mixing personality traits with socioemotional abilities (Bar-On, 1997; Goleman, 1998; Petrides & Furnham, 2003), producing what Mayer et al., 2000 refer to as "mixed models" of EI. This state of affairs has spurred various critiques of EI, arguing that EI is too all encompassing to have scientific utility (Eysenck, 2000; Locke, 2005).

Agreeing with these criticisms, Mayer, Salovey, & Caruso (2008) argue for a four-branch model of EI that they believe offers a more precise formulation of the construct that is ability based. According to their model, EI involves the ability to (ordered from lower-level to higher-level emotional abilities): "(a) perceive emotions in oneself and others accurately, (b) use emotions to facilitate thinking, (c) understand emotions, emotional language, and the signals conveyed by emotions, and (d) manage emotions so as to attain specific goals (p. 506)." To measure these

abilities, the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT) was developed (Mayer, Salovey, & Caruso, 2002). The MSCEIT consists of eight tasks, including two tasks for each branch of the EI model. Correct answers are identified by pooling experts (i.e., emotion researchers), which show strong agreement with each other (Mayer, Salovey, Caruso, & Sitarenios, 2003). Research shows that the MSCEIT correlates moderately with verbal intelligence as well as the Big Five personality dimensions of Openness and Agreeableness (Brackett & Mayer, 2003; Mayer & Salovey, 1993, Petrides & Furnham, 2001; van der Zee, Thijs, & Schakel, 2002), and predicts various important outcomes such as social competence, quality of relationships, interpersonal sensitivity, work relationships, drug use, deviancy, aggressiveness, and psychiatric symptoms (Brackett & Mayer, 2003; Brackett, Mayer, & Warner, 2004; Brackett, Rivers, Shiffman, Lerner, & Salovey, 2006; Brackett, Warner, & Bosco, 2005; Côté & Miners, 2006; David, 2005; David, 2005; Kerr, Garvin, Heaton, & Boyle, 2006; Lopes, et al., 2004; Lopes, Salovey, Côté, Beers, & Petty, 2005; Lopes, Salovey, & Straus, 2003; Lopes, Grewal, Kadis, Gall, & Salovey, 2006; Mayer, Perkins, Caruso, & Salovey, 2001; Rosete, 2007; Rosete & Ciarrochi, 2005; Rubin, 1999; Trinidad & Johnson, 2002; see Mayer, Salovey, et al., 2008 and Mayer, Roberts, & Barsade, 2008 for a recent review). Many of these relations held after controlling for measures of general intelligence and personality.

The EI model of Mayer, Salovey and Caruso (2000) has received various criticisms (Brody, 2004; Oatley, 2004 Oatley, 2004; Zeidner, Matthews, & Roberts, 2001; Zeidner, Roberts, & Matthews, 2004). Brody (Brody, 2004) argues that the

MSCEIT tests knowledge of emotions but not necessarily the ability to put the knowledge to use. Brody also questions the expertise of those who decide the correct answers, wondering whether these experts are actually emotionally intelligent in their daily lives. Additionally, Brody questions the predictive validity of the MSCEIT, outlining the characteristics that are required to demonstrate adequate validity of a test and arguing that the MSCEIT does not fit his criteria. One of his criteria includes a demonstration that EI displays incremental predictive validity over and above the predictive validity of psychometric tests of intelligence and the Big Five personality traits (see Lopes, et al., 2004 for a study that provides incremental predictive validity over and above the Big Five and Lopes, et al., 2003 and Lopes, et al., 2005 for incremental predictive validity over and above measures of fluid and crystallized intelligence in relation to quality of social relationships).

Speaking to this point, Schulte, Ree, & Carretta (Schulte, Ree, & Carretta, 2004) administered the MSCEIT, the Big Five personality dimensions, and a measure of general intelligence. They found that the MSCEIT was negatively correlated with neuroticism, and positively correlated with extraversion, openness, agreeableness, and conscientiousness. Furthermore, multiple regression analyses with all of the personality variables and g entered into the equation showed that a model consisting of g, agreeableness, and sex of the participant explained 38% of the variance in EI. Correcting for the reliability of both the EI and Agreeableness measures caused the multiple R to increase to .81. The researchers conclude, "These findings lead us to speculate about the usefulness of EI for enhancing our

understanding of the determinants of human performance. p. 1067).” It should be noted, however, that other studies have found very weak relations between particular components of ability measures of EI and measures of both fluid and crystallized intelligence in college samples (Barchard & Hakstian, 2004; Davies, Stankov, & Roberts, 1998; Mayer, Caruso, & Salovey, 2000; Roberts, Zeidner, & Matthews, 2001). Therefore, just like Gardner and Sternberg’s theories, it is still an open question the extent to which EI (both a common factor and each of the specific abilities that are hypothesized to comprise EI) can provide incremental validity above and beyond general intelligence and the Big Five personality dimensions, with effect sizes that are meaningful and practical (Brody, 2004).

The DP model incorporates aspects of EI into the model, most notably Branch 2—the ability to use emotions to facilitate thinking. The Affective Engagement construct goes beyond just this ability though, as it relates more to a general Openness to the Experience of Affect, a conceptualization that is not part of the EI model.

The Current Approach

The alternative models of intelligence surveyed above have made important theoretical and empirical contributions to the understanding of the broad, contextual, and emotional nature of human intelligence. Alternative models of g are not without their critics however. A reoccurring criticism of alternative ‘intelligences’ is that they are poorly defined, measured, and even sometimes highly g-loaded (Gottfredson, 2003; Visser, et al., 2006). Some g theorists question whether

these proposed intelligences are really independent forms of intelligence, and not just a combination of *g* and personality traits (Jensen, 1998).

Contemporary debates about intelligence are reminiscent of the debate between Thurstone and Spearman over a century ago. In the current dissertation, I propose a different approach to understanding the nature of human intelligence. Alternative models of intelligence focus on differences in content. For instance, Sternberg's theory of Successful Intelligence posits three 'kinds of intelligence' which are important for successful adaptation of the environment: Analytical, Creative, and Practical Intelligence. In contrast, the current dissertation emphasizes the dual-process nature of human information processing, attempting to put boundaries around the mechanisms that are associated with general intelligence, as well as push beyond the boundaries to investigate the role of mechanisms that are associated with Autonomous Cognition in performance on tasks that require complex cognition. Therefore, the current approach is complementary to and can accommodate both hierarchical models of intelligence as well as theories of multiple intelligence, in that various domains of intellect may differ in the extent to which Controlled or Autonomous processes are activated, and a more complete understanding of the range of information processing mechanisms and associated independent sources of individual differences can help to put boundaries on different 'kinds of intelligence' in a scientifically respectable manner.

Clearly conceptualizations of the cognitive unconscious (and associated Autonomous Cognitions) have implications for understanding human intelligence,

and theories of human intelligence have implications for understanding the cognitive unconscious. In this dissertation, I explore individual differences in both processes in order to elucidate the nature of human cognition, and in doing so hopefully come to a more complete picture of human intelligence.

The data that is presented in this dissertation is a result of approximately 9 months of data collection in Cambridge, England in 2006-2007. All participants were aged 16-18 years, and attended a selective sixth form college (which takes students who are in their last 2 years of secondary education).

Tests were administered in groups at PC desktop terminals during the course of three 1.5-h sessions. For most participants, test sessions were administered on different days. In total, there were five separate groups of participants. The precise breakdown was as follows: **Testing Group 1** consisted of 21 participants (one participant not included in this count was excused from the experiment before any tests were taken since they were blind in one eye and therefore considered inappropriate for inclusion in the study); **Testing Group 2** consisted of 36 participants; **Testing Group 3** consisted of 36 participants, **Testing Group 4** consisted of 37 participants, and **Testing Group 5** consisted of 51 participants).

In total, 181 participants completed at least the first test session. Two participants were removed from all analyses due to their Ravens Advanced Progressive Matrices scores being lower than chance, presumably indicating a lack effort. One participant was removed from all analyses because this individual ostensibly did not take the study seriously during the first test session by constantly chatting, and did not return to any subsequent sessions. One other participant was removed from all analyses since this person did not complete two out of the three markers of intelligence, thus leaving their intelligence score incapable of being estimated.

Out of the remaining 177 participants, 169 completed all three testing sessions. Not all participants completed all the tests, due to a variety of factors such as computer malfunction or time constraints. Whenever possible, all participants received all the tests in the same order. The order was held constant because the current study focuses on individual differences and if order had any effect on task performance, then varying the order of the tasks for different participants would have introduced additional noise into the individual-difference data.

Each participant earned £20 (roughly the equivalent of $40) for their participation in all three testing sessions (approximately 4 ½ hours of their time). Table 2-1 lists the order of test administration.

Table 2-1
Order of Test Administration[a].

<u>**Testing Session 1:**</u>

Probabilistic Serial Reaction Time Learning (approx. 10 min.)[b]
Artificial Grammar Learning (approx. 10 min.)
Invariance Learning (approx. 5 minutes)[c]
Contextual Cueing (approx. 10 minutes)[d]
Operation Span (approx. 15 minutes)
MRT-A (8 minutes)
DAT Verbal Reasoning (15 minutes)
Creative Achievement Questionnaire (approx. 5 minutes)

<u>**Testing Session 2:**</u>
Ravens Advanced Progressive Matrices (40 minutes)
Latent Inhibition Task (approx. 10 minutes)
Verbal Speed Test (1 minute)
Number Speed Test (1 minute)
Figural Speed Test (90 seconds)

<u>**Testing Session 3:**</u>
Three-Term Contingency Learning (approx. 20 minutes)
Paired-Associates Learning (approx. 15 minutes)
Myers-Briggs Type Indicator Thinking/Feeling and Intuitive/Senate and subscales (approx. 8 minutes)
Big Five Aspect Scales (approx. 15 minutes)
NEO Openness to Experience subscales (approx. 10 minutes)[e]
Rational-Experiential Inventory, (approx. 8 minutes)
The UPPS Impulsivity Scale (10 minutes)
Need for Uniqueness Scale (5 minutes)
Wason Card Selection Task (15 minutes)

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[a] In addition to the following tests, I also administered a few additional tests in certain testing sessions that are tangential to the main aims of the dissertation.
[b] In the first test session, two version of the SRT were administered—first a deterministic version with 6 learning blocks and then the probabilistic version with 6 learning blocks. After the first learning cycle, I decided that it was unnecessary to include two SRT tasks, and since the probabilistic version was thought to better capture implicit learning (see below), I decided to extend the probabilistic version by two blocks and discontinued administering the deterministic version. Therefore, the current study does not include SRT data for the first 21 participants.
[c] Described in Appendix A
[d] Described in Appendix A
[e] This scale was administered after the first test session. Therefore, the current study does not have data for the first 21 participants for this personality test.

Description of Tasks

General Intelligence (*g*)

Using one of the largest batteries of cognitive tests ever collected, Johnson and Bouchard (2005) demonstrated that, below the *g* factor, there are three separable second-stratum domains of cognitive ability which they label verbal, perceptual, and mental rotation. Therefore, use of one test from each domain should produce a well balanced *g*.

Raven's Advanced Progressive Matrices Test, Set II (RAPM)*.* The RAPM (Raven, Raven, & Court, 1998) is a measure of abstract perceptual reasoning. Each item consists of a 3 x 3 matrix of geometric patterns with the bottom right pattern missing. The participants' task is to select the option that correctly completes the matrix. There are eight alternative answers for each item. The test is presented in increasing order of difficulty. After two practice items with feedback, participants were then given 45 min to complete 36 items.

DAT verbal reasoning test. The verbal reasoning section of the Differential Aptitudes Test (DAT-V, The Psychological Corporation, 1995) was administered to each participant. Each problem consisted of a sentence with two words missing, and participants chose a pair of words from the answer options that were analogically related to the words in the sentence. After two practice items, participants had 15 min to complete 40 problems.

Mental Rotations Test, Set A (MRT-A). The MRT-A (Vandenberg & Kruse, 1978) contains 24 problems and measures mental rotation ability, and appears to

be a distinct component of intelligence to the same extent as verbal ability and perceptual ability (Johnson & Bouchard Jr., 2005). Each problem in the MRT-A shows a three-dimensional target figure paired with four choice figures, two of which are rotated versions of the target figure. To score a point, both rotated versions must be identified. After two practice items with feedback and an explanation, the first 12 problems were attempted in 4 min with a 2 minute break before attempting the second 12 in another 4 min. The maximum score is 24.

Mean scores on the three cognitive ability measures (RAPM, DAT-V, and MRT-A) suggested a mean IQ for the entire sample in the range of 100 to 110 (see Table 1).

Elementary Cognitive Tasks (ECT's)

Working memory. The Operation Span Task (Ospan; Turner & Engle, 1989) was administered as a measure of working memory. Ospan requires participants to store a series of unrelated words in memory while simultaneously solving a series of simple math operations, such as "Is (9/3) – 1 = 1?". After participants selected the answer, they were presented with a word (e.g., DOG) to recall. Then participants moved on to the next operation-word string. This procedure was repeated until the end of a set, which varied from two to six items in length. Participants were then prompted to recall all the words from the past set in the same order in which they were presented by typing each word into a box, and using the up and down arrow keys on the keyboard to cycle through the boxes.

Before the main task, participants encountered three practice problems with set size two, where they received feedback about their performance. During these practice trials, we calculated for each participant how long it took them to solve the math operations. Consistent with the methodology of the Automated Ospan task (Unsworth, Heitz, Schrock, & Engle, 2005), we did this to control for individual differences in the time required to solve the math operations. Their mean performance time to solve the equations, plus 2.5SD was used as the time limit for the presentation of the math equations during the main task.

The Ospan score is the sum of all correctly recalled words in their correct positions. The number of operation word-pairs in a set was varied between two, three, four, five, and six with three sets of each. Overall score could range from 0 to 60. Prior research has demonstrated significant correlations between Operation Span and *g* (e.g., Unsworth & Engle, 2005b) and a high loading of Operation Span on a general working memory factor (Kane, et al., 2004).

Processing speed

Verbal speed test (Speed-V): an English adaptation of a sub-test from the Berlin model of Intelligence Structure (BIS; Jaeger, 1982, 1984). The task was to fill in the missing letter from a 7-letter word; 60 seconds were given to complete the 57 items. The score is the number completed correctly in 60 seconds.

Numerical speed test (Speed-N): the Speed of Information Processing sub-test from the British Ability Scales (Elliot, 1996). The task was to cross out the

highest number in each row of five numbers; 60 seconds were given to complete 48 items. The score is the number completed correctly in 60 seconds.

Figural speed test (Speed-F): Digit-Symbol, Coding, a sub-test of the WAIS-R that loads on the "processing speed" factor (Deary, 2001). The test was to enter the appropriate symbol (given by a key at the top of the form) beneath a random series of digits; 90 seconds were given to complete 93 items. The score is the number completed correctly in 90 seconds.

Explicit learning

For both Associative Learning tasks, all stimuli were initially randomized but then presented in the same fixed order for each participant. This was done to maximize the extent to which individual differences reflect trait differences rather than differences in item order.

Three-Term Contingency Learning (Williams & Pearlberg, 2006). The Three-Term Contingency Learning (3-Term) task consists of four learning blocks, each followed immediately by a test block. In each learning block, participants were presented with 10 unique words. Each word was associated with three different words, contingent on a key press. The participants' task was to learn the word associated with each stimulus-response pair. For instance, on one trial the word "LAB" might show on the screen with the letters "A", "B", and "C" listed underneath. When participants selected "A", they saw one association (e.g., PUN), when they selected "B", they saw a second association (e.g., TRY), and when they selected "C" they saw a third association (e.g., EGG). The duration of exposure to each association

was self-paced (max 2.5 s) with changeover intervals set at 0.2 s. After the single

presentation of all ten stimulus words with the 30 outcome words, subjects were

immediately presented with a test block.

The test blocks were identical to the learning blocks with one exception:

instead of typing the letters "A", "B", or "C" to produce the outcome words on the

screen, a stimulus word appeared on the screen along with one of "A", "B", or "C",

and participants were required to type in the outcome word corresponding to that

stimulus-response pair. Together with feedback on their answer, the correct

association was shown to the participants until they pressed "ENTER", when the

next stimulus word was presented. Once the test block was completed, participants

immediately moved to a second learning block in which the same stimulus words

were presented in a different order. Across the four test blocks, possible overall

scores ranged from 0 to 120.

Paired –associates (PA) learning (Williams & Pearlberg, 2006). In this

task, participants were presented with 30 pairs of words. A cue word was presented

until the participant pressed ENTER, or until 2.5 s elapsed, after which the cue's pair

appeared on the screen. They then remained together on screen, again until the

participant pressed ENTER, or until 2.5 s elapsed, after which both disappeared and

the next cue word was displayed. The test phase was identical to training, except

instead of pressing "ENTER" to view the second word of each pair subjects were

required to type that word. Together with feedback on their answer, the correct

association was shown to the participant until they pressed "ENTER", when the next

word cue was presented. Once the test phase was completed, participants immediately moved to a second learning block in which the same stimulus words were presented in a different order. In total, there were four learning and four test blocks, with possible overall scores ranging from 0 to 120.

Implicit Cognition

(Artifcial Grammar Learning, Contextual Cueing, and Invariance learning are described in *Appendix C: Additional Implicit Learning Tasks*, along with their psychometric properties.)

Implicit Learning. Implicit learning was measured employing a measure of Probabilistic Serial Reaction Time Learning (SRT). In the SRT task, participants saw a stimulus appear at one of four locations on the computer screen, and their task was to press the corresponding key as fast and as accurately as possible. Unknown to the participants, the sequence of successive stimuli followed a repeating sequence intermixed 15% of the time with an alternate sequence (Schvaneveldt & Gómez, 1998). In particular, Sequence A (1-2-1-4-3-2-4-1-3-4-2-3) occurred with a probability of 0.85, and Sequence B (3-2-3-4-1-2-4-3-1-4-2-1) occurred with a probability of 0.15. Figure 2-2 shows a representation of this procedure.

Note that these two sequences have been built to differ exclusively in the second-order conditional (SOC) information that they convey (Reed & Johnson, 1994). Thus, each location appears with the same likelihood in each of these two structures, and each first-order transition is also equally likely in both sequences. However, second-order information leads to a different prediction for each

sequence, so that learning about this SOC information will lead to a difference in responding to each sequence.

Figure 2-1
Representation of the procedure used for the probabilistic SRT learning task.

Note: Thick lines represent more probable transitions (.85) whereas thin lines represent less probable ones (.15). Only a partial set of these transitions is represented, to illustrate that both series are communicated precisely at those points in which they share a context: After 1-2, the most probable successor is 1 (upper row) but in 15 % of the cases the next element could be 4 (bottom row).

To elaborate on the probabilistic nature of the design: on each trial, the successor could follow either Sequence A (upper stream) or Sequence B (bottom stream). For example, the most common successor in Sequence A after 1-2 was 1, but on some trials (15% of the time) the successor was instead the one stipulated by Sequence B after the context 1-2 (4). After this substitution, the context would be 2-4, and hence the most common successor (85% of the time) was the usual location marked by Sequence A to appear in this context (1). However, there was a certain probability (15%) that the successor marked by Sequence B (3) could occur.

During the practice block (0), probable and improbable transitions occurred with equal likelihood. Thus, the next trial in sequence was equally likely to be determined by Sequence A as by Sequence B. After this practice block, participants completed 8 training blocks in which transitions were generated from Sequence A 85% of the time and from Sequence B 15% of the trials. Participants completed 120 trials in each block, 960 trials in total. Within each block, all trials were initially randomized but then presented in the same fixed order for each participant. This was done to maximize the extent to which individual differences reflect trait differences rather than differences in item order.

There are reasons to believe that this probabilistic version of the SRT is a pure measure of implicit learning (Jiménez & Vázquez, 2005). For one, the probabilistic version does not contain any first order information that could account for learning, because after each location any other is equally probable. Secondly, the probabilistic nature minimizes the effect of chunk learning, and instead maximizes the need to learn the conditional probabilities of each successor in each context. During post-experiment interviews, no participants indicated knowledge that the transitions were probabilistic or conditional on the two previous locations.

To assess learning on the probabilistic SRT task for each participant, I first took the difference between the average time to respond to probable trials and the average time to respond to improbable trials. Error responses were discarded (3.5 % of trials), as well as outliers more than three standard deviations from the mean,

which were computed individually for each block and participant. On average, 2% of the trials qualified as outliers according to these criteria.

When investigating individual differences, it has been assumed that such a learning score can be used to provide a rank ordering of ability to learn on the SRT. However, this assumption may be flawed because the exact difference in RT may not be stable enough to provide a reliable rank order. More important than the exact RT difference between probable and improbable trials may be simply whether or not individuals show any reliable difference between RTs to probable and improbable trials.

I therefore employed a new scoring method to assess whether each participant learned in each block. Rather than calculate an exact RT difference, I simply assessed whether participants showed a learning effect at least as large as the significant learning effect evident in the sample as a whole across blocks three through eight (blocks 1 and 2 were not included because they showed evidence of less learning in the sample as a whole; see *Chapter 4: Implicit Learning* for details). The average Cohen's *d* across these blocks was .19. Because the average difference between the conditions across these blocks was .19 standard deviations, we assessed for each participant in each block of learning whether their mean RT for probable trials was less than the difference between their mean RT for improbable trials and .19 times the standard deviation for RT on improbable trials. If it was less, they received a score of 1. If it was not, they received a score of 0. To calculate a total

score for each participant, we summed their score across the last six blocks, yielding a minimum score of 0 and a maximum score of 6.

The new scoring method demonstrated an acceptable split-half reliability (using Spearman-Brown correction) of .44 and the distribution was normal. The old scoring method relying on RT differences demonstrated a split-half reliability of .33. The correlation between the old scoring method and the new scoring method was .76. For all analyses presented in *Chapter 4: Implicit Learning*, a side by side comparison of the old and new scoring methods showed similar patterns of correlations, but with consistently stronger effects using the new, more reliable scoring method. Therefore, all results will be presented utilizing the new scoring method.

Latent Inhibition (LI). The latent inhibition task that I administered is identical to that used by Carson, Peterson, and Higgins, 2003. All participants were seated at a computer terminal and received auditory instructions through a pair of headphones. In the pre-exposed phase, participants were presented with 30 nonsense syllables, repeating 5 times with white noise bursts superimposed randomly 31 times over the course of the recording. Participants were instructed to determine how many times they heard the third nonsense syllable ("bim"). Therefore, during this first phase, the white noise bursts were irrelevant to the task.

During the second task, the test phase, the same recording of the syllables was replayed but participants also watched yellow disks appear one by one in rows on the computer monitor. This time, the white noise bursts were relevant to the

task: each yellow disk appeared prior to the white noise bursts. Participants were instructed to try to discover the auditory stimulus that caused the yellow disks to appear (the correct answer is the white noise bursts) and to write down their answer and raise their hand when they thought that they had figured out the rule. If participants got an incorrect answer, they continued with the task until either they figured out the correct answer, or all the yellow disks were revealed (whichever came first). The individual's score for the task was the number of disks still on the screen when the correct answer was given. In total, there were 31 yellow disks, and thus scores could range from 1 to 31.

Participants in the nonpreexposed condition had the same two tasks, except there were no white noise bursts in the pre-exposure phase of the task. The nonpreexposed condition is often introduced into latent inhibition studies as a control, so that the experimenter can compare differences between a condition where latent inhibition occurs and a condition in which there are no stimuli for latent inhibition to act upon (i.e., there is nothing to inhibit that is relevant at a later point in time).

Personality

All Personality items except for the MBTI were measured on a 5-point Likert scale.

Myers-Briggs Type Indicator (MBTI). The MBTI (Myers, McCaulley, Quenk, & Hammer, 1998) measures individual differences in personality as a function of four constructs: extraversion/introversion, intuition/sensation, thinking/feeling, and judging/perceiving after Jung's (1921/1971) theory of psychological types. The

subscales of the MBTI that we administered were the thinking/feeling scale and the intuition/sensation scale. "Intuitive" individuals are described as concentrating on patterns and possibilities rather than concrete details, whereas a "sensing" person is more concerned with details and facts than an intuitive person. The Thinking/Feeling scale was scored as a continuous dimension ranging from low (thinking) to high (feeling). The Intuition scale was scored as a continuous dimension ranging from low (sensation) to high (intution). The MBTI subscales that were administered in the current dissertation have demonstrated adequate reliability and validity, with reported internal consistencies in the range of .86 to .95 and test-retest consistencies in the range of .93 to .95 (see Myers, McCaulley, Quenk, & Hammer, 1998).

The MBTI subscales were included in the current dissertation for two reasons. The first reason is to increase the breadth of self-report intuition measures included in the dissertation. Recent research suggests that the MBTI Feeling and MBTI Intuition scales are measuring different forms of intuition (Pretz & Totz, 2007). The second reason is to increase the prediction of self-reported creative achievement. Prior research has show relations between the MBTI Intuition scale and endorsement of innovative styles on the Kirton Adaption-Innovation Inventory (Carne & Kirton, 1982; Fleenor, 1997; Fleenor & Taylor, 1994; Gryskiewicz & Tullar, 1995; Jacobson, 1993; Van Rooyen, 1994), college students' artistic interests and a creativity value scale (Myers, et al., 1998).

The Big Five Aspect Scales (BFAS). The Big Five Aspect Scales (BFAS) assess the personality traits of the five factor model or Big Five (DeYoung, et al., 2007). In the BFAS, each of the five major domains is broken down into two subtraits that capture key aspects of the domain. These aspects were derived empirically from factor analysis of facet-level scales from two major Big Five instruments, the NEO PI-R (Costa & McCrae, 1992) and the AB5C-IPIP (Goldberg, 1999). Additionally, the two aspects in each domain appear to correspond to genetic factors found within the facets of the NEO PI-R (Jang, Livesley, Angleitner, Riemann, & Vernon, 2002).

For the Big Five domain of *Neuroticism*, the BFAS distinguishes between the Volatility (e.g., "Get easily agitated") and Withdrawal (e.g., "Worry about things") aspects. For the Big Five domain of *Agreeableness*, the BFAS distinguishes between the Compassion (e.g., "Feel others' emotions") and Politeness (e.g., "Hate to seem pushy") aspects. For the Big Five domain of *Conscientiousness*, the BFAS distinguishes between the Industriousness (e.g., "Carry out my plans") and Orderliness (e.g., "Keep things tidy") aspects. For the Big Five domain of *Extraversion*, the BFAS distinguishes between the Enthusiasm (e.g., "Have a lot of fun") and Assertiveness aspects ("Know how to captivate people"). And finally, for Big Five domain of *Openness/Intellect*, not surprisingly, the BFAS distinguishes between the Openness and Intellect aspects.

NEO-PI-R. The Openness to Experience scale of the NEO-PI-R (Costa & McCrae, 1992) was administered. According to Piedmont (1998), "Openness to

Experience is defined as the proactive seeking and appreciation of experience for its own sake, and as toleration for and exploration of the unfamiliar. (p.87)"

The Openness to Experience scale is divided into six subscales or "facets" (descriptions according to Piedmont, 1998): Openness to Aesthetics (deep appreciation for art and beauty), Openness to Action (preference for novelty and variety), Openness to Fantasy (vivid imagination and active fantasy life), Openness to Feelings (receptivity to one's own inner feelings and emotions), Openness to Ideas (active pursuit of intellectual interests for their own sake and a willingness to consider new, perhaps unconventional ideas), and Openness to Values (readiness to reexamine social, political, and religious values). The Aesthetics, Fantasy, Feelings, and Actions facets are good markers of the Openness aspect of the domain, whereas the Ideas facet is a good marker of Intellect (DeYoung, et al., 2007).

Rational-Experiential Inventory (REI). The Rational-Experiential Inventory (REI) was designed to measure the two different aspects of Epstein's Rational-Experiential model of personality (Epstein, Pacini, & Norris, 1998; Pacini & Epstein, 1999). The REI is a 40-item questionnaire consisting of two scales— the rational and experiential inventories. Each scale has two subscales, each with 10-items, which measure both the ability and preference for each style of thought. The rational inventory attempts to quantify an individual's ability and preference for relying on logic and analysis in making decisions and solving problems. This scale is based on the Need for Cognition Scale (Cacioppo & Petty, 1982), which correlates very highly with the Ideas facet of the NEO PI-R ($r = .78$; Cacioppo, Petty, Feinstein,

& Jarvis, 1996). The experiential inventory estimates the degree to which an individual prefers to rely on intuition or hunches when making decisions.

The UPPS Impulsivity Scale. The UPPS Impulsivity Scale was derived from factor analysis of a large number of scales commonly used to measure impulsivity-related constructs (Whiteside & Lynam, 2001). This analysis found four factors, labeled Urgency, (lack of) Premeditation, (lack of) Perseverance, and Sensation Seeking. According to Whiteside, Lynam, Miller, & Reynolds (2005, p. 561), urgency "refers to the tendency to engage in impulsive behaviors under conditions of negative affect despite the potentially harmful longer-term consequences", (lack of) Premeditation "refers to a difficulty in thinking and reflecting on the consequences of an act before engaging in that act", (lack of) Perseverance "refers to an individual's inability to remain focused on a task that may be boring or difficult", and to a "difficulty completing projects and working under conditions that require resistance to distracting stimui", and Sensation Seeking reflects "a tendency to enjoy and pursue activities that are exciting and an openness to trying new experiences that may be dangerous."

The Need for Uniqueness Scale. The Need for Uniqueness scale is a 32-item measure of each participant's motivation for uniqueness seeking (Snyder & Fromkin, 1977; 1980).

Deductive Reasoning

Wason Card Selection Task. The version of the Wason Card Selection Task that was administered was a shortened version of the Wason Card Selection task

administered by Reis et al., (2007). Participants completed 15 problems. For each problem, participant read a brief scenario describing both a situation and a rule of generic form "If p, then must Q" or "If P, then have to Q". Scenarios were pseudorandomly ordered to ensure that problems of the same type were not repeated. All participants then received the same scenarios in the same order. To avoid confounding RT with time spent reading each card, the length of text shown on the cards was matched across all three conditions.

Participants then saw cards presented individually along with the rule. (For each scenario, there was one rule and four different cards: P, not-P, Q, not-Q). For each card, participants had to indicate either "definitely turn over", or "no need to turn over" to be able to tell whether the rule was being broken. The rule remained on the screen throughout the card response period. Participants were given 20s to read each scenario and 4 s to respond to each individual card. If a response was not made within 4 s, an error was scored and the computer automatically advanced to the next card. No feedback was given about performance.

Accuracy was calculated by taking the percentage of individual cards responded to correctly for each form of reasoning. RT for each card was measured as the time elapsed from when the card was displayed until the response was made. RT for each problem type (Descriptive, Precautionary, Social Exchange) was computed as the mean of the RTs for all cards responded to correctly, regardless of card type (P, not P, q, not Q). All responses <200msec were trimmed from all analyses and all timed out trials were excluded from the RT analyses.

Creative Achievement

Creative Achievement Questionnaire (CAQ). The CAQ is a measure of self-reported lifetime creative accomplishment in the arts and sciences, and is affected by both opportunities as well as abilities (see *Chapter 8: Creative Achievement*). The CAQ has demonstrated good test-retest reliability, as well as good convergent, discriminant, and predictive validity (Carson, et al., 2003). Participants received a computerized version of the CAQ, where they indicated their achievements in the following ten separate domains of creative accomplishment: Architecture, Domestic Arts, Visual Art, Music, Theatre/Film, Dance, Inventions, Scientific Discovery, and Humor. Each accomplishment was weighted based on the ranking of experts within that domain. Participants received a sum of the weighted scores for each domain, and all of the domain scores were summed to yield a total creative achievement score.

PART I:

Ability

Over a century ago, Spearman (1904) discovered that when a battery of

diverse cognitive tests is administered to a diverse group of people, there is

consistent tendency for all the tests to be positively correlated with one another,

producing what has been referred to as the "positive manifold". Many studies since

then have replicated this finding (Carroll, 1993; Jensen, 1998; Johnson, Bouchard Jr.,

Krueger, McGue, & Gottesman, 2004). Although the existence of general intelligence

(g), in the sense of a statistical feature (a "positive manifold"), is a robust finding, it

is less clear what the mechanisms are that support g. The best established candidate

processes, as mechanistic substrates of g, are processing speed (Deary, Der, & Ford,

2001) and working memory (Conway, Jarrold, Kane, Miyake, & Towse, 2007). It

remains important to discover other processes that might similarly contribute to

general intelligence (Sternberg & Pretz, 2005). Toward this aim, the purpose of this

chapter is to investigate the cognitive mechanisms supporting explicit cognitive

ability, particularly focusing on explicit associative learning as an independent

mechanism supporting explicit cognitive ability.

Since one of the original purposes of intelligence tests was to assess students'

ability to learn (Binet & Simon, 1916), it is reasonable to suppose that one of the

ingredients of explicit cognitive ability is explicit learning. Furthermore, there is

good reason to suspect that a major type of explicit learning—explicit *associative*

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[f] Some of the content of the current chapter was taken from the manuscript entitled *Associative learning predicts intelligence above and beyond working memory and processing speed*, currently in press in the journal *Intelligence* (doi:10.1016/j.intell.2009.03.004) and co-authored with Colin DeYoung, Jeremy Gray, Jamie Brown, and Nicholas Mackintosh.

learning—might support explicit cognitive ability. Intelligent behavior seems certain to require memory and voluntarily recall specific associations between stimuli. Relations among associative learning, general intelligence, and cognitive mechanisms that subserve general intelligence are thus of interest for both theoretical and historical reasons.

Only recently has explicit associative learning become a serious contender as a substrate of g (Alexander & Smales, 1997; Tamez, Myerson, & Hale, 2008; Williams, Myerson, & Hale, 2008; Williams & Pearlberg, 2006). Although early studies found a weak or no relation between associative learning and general cognitive ability (Woodrow, 1938, 1946; Malmi, Underwood, & Carroll, 1979; Underwood, Boruch, & Malmi, 1978), the failure to find a relation seems likely to be due to the fact that the explicit associative learning tests that were used in these studies were easy and thus unlikely to be related to complex cognition (Estes, 1970). Consistent with this hypothesis, a more difficult explicit associative learning task, in which subjects were required to learn multiple response-outcome contingencies for each trial, appears to be more strongly associated with g than a simpler associative learning task involving associations between pairs of stimuli (Williams & Pearlberg, 2006).

Using the same explicit associative learning tasks as Williams & Pearlberg, , the current chapter investigates explicit associative learning as a potential additional candidate process, which might contribute to g over and above processing speed and working memory. To be confident that associative learning is

indeed a substrate of g though, it is important to demonstrate that individual differences in associative learning make a contribution to the prediction of g that is statistically independent of the contributions of other candidate mechanisms. Otherwise, it might be the case that associative learning showed zero-order correlations with g merely because of its relation to some other important mechanism, such as working memory or processing speed. To the extent that g relies on multiple separable processes that are at least partially independent of one another, each should provide some incremental contribution to g. By examining the incremental validity of elementary cognitive tasks (ECTs, Jensen, 1998) that tap candidate cognitive mechanisms, one can effectively address the question of whether associative learning provides incremental prediction of g above and beyond two of the most well studied ECTs, working memory and processing speed tests.

Working memory is the ability to maintain, update, and manipulate information in an active state, over short delays (in the range of seconds rather than minutes). Individuals differ in their working memory, and those with higher working memory are better able to control their attention so as to maintain their task goals in the presence of interference (Kane, Bleckley, Conway, & Engle, 2001; Unsworth, Schrock, & Engle, 2004; Conway, Cowan, & Bunting, 2001). Working memory is strongly correlated with g (Conway, et al., 2007; Engle & Kane, 2004; Heitz, Unsworth, & Engle, 2004). There is convincing evidence for a mechanistic link between working memory and g: tasks assessing g and working memory engage

shared neural substrates, in lateral prefrontal cortex (PFC) as well as left and right parietal regions (Gray, Chabris, & Braver, 2003; Gray & Thompson, 2004). At least one additional cognitive mechanism has been identified that is very strongly related to g, namely processing speed.

Processing speed involves the speed at which even simple operations can be performed. Higher-IQ subjects respond faster in simple and choice reaction time paradigms (Deary, et al., 2001) and are faster at perceiving a difference between two similar line segments in experiments on inspection time (Deary, 2000; Grudnik & Kranzler, 2001). In the Horn-Cattell theory of intelligence (Horn & Cattell, 1966), processing speed was described as "perceptual speed" (Gs), and, in Caroll's three-stratum theory of intelligence, as "general speediness" (Carroll, 1993). Finally, analysis of the factor structure of subtests from the WAIS (the standard IQ test) has demonstrated that processing speed is one of four second level factors below g (Deary, 2001).

The moderate link between processing speed and g has led some researchers to argue that differences in g are primarily a result of differences in overall efficiency and speed of the nervous system (M. Anderson, 1992; Jensen, 1998). Others have criticized this view, on the grounds that performance on tests of processing speed may be a function of vigilance or ability to avoid distraction, rather than mere neural efficiency (Mackintosh, 1998). In any case, it seems unlikely that processing speed is the central mechanism underlying intelligence because

measures of processing speed (Gs) tend to load less strongly on *g* than other
cognitive tests (Deary, 2001).

The possibility remains open that working memory and processing speed
make separable, statistically independent contributions to *g*. Processing speed
accounts for the link between working memory and *g* in some studies (Fry & Hale,
1996; Jensen, 1998; Kail & Salthouse, 1994; Salthouse, 1996), while others have
found that working memory is the primary predictor of *g*, even while controlling for
processing speed (Conway, Cowan, Bunting, Therriault, & Minkoff, 2002; Carpenter,
et al., 1990; Engle, Tuholski, Laughlin, & Conway, 1999; Kyllonen, 1996; Kyllonen &
Christal, 1990). Conway et al. (2002) argue that these conflicting conclusions result
from the use of processing speed tasks with different levels of working memory
demand. At any rate, it is generally agreed that working memory capacity is not
identical to *g* (Ackerman, Beier, & Boyle, 2005; Kane, Hambrick, & Conway, 2005;
Oberauer, Schulze, Wilhelm, & Süß, 2005), leaving room for other processes to
contribute additionally to *g*.

Explicit associative learning and working memory correlate at the behavioral
level of analysis (DeYoung, Peterson, & Higgins, 2005), and both appear to engage
the PFC. However, working memory typically recruits dorsolateral areas of the PFC
in Brodmann areas 9 and 46 (Petrides, 1995; 2000), whereas explicit associative
learning engages adjacent, more posterior frontal regions, in Brodmann areas 6 and
8 (Petrides, Alivisatos, Evans, & Meyer, 1993). The fact that the neural correlates of

explicit associative learning and working memory appear to be separable suggests that the two processes might make distinct contributions to general intelligence. In support of this idea, a recent study found that learning of three-term contingencies predicted performance on Ravens Advanced Progressive Matrices (RAPM), a good measure of g, above and beyond working memory (Tamez, et al., 2008). Further, once the variance between learning and g was accounted for, working memory no longer made a unique contribution to g. A limitation of this study, as well as that of Williams & Pearlberg (2006), is the analysis of single observed measures of g and learning rather than latent variables that model the shared variance of relevant tests and exclude error and unique method variance. Williams and Pearlberg (2006) found a more complex measure of learning to predict g more strongly than a simpler one, but the variance shared by both tasks may provide a better assessment of learning than either task alone. The current study was designed to overcome this limitation.

The Present Analysis

I administered the two explicit associative learning tasks used by Williams and Pearlberg (2006; see *Chapter 2: Methodology*); the more complex of these two tasks was found to be more strongly associated with g than was the simpler. Having examined these tasks individually, I proceeded to investigate explicit associative learning as a latent construct by modeling their shared variance. I used structural equation modeling to test the hypothesis that explicit associative learning would predict g while controlling for working memory capacity and processing speed.

Support for this hypothesis would demonstrate that associative learning is a promising candidate as an elementary cognitive process contributing to *g*, separable from two of the best-established ECTs, working memory capacity and processing speed.

Methodology

Participants

169 participants (54 males and 115 females) were included in the analyses presented in this chapter. Out of the total sample of 177 (see *Chapter 2: Methodology*), 9 participants were removed from these analyses because they failed to complete all tasks that were markers for one or more of the latent variables (and therefore their missing values could not be estimated).

Missing values

Some participants were missing values for certain variables, which I estimated using expectation-maximization based on the other markers of the relevant latent construct. Due to computer error, values were missing for 13 participants for one of the three markers of *g*. Data from the other two markers of *g* were used to impute 11 missing RAPM values, 1 missing DAT-V value, and 1 MRT-A value. For Speed-F, 10 participants did not follow the directions correctly and their scores could not be included in the analysis. Therefore, I used data from the other two markers of processing speed (Speed-V and Speed-N) to impute 10 missing values on Speed-F. Finally, due to a computer error, performance on the last trial of PA was not recorded for one participant. Since this participant achieved a maximum

score on the third trial, I estimated that performance on the last trial was also a perfect score.

Measures

The following tests were included in the analyses for this chapter (see *Chapter 2: Methodology* for a full description of each task): **General intelligence**: Raven's Advanced Progressive Matrices Test, Set II (RAPM), DAT verbal reasoning test (DATV), and Mental rotations test (MRT-A); **Explicit Associative Learning**: Three-term contingency learning (3-Term) and Paired-associates learning (PA); **Processing speed**: Verbal speed test (Speed-V), Numerical speed test (Speed-N), and Figural speed test (Speed-F); **Working Memory**: Operation Span Task (Ospan).

Results

Psychometric Properties of the Associative Learning Tasks

Table 3-1 shows the descriptive statistics for each trial of learning on both PA and 3-Term.

Table 3-1

Descriptive statistics for learning trials on 3-Term and PA (N = 169)

Trial	Mean	S.D.	Min	Max	Correlation with g
3-Term Trial 1	3.28	3.50	0	21	.19*
3-Term Trial 2	9.27	6.61	0	30	.34**
3-Term Trial 3	14.62	7.91	0	30	.33**
3-Term Trial 4	18.82	8.17	0	30	.33*
PA Trial 1	11.85	6.65	1	28	.19*
PA Trial 2	20.54	7.36	2	30	.29**
PA Trial 3	24.08	6.73	2	30	.27**
PA Trial 4	25.79	5.85	5	30	.29**

Note: * $p < .05$; ** $p < .01$.

The first block of learning on 3-Term had both an exceptionally low mean of 3.19 out of 30 correct and a standard deviation about half that of the other three learning trials. Similarly, the first block of learning on PA displayed a mean of 11.85 out of 30 correct, also low compared to performance on the other three blocks of learning on PA. Even so, performance on the first block of PA is significantly higher than performance on the first block of 3-Term [t(168)=-19.11, p <.001], suggesting a faster acquisition function and lower difficulty of the PA task relative to 3-Term.

To investigate the relation between g and each block of learning, I calculated each participant's g score by assessing the common variance across RAPM, DAT-V, and MRT-A using Principal Axis Factoring. Performance on the four blocks of each

learning task and the relation of g to performance across blocks was analyzed using a repeated measures GLM.

For both the 3-Term and PA learning tasks, there was a significant main effect for block [3Term: $F(3,165) = 277.56$, $p < .001$; PA: $F(3,165)=370.45$, $p < .001$] and a significant g x block interaction [3Term: $F(3,165) = 7.21$, $p < .001$; PA: $F(3,165) = 2.88$, $p < .05$]. This interaction indicates that for both learning tasks, g is more strongly associated with some learning blocks than others. Table 1 shows the correlation between g and each block of learning on both PA and 3-Term. The correlation of each block of learning with g stabilizes after the first block of learning, suggesting that the first block of learning for both measures of associative learning may be too difficult for reliable individual differences to emerge. For this reason, further analyses will exclude the first block on both 3-Term and PA.

Associative Learning and g

Cronbach's alpha was used to estimate the reliability of the two associative learning tasks. For both measures of associative learning, reliability was calculated across blocks 2, 3, and 4. Both 3-Term ($\alpha = .93$) and PA ($\alpha = .95$) showed high reliability. The correlation matrix for scores on observed variables appears in Table 3-2, with descriptive statistics for each test.

The correlation between the total scores on 3-Term and PA was significant and high, suggesting that the two measures were engaging the same ability, or at least similar processes. It is also noteworthy that 3-Term and PA were both significantly correlated with RAPM.

Table 3-2

Correlations, means, and standard deviations of observed variables (N = 169)

Measure	1	2	3	4	5	6	7	8	9
1. RAPM (/36)	–								
2. DAT-V (/40)	.53**	–							
3. MRT-A (/24)	.59**	.43**	–						
4. Ospan (/60)	.30**	.42**	.24**	–					
5. Speed-V (/57)	.17*	.24**	.14	.22**	–				
6. Speed-F (/90)	.24**	.15*	.17*	.15	.24**	–			
7. Speed-N (/48)	.25**	.10	.21**	.10	.14	.51**	–		
8. 3-Term (/90)	.32**	.35**	.21**	.21**	.09	.16*	.02	–	
9. PA (/90)	.31**	.23**	.14	.14	.17*	.17*	-.05	.64**	–
Mean	21.72	24.52	13.21	44.53	41.36	64.70	30.90	42.70	70.42
S.D.	5.53	5.86	5.34	7.61	9.05	10.50	4.19	21.37	19.15
Reliability	.81	.78	.85	.73	.60	.60	.60	.93	.95

Notes: All reliability analyses are alpha coefficients, except for the three processing speed tests, in which the Spearman-Brown split-half coefficient was calculated across all three tests. The parenthetical next to each test refers to the total score for each test. *$p < .05$, **$p < .01$.

To test predictions about the independent prediction of *g* by associative learning (AL), working memory capacity (WMC), and processing speed (Gs), I used structural equation modeling. The model was analyzed using Amos 7.0 (Arbuckle, 2006) with maximum likelihood estimation. (*Appendix B: Additional Covariance Analyses* includes the full covariance matrix used to fit the model in Figure 3-1.)

The shared variance of blocks 2, 3, and 4 of the 3-Term test phases formed the latent variable "3-Term," and the shared variance of blocks 2, 3, and 4 of the PA test phases formed the latent variable "PA." These two latent variables then formed

the latent AL variable. The shared variance across Ospan trials of set size two, three, four, five, and six formed the latent variable representing WM. The shared variance across Speed-V, Speed-F, and Speed-N formed the latent variable representing Gs. The shared variance across RAPM, DAT-V, and MRT-A formed the latent variable representing g.

Prior to fitting the structural model predicting g (Figure 3-1), I fit a model simply allowing the predictor variables to correlate with each other and with g, in order to assess their zero-order associations. The fit of this model was almost identical to that in Figure 3-1. Correlations among the latent variables appear in Table 3-3.

Table 3-3
Correlation matrix of latent variables in structural model (N = 169)

Measure	1	2	3	4
1. *g*	–			
2. Working Memory (WM)	.48**	–		
3. Processing Speed (Gs)	.38**	.24*	–	
4. Associative Learning (AL)	.45**	.22*	.17	–

Note: *p < .05, **p < .01.

AL, WM, and Gs are significantly correlated with *g*. Although correlations are not shown in Figure 1, all predictors of *g* were allowed to correlate with each other.

In the model shown in Figure 1, AL, WM, and Gs all make significant independent contributions to *g*. The model accounts for 40% of the total variance in *g*. Also listed in Figure 1 is the χ^2 test for significant discrepancies between the predicted and observed covariance matrices, as well as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). A significant χ^2 does not necessarily indicate poor fit because the χ^2 value is sensitive to sample size (Kline, 2005). Other fit indices are designed to surmount this limitation. CFI and TLI values over .90 indicate adequate fit and values of .95 or higher indicate close fit (Kline, 2005). RMSEA values less than 0.08 indicate acceptable fit, while values of 0.05 or less indicate close fit (Kline, 2005). The $p_{(close)}$ statistic indicates whether the RMSEA value is significantly greater than 0.05. The fit indices reported in Figure 1 reveal that the structural model provides a good fit to the data.

Figure 3-1

Associative learning, working memory capacity (WMC), and processing speed (Gs)
independently predict g (N=169)
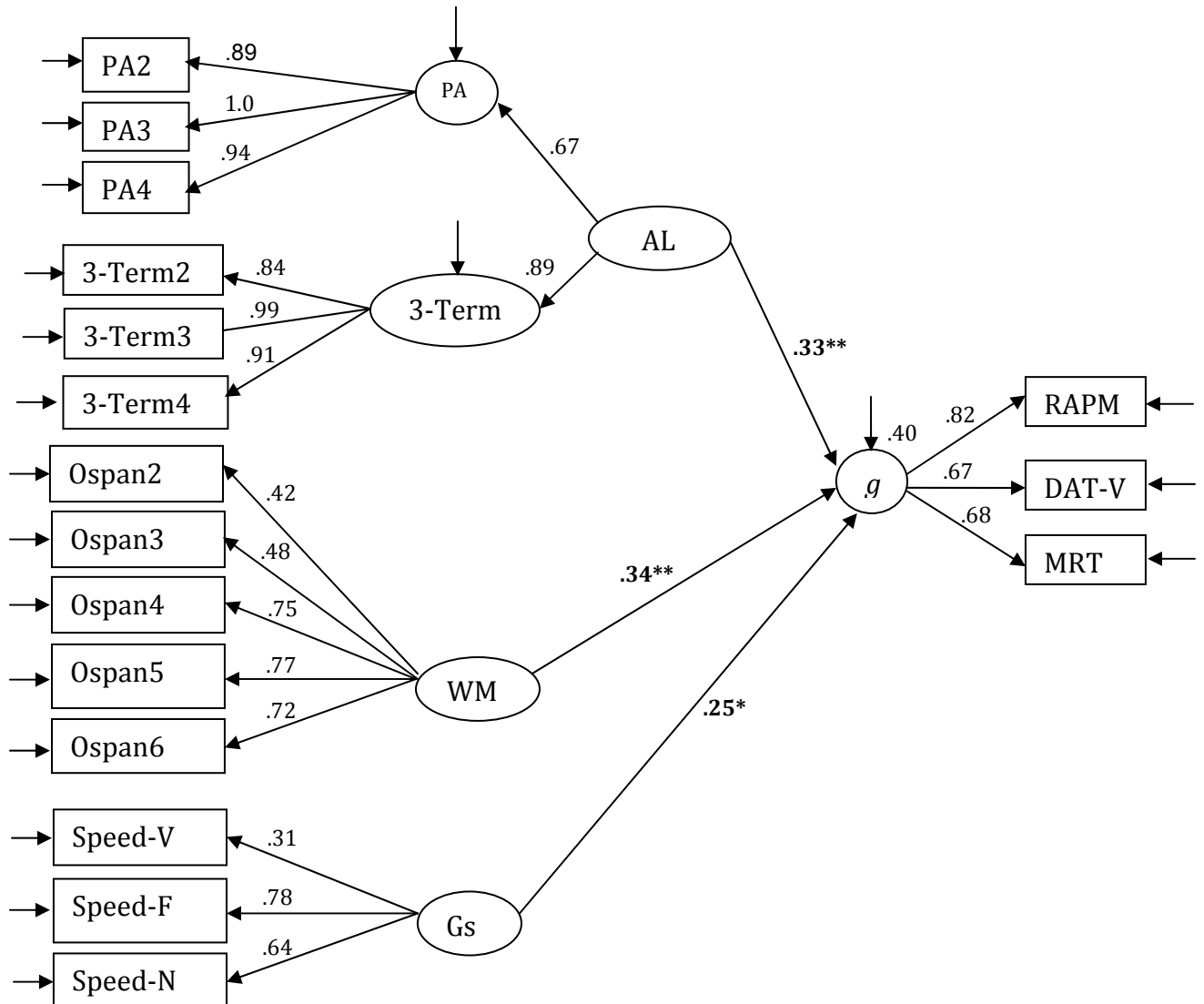
Discussion

The main aim of this chapter was to investigate the cognitive mechanisms underlying *g*, thereby clarifying the construct explicit cognitive ability. In particular, the contribution of explicit associative learning to *g*, above and beyond working memory capacity and processing speed, was assessed. In line with this goal, I first examined the psychometric properties of two associative learning tasks—three-term contingency learning and paired-associates learning. Analyses indicated that 3-Term was a more difficult task than PA overall, but both tasks demonstrated a relatively low score on the first block of learning. Further, while *g* was significantly associated with learning on each block, correlations with *g* changed significantly over the four blocks, becoming stronger on blocks 2, 3, and 4 for both 3-Term and PA. I therefore excluded the first block of learning from both measures of associative learning from the structural analysis. Any study that assesses the relation between associative learning and *g* must consider the psychometric properties of the tasks, to ensure that they are good measures of individual differences.

Structural equation modeling showed that associative learning, working memory capacity, and processing speed all made statistically independent contributions to *g*. This finding suggests that each of these elementary cognitive processes may represent a mechanism that contributes differentially to explicit cognitive ability. The current study is consistent with three recent studies that have demonstrated a link between associative learning and *g*. Firstly, Williams & Pearlberg (2006) found that 3-Term learning was related to RAPM but was not

significantly related to various measures of processing speed, which matches my results (although their results differ from mine in that they did not find a significant association between PA and RAPM). Secondly, a more recent study conducted by Tamez et al. (2008) replicated the correlation between 3-Term and RAPM, but also found that 3-Term correlated with RAPM even after controlling for working memory. Thirdly, Alexander & Smales (1997) found that the composite of various verbal and nonverbal learning tasks was correlated at .49 with the composite of various measures of general ability. The current study is consistent with these studies but goes further, in that it indicates the existence of a *general* associative learning ability factor that is related to a latent *g* factor, even after controlling for both processing speed and working memory capacity.

The finding of a significant correlation between working memory capacity and *g* is consistent with a growing and consistent literature on the strong relation between variation in working memory capacity and general cognitive ability (Conway, et al., 2007; Engle & Kane, 2004; Heitz, et al., 2004; Kyllonen, 1996; Kyllonen & Christal, 1990; Engle, et al., 1999). The finding of a significant relation between processing speed and *g* is also well supported by a large literature (Deary, et al., 2001; Jensen, 2006).

It should be noted that even though WM significantly predicted *g* independently of the other variables, the effect size of association between WMC and *g* in the SEM models is lower than what has been reported elsewhere (e.g., Kyllonen & Christal, 1990; Conway, et al., 2002). This difference may be due to the

fact that only one test of working memory capacity was administered in the current study. Adding more varied indicators to the WMC latent variable would most likely have increased the relation between WMC and g. Nonetheless, the measure of working memory administered in the current study, Operation Span, displayed similar zero-order correlations with RAPM as in other studies (Unsworth & Engle, 2005b; Conway, et al., 2002; Engle, et al., 1999; Kane, et al., 2004), including a study that found an association between the 3-Term learning task and RAPM, when controlling for WM (Tamez, et al., 2008).

A parallel concern to the use of only one working memory task is the use of multiple associative learning tasks, creating a model that is slightly unbalanced in the number of markers for each of our three predictors, with the most markers for associative learning. To address this concern I tested two additional structural models, one excluding the PA task and one excluding the 3-Term task. In both of these models, with only one task used to create a latent associative learning variable, the overall pattern of findings remained the same as in Figure 1, with all three latent variables significantly predicting g. In both these models, the paths from WM to AL to g were not significantly different from each other.

Although more thorough measurement of WM might have reduced the amount of variance in g explained by AL, it is equally plausible that more thorough measurement of associative learning could have reduced the variance explained by WM. Indeed, Tamez et al. (2008) found that Ospan's correlation with RAPM was no longer significant after controlling for 3-Term, suggesting that it is an open question

whether WM or AL is the primary predictor of *g*. Indeed, Williams et al. (2008) have recently suggested that individual differences in the ability to learn which word to recall in the face of competing associations may be what underlies differences in *g*. According to these researchers, "In fact, learning in the presence of competing stimuli may be an important part of what glues the various components of *g* together and gives rise to the consistency of individuals' behavior across different tests and in quite different situations. (p.229)." Indeed, the researchers suggest that associations found between working memory and associative learning may reflect a common ability to efficiently constrain search of long-term memory, a central aspect of working memory function (Unsworth & Engle, 2007). And of course there is a third alternative, suggested by the present study, which is that both WM and AL predict *g* independently. Future studies will hopefully provide a more thorough test of this hypothesis by including more measures of both WM and AL. It will be important for researchers to assess the critical components of both working memory and associative learning tasks that increase prediction of *g*. Constructing additional associative learning tasks that tap into a general associative learning ability factor will be an important step in this direction (Williams, et al., 2008).

The independent prediction of *g* by both working memory capacity and processing speed is inconsistent with work by Conway et al. (2002) who found that processing speed no longer predicted *g* after controlling for working memory capacity. A comparison of the processing speed tasks administered in their study and the current study shows that very similar tasks were administered, with one

being identical (Digit-Symbol Coding). There are at least four possible reasons for the discrepancy between my findings and theirs. First, their assessment of g is not as comprehensive as mine, as they utilized only the RAPM and one other very similar test. Thus, their g is most closely related to the perceptual ability component of the second-stratum factors identified by Johnson and Bouchard (2005). Arguing against this explanation, however, is the fact that when I re-ran the structural model using observed RAPM scores as my criterion variable instead of g, all three latent predictors remained significant. The second possible reason for the discrepancy is that they included a latent short-term memory variable as a predictor in addition to working memory and processing speed. Short-term memory was correlated with processing speed and could have suppressed the latter's association with g. The third possibility relates to my measurement of working memory, discussed above. If I had used additional measures of WMC, WMC might have related more strongly to g and this additional variance predicted by WMC might have rendered that predicted by processing speed non-significant. Even if this were the case, however, it might simply indicate that processing speed is a lower-level mechanism that contributes to WMC as well as to g. The fourth possible reason for the discrepancy is a difference in the developmental stage of the participants. Their sample consisted of college students, who were older than the current sample of Sixth Form students.

Conclusion

The results of the current study add to a growing literature on the existence of multiple cognitive mechanisms that support explicit cognitive ability (Sternberg & Pretz, 2005). The findings suggest that multiple cognitive processes – including the abilities to process information quickly, to maintain, update, and manipulate information in working memory, and to learn specific associations between stimuli – should contribute to performance on any highly g-loaded task. Identification of separable elementary cognitive mechanisms that support g should further attempts to develop neurobiological theories of intelligence. Such theories may help to resolve current debates regarding the nature of the mechanisms underlying g (e.g.,Colom, Franciso, Quiroga, Shih, & Flores-Mendoza, 2008). Evidence exists already that working memory and associative learning rely on different regions of the PFC (Petrides, 1995, 2000; Petrides, et al., 1993), and processing speed seems likely to be determined by a distinct set of biological parameters that are not yet known. The investigation of the precise number and nature of the mechanisms that underlie explicit cognitive ability remains a promising line of research.

Before concluding, I should note that the associative learning ability assessed in this study is distinct from the associative paradigms that are used to assess implicit learning and tacit knowledge (e.g., Gebauer & Mackintosh, 2007; Reber, Walkenfeld, & Hernstadt, 1991). In implicit learning, associations between stimuli are not acquired voluntarily, but rely on mere exposure without awareness of the association. In the associative learning tasks employed here, by contrast, subjects

consciously and voluntarily remember associations. Different mechanisms are likely to be involved in explicit versus implicit associative learning, and the findings in this chapter should not be assumed to generalize to implicit learning. With this in mind, in the next chapter I directly test the relation between explicit and implicit learning.

Detecting complex regularities, contingencies, and covariances in our environment is a fundamental aspect of human cognition. Much of this learning takes place on a daily basis without our intent or conscious awareness, and plays a significant role in structuring our skills, perceptions, and behavior (Hassin, et al., 2005; Kihlstrom, 1987; Lewicki & Hill, 1987; Lewicki, et al., 1987; Reber, 1967, 1993; Stadler & Frensch, 1997). This type of learning is often referred to as implicit learning (Reber, 1967, 1993; Stadler & Frensch, 1997) and is typically characterized by a set of automatic, associative, nonconscious, and unintentional learning processes, as distinguished from the conscious, deliberate, and reflective learning processes that are thought to be associated with Central Executive Functioning and working memory (e.g., Barrett, Tugade, & Engle, 2004).

Despite considerable interest in implicit processes, few researchers have conceptualized implicit learning as an ability. Consequently, little research has investigated whether there exist meaningful individual differences in implicit learning or the correlates of such individual differences. The current study investigates the association of implicit learning ability with a variety of cognitive and personality variables, building on previous research examining the relation of implicit learning to explicit cognitive ability, basic cognitive mechanisms, and personality traits.

ᵍ Some of the content of the current chapter was taken from the manuscript entitled *Implicit learning as an ability: Relation to psychometric intelligence, basic cognitive mechanisms, and personality*, submitted for publication and co-authored with Colin DeYoung, Jeremy R. Gray, Jamie Brown, Luis Jiménez and Nicholas Mackintosh.

Implicit Learning and Explicit Cognitive Ability

In this dissertation, explicit cognitive ability is synonymous to Spearman's *g* (short for "general intelligence"), the common variance extracted across disparate tests of cognitive ability (Spearman, 1904). What is the link between implicit learning and explicit cognitive ability? According to Reber (1989, 1993) and Reber and Allen (2000), individual differences in implicit learning should be expected to be largely independent of individual differences in explicit cognitive ability. The argument is based on the assumption that implicit learning is evolutionarily older than explicit cognition, with the latter developing only with the rise of *Homo sapiens*. The older mechanisms of implicit learning are believed to have been unaffected by the arrival of explicit cognition, which includes hypothesis-guided learning and deduction, and they continue to function independently of one another today.

The arrival of explicit cognition, which includes processes of hypothesis-guided learning and deduction, is hypothesized not to have modified the older mechanisms of implicit learning that continue to function independently. These thoughts converge with arguments advanced by Mackintosh and colleagues (Mackintosh, 1998; McLaren, Green, & Mackintosh, 1994) that the processes underlying performance on implicit learning tasks may be automatically associative rather than cognitive in nature, and are consistent with various other dual-process theories of human cognition (Chaiken & Trope, 1999; Epstein, Pacini, Denes-Raj, & Heier, 1996; Evans & Frankish, 2009; Sloman, 1996; Stanovich & West, 2000).

Thus far, evidence that performance on implicit learning tasks is independent of differences in IQ has been somewhat mixed, although on the whole supportive. Some paradigms have never shown an association with explicit cognitive ability (e.g., artificial grammar learning; Gebauer & Mackintosh, 2007; McGeorge, Crawford, & Kelly, 1997; Reber, et al., 1991), whereas for other paradigms the majority of studies have not found a significant association (e.g., serial reaction time learning; Feldman, Kerr, & Streissguth, 1995; Unsworth & Engle, 2005a ; but see Salthouse, et al., 1999). The relation between IQ and one other implicit learning paradigm, which involves incidental exposure to pictures has been investigated only once but did show an association with explicit cognitive ability (Fletcher, Maybery, & Bennett, 2000). A possible explanation for these mixed results is that different implicit learning paradigms are only weakly correlated with one other (Gebauer & Mackintosh, 2007, 2009; Salthouse, et al., 1999) and may differ in the extent to which they are measuring implicit learning without relying on intentional processes (e.g., Seger, 1994).

Direct comparisons of implicit and explicit versions of specific tasks may further help to explain these contradictory results. In some studies, researchers administered the same implicit learning task under two conditions: in one condition, participants were explicitly instructed to detect the underlying covariation, and in the other condition participants did not receive such an instruction, thereby making learning 'incidental' to the task requirements. In these studies, explicit cognitive ability was more highly correlated with the task under explicit instructions than

incidental conditions (Unsworth & Engle, 2005a; Gebauer & Mackintosh, 2007).

Similarly, in study of 455 adolescents, Feldman, Kerr, and Streissguth (1995)

separated an intentional declarative component of an implicit learning task from the

procedural component and found that while the declarative learning component

significantly correlated with explicit cognitive ability, the procedural component did

not. Overall it appears that individual differences in explicit cognitive ability, which

are clearly associated with variation in explicit cognition, are either weakly or not at

all associated with variation in implicit learning (e.g. McGeorge, et al., 1997; Reber,

et al., 1991).

While implicit learning is only weakly related to explicit cognitive ability,

recent research suggests that individual differences in implicit learning may make

an independent contribution to complex cognition. Gebauer & Mackintosh (2009)

administered a battery of 15 traditional implicit learning tasks and 9 traditional

explicit cognitive ability tests to 195 German school pupils. Factor analyses revealed

a low correlation between two second-order principal components, the first

corresponding to explicit cognitive ability and the second corresponding to implicit

learning. In addition, their second-order factor of implicit learning correlated

significantly with school grades in Math and English, which was considered a foreign

language for the German participants in the study. Controlling for explicit cognitive

ability, the correlation between the implicit learning factor and English grades

remained, while the relation to Math was no longer significant. Similarly, Pretz, Totz,

& Kaufman (2009) found a significant relationship between a measure of SRT

probabilistic learning and ACT Math and English scores. This effect remained significant after controlling for a rational cognitive style. These results suggest there is a source of variance associated with implicit learning that is independent of explicit cognitive ability but nevertheless related to some aspects of school learning.

Implicit Learning and basic cognitive mechanisms

A number of basic cognitive mechanisms, including working memory, explicit associative learning, and processing speed, have been posited as contributors to intelligence (e.g., *Chapter 3: Explicit Cognitive Ability*; Kaufman, DeYoung, Gray, Brown, & Mackintosh, 2009). Examining their relations to implicit learning may help to clarify the relation of implicit learning to other aspects of cognition. Below we review the available evidence on the relation of these cognitive mechanisms to implicit learning.

Implicit Learning and Working Memory/Executive Attention

Working memory is defined as the ability to maintain, update, and manipulate information in an active state, over short delays. It depends heavily on executive attention; those with a high working memory are better able to control their attention, maintaining task goals in the presence of interference (Kane, et al., 2001; Unsworth, et al., 2004; Conway, et al., 2001). Over the last two decades, considerable debate has arisen over the question of whether implicit learning, like working memory, depends on the executive functions of attention, or whether it arises automatically as a by-product of processing a set of correlated events (Jiménez, 2003; Shanks, 2003). Much experimental work (e.g., Baker, et al., 2004;

Frensch & Miner, 1995; Jiang & Chun, 2001; Jiménez & Mendez, 1999; Turke-Browne, et al., 2005) appears to be converging on the conclusion that, for implicit learning to occur, selective attention to the relevant stimuli is required. However, learning about the stimuli that are selectively attended to then occurs automatically, regardless of an intention to learn, and without necessitating any further executive processing resources.

One implication of this conclusion is that Central Executive resources should be engaged under explicit learning instructions, to guide the focus of attention, whereas only selection processes should be required for incidental learning (Cowan, 1988, 1995; Frensch & Miner, 1995, Johnson & Hirst, 1993). Working within this framework, Unsworth and Engle (2005a) demonstrated that working memory differences emerge in an implicit learning task under explicit instructions to detect the covariation, but not under incidental conditions where no such instructions were given. Similarly, Feldman, Kerr, and Streissguth (1995) found nonsignificant correlations between implicit learning and measures of working memory.

In sum, the available data suggest that implicit learning operates in an automatic fashion once relatively low-level perceptual attention is selectively allocated to the appropriate stimuli, without necessarily requiring executive attention. This leads us to hypothesize that individual differences in implicit learning are not associated with individual differences in working memory.

Implicit learning and explicit associative learning

Associative learning as conceived in the implicit learning literature differs from the type of associative learning typically discussed in the intelligence literature (e.g., Underwood, et al., 1978; Williams & Pearlberg, 2006). Learning in the implicit literature is often termed as associative (as opposed to cognitive) when learning proceeds incidentally, because it describes the incidental formation of associations, which is thought to underpin this form of learning. Connectionist modeling based on this assumption has successfully modeled many aspects of implicit learning (e.g., Cleeremans, 1993; Cleeremans & Dienes, 2008). By contrast, in the intelligence literature, associative learning is often used to describe the learning of associations acquired consciously and explicitly according to explicit instruction and feedback. To date, no study has investigated the relationship between implicit learning and explicit associative learning. While prior studies have ostensibly compared explicit and implicit learning (e.g., Reber, et al., 1991), measures of "explicit learning" in these studies have typically been measures of explicit reasoning, such as series completion, that do not, in fact, involve learning during the course of the experiment. Despite the fact that both implicit learning and explicit associative learning must involve the formation of associations, we hypothesized that they are unrelated as abilities, for the same reasons that working memory seems likely to be unrelated to implicit learning: executive attention should be required only when learning is explicit.

Implicit learning and processing speed

Processing speed involves the speed at which very simple operations can be performed. Differences in intelligence may partly reflect the overall efficiency and speed of the nervous system (M. Anderson, 1992; Jensen, 1998), in addition to more specific capabilities like working memory (see *Chapter 3: Explicit Cognitive Ability*; Kaufman, 2007c). Given the primitive and broad nature of processing speed as a parameter, one might expect it to be related to individual differences in implicit learning, even in the absence of implicit learning's association with more complex cognitive mechanisms. Accordingly, Salthouse, et al., 1999 found a significant relationship between two reaction time measures and implicit learning. One of these measures was the Digit-Symbol Coding test, part of the standard WAIS battery for IQ. Although the factor structure of the WAIS indicates a processing speed factor as one of four second-level factors below *g*, the processing speed tests load on *g* more weakly than other types of test (Deary, et al., 2001). I therefore expected that, although implicit learning may be only weakly or not at all related to *g*, it may show a significant relation to processing speed.

Implicit learning and Personality

Research on the personality correlates of implicit learning is limited. However, theoretical links between implicit learning and intuition allowed us, in conjunction with the available evidence, to make predictions regarding personality traits reflecting an intuitive cognitive style, especially those related to the Big Five trait domain of Openness/Intellect and to impulsivity.

Intuition

Implicit learning and intuition are closely related constructs. Indeed, it has been argued that intuition is the subjective experience associated with the accumulated knowledge gained through an implicit learning experience (Dienes, 2008; Lieberman, 2000b, Reber, 1989). Reber (1989) further explains how implicit learning and intuition can be related:

> *To have an intuitive sense of what is right and proper, to have a vague*
>
> *feeling of the goal of an extended process of thought, to "get the point"*
>
> *without really being able to verbalise what it is that one has gotten, is to*
>
> *have gone through an implicit learning experience and have built up the*
>
> *requisite representative knowledge base to allow for such a judgement*
>
> *(p. 233).*

Woolhouse and Bayne (2000) looked at the relationship between personality as measured by the Myers-Briggs Type Indicator (MBTI) (Myers, et al., 1998), and performance on a hidden covariance detection task (Lewicki, Hill, & Sasaki, 1989), in which participants implicitly learned to judge the job suitability of job applicant personality profiles based on the covariance between personality profiles and information about job suitability in the training phase. A test phase with new profiles showed that participants learned the covariation regardless of whether they were explicitly aware of the rules. Individual differences emerged, however, when considering task performance along the MBTI dimension of sensing-intuition, which was designed to measure the extent to which people prefer to make decisions using

factual, simple, and conventional methods (sensing) vs. a preference for the possible, complex, and original (intuition) (McCrae, 1994). Woolhouse and Bayne found that sensing types were more likely to be consciously aware of the covariation and apply it effectively. Among those who lacked awareness of the underlying rule, however, there was a tendency for participants with a more intuitive personality to make greater and more accurate use of their intuition on the implicit learning task. These authors suggested that sensing and intuitive types employ different strategies on implicit learning tasks, and therefore that personality influences whether people will use intuition based on implicit knowledge to help them arrive at a correct answer in the absence of explicit knowledge.

Openness/Intellect

The five factor model or Big Five is the most widely used and best validated taxonomy of personality traits (Goldberg, 1990; Markon, Krueger, & Watson, 2005). Within the Big Five, the MBTI dimension of sensing-intuition falls within the domain of Openness/Intellect (McCrae, 1994). The compound label for this dimension reflects an old debate about how best to characterize this personality factor, with some researchers favoring the label "Intellect" (e.g., Goldberg, 1990) and others favoring "Openness to Experience" (e.g., Costa & McCrae, 1992). This debate has been largely resolved by the recognition that Openness and Intellect reflect separable but related aspects of the larger domain (Johnson, 1994; Saucier, 1992). This distinction was recently given more empirical support by the finding of two correlated factors within 15 scales measuring different lower-level facets of

Openness/Intellect (DeYoung, et al., 2007). The two factors were clearly recognizable as Intellect and Openness, with Intellect reflecting a combination of cognitive ability and tendency toward a desire for engagement in deliberate effortful thought, and Openness reflecting artistic qualities and engagement with sensory and perceptual information. The analysis of DeYoung et al. (2007) generated new scales to measure Openness and Intellect separately and also demonstrated that different subscales of the NEO PI-R Openness to Experience scale (Costa & McCrae, 1992) could be used as markers of Openness and Intellect. McCrae (1994) found that the MBTI intuition scale was more strongly related to Openness than to Intellect, at the facet level.

Based on the link between Openness and intuition, we hypothesized that scales loading on Openness would be positively associated with implicit learning. Scales related to intellect, in contrast, appear to be more closely linked to intelligence, working memory, and explicit associative learning (DeYoung, et al., 2005). I hypothesized that they would be associated with these other cognitive abilities, but not with implicit learning.

Impulsivity

In recent years, dual-process theories of reasoning have gained popularity (see Evans & Frankish, 2009). While the precise specifications of the theories differ, most have in common the idea that humans possess both automatic and controlled processes that jointly contribute to behavior. This idea has recently been elaborated

on by Strack & Deutch (2004) who argue that behavior is multiply determined by both impulsive and reflective processes.

Prior research shows that impulsivity is negatively related to both g and working memory (Kuntsi, et al., 2004; Shamosh & Gray, 2007; Shamosh, et al., 2008). Here I investigate the relationship between implicit learning and impulsivity. According to Strack and Deutsch (2004), the impulsive system involves an associative network that is automatically activated through learning and experience. They argue that "structures emerge in the impulsive system that bind together frequently co-occurring features and form associative clusters (p. 223)." They further state that "the impulsive system has low flexibility but is fast and needs no attentional resources (p. 224). This characterization strongly suggests that implicit learning ability might be positively associated with trait impulsivity.

Whiteside and Lynam (2001) identified four major dimensions of variance pertaining to impulsivity: urgency, lack of premeditation, lack of perseverance, and sensation seeking. I hypothesized that the most relevant form of impulsivity for implicit learning is lack of premeditation, in that individuals that deliberate extensively may do so in part because they are poor at detecting incidental covariances and would otherwise generate quick and intuitive decisions that were incorrect.

Hypotheses

Hypothesis 1: Explicit cognitive ability is correlated more strongly with explicit associative learning than with implicit learning.

Hypothesis 2: Implicit learning is not related to working memory, or explicit associative learning, but is related to processing speed. Implicit learning is also related to other measures of cognitive performance independently of explicit cognitive ability and the elementary cognitive tasks associated with explicit cognitive ability.

To assess these first two hypotheses, I examined zero-order correlations between individual differences in implicit learning and tests of these other cognitive variables, including tests of academic achievement. Then I assessed the association of latent cognitive constructs with implicit learning.

Hypothesis 3: Implicit learning is significantly associated with Openness and the related trait of Intuition but is not associated with Intellect. Further, there is a double dissociation, with Intellect related to working memory (DeYoung, et al., 2005; DeYoung, Shamosh, Green, Braver, & Gray, in press) and Openness related to implicit learning.

To assess this hypothesis, I examined zero-order correlations between implicit learning and markers of Openness and Intellect, including MBTI Intuition, as well as correlations of implicit learning with latent Openness and Intellect variables. To test the double dissociation, I tested a structural model using Intellect and Openness as simultaneous predictors of implicit learning and working memory.

Hypothesis 4: Impulsivity—and particularly lack of premeditation—is positively correlated with implicit learning.

To assess this hypothesis, I examined zero-order correlations between implicit learning and the four impulsivity dimensions identified by Whiteside and Lynam (2001).

Methodology

Participants

153 participants (47 males and 106 females) were included in the analyses presented in this chapter. Out of the total sample 177 (see *Chapter 2: Methodology*), 24 participants were remove from this chapter's analysis because they were missing implicit learning scores, 2 were removed because their Raven Advanced Progressive Matrices scores were below chance, and 1 participant was removed due to obvious lack of effort (e.g., frequent chatting). 147 participants completed all three testing sessions. Due to computer errors and time constraints, not all participants completed all the tests. Where possible, I imputed missing values (see below).

Missing values

In instances where I could reliably estimate missing values, I did so using expectation-maximization based on scores on other tests measuring the same construct. Data from the other two markers of g were used to impute 17 missing RAPM values. For Speed-F, 6 participants did not follow the directions correctly and their scores could not be included in the analysis. Therefore, I used data from the other two markers of processing speed (Speed-V and Speed-N) to impute 10 missing values on Speed-F.

Measures

The following tests were included in the analyses for this chapter (see Chapter 2: Methodology for a full description of each task): **General intelligence**: Raven's Advanced Progressive Matrices Test, Set II (RAPM), DAT verbal reasoning test (DATV), and Mental rotations test (MRT-A); **Explicit Associative Learning**: Three-term contingency learning (3-Term) and Paired-associates learning (PA); **Processing speed**: Verbal speed test (Speed-V), Numerical speed test (Speed-N), and Figural speed test (Speed-F); **Working Memory**: Operation Span Task (Ospan); **Implicit Learning**: Probabilistic Serial Reaction Time (SRT) task; **Personality**: Myers-Briggs Type Indicator (MBTI), The Big Five Aspect Scales (BFAS), NEO-PI-R, Rational-Experiential Inventory, The UPPS Impulsivity Scale.

Results

Validation

I first validated that implicit learning took place on the probabilistic serial reaction time (SRT) learning task. Figure 4-1 shows learning on each block at the group level of analysis, comparing mean RT for trials that followed the most probable (85%) sequence with the mean RT for trials that do not follow the most probable sequence (15%).

Figure 4-1

SRT Learning Performance for probable (SOC-85) and non-probable (SOC-15) trials across one practice and eight learning blocks (N = 153)
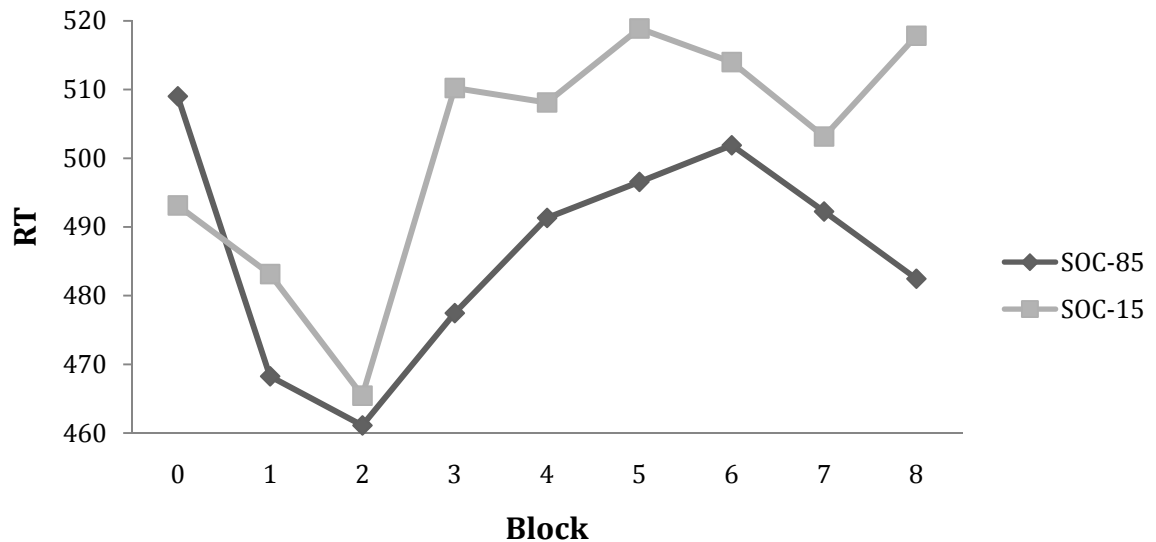
A repeated-measures analysis of variance (ANOVA) with block (8) and type of trial (2, training vs. control) was conducted on the measures of RT. The results showed a significant effect of block, $F(7,1064) = 38.77$; $p < .0001$ partial $\eta^2 = .20$, and type of trial, $F(1,152) = 328.14$ $p < .0001$, partial $\eta^2 = 0.68$, as well as a significant interaction block x type of trial, $F(7,1064) = 19.88$ $p < .0001$, partial $\eta^2 = 0.12$, indicating the acquisition of learning about the training sequence. As is evident from an inspection of Figure 4-1, a change in the response trends seems to occur from block 3 onwards, in which RT became slightly slower, but the differences between responding to training and control trials became larger. A comparison of the effect of learning between the first two and the last six blocks of training showed that the

difference between responding to training and control trials was significantly larger over the latter blocks F(1, 152)= 233.51, p <.0001. Furthermore, the average Cohen's *d* across the last six blocks was .19. Thus, I decided to use this average effect as the criterion for my scoring procedure (see Chapter 2: *Methodology*).

H1. Explicit cognitive ability is correlated more strongly with explicit associative learning than with implicit learning and implicit learning is not related to working memory, or explicit associative learning, but is related to processing speed

Table 4-1 includes all the correlations, descriptive statistics, and reliabilities among all of the variables. To investigate our first hypothesis, I looked at the zero-order correlations between IL, E-AL, and the three markers of explicit cognitive ability. Among the three markers of explicit cognitive ability, IL is significantly correlated only with DAT Verbal Reasoning, *r* =.22, p < .01. To assess IL's relationship to *g* and the ECT's related to *g*, I constructed latent variables using Amos 7.0 (Arbuckle, 2006), and then analyzed the association among these latent variables and IL. Missing values were estimated by Amos using Maximum Likelihood. A latent variable approach allows for more accurate measurement of the constructs of interest.

The shared variance of RAPM, DAT-V, and MRT-A formed the latent variable representing *g*. The shared variance of Speed-V, Speed-F, and Speed-N formed the latent variable representing Gs. The shared variance of Ospan trials of set size two, three, four, five, and six formed the latent variable representing WM. The shared

variance of blocks 2, 3, and 4 of the 3-Term test phases formed the latent variable "3-Term," and the shared variance of blocks 2, 3, and 4 of the PA test phases formed the latent variable "PA."

Table 4-1

Correlations among all measures of g, ECTs, IL, Intellect, Openness, Intuition, and Impulsivity

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. RAPM	–																							
2. DAT-V	.50	–																						
3. MRT-A	.58	.41	–																					
4. Ospan	.34	.44	.27	–																				
5. Speed-V	.22	.22	.17	.23	–																			
6. Speed-F	.26	.12	.16	.10	.23	–																		
7. Speed-N	.25	.10	.21	.12	.14	.56	–																	
8. 3-Term	.31	.37	.23	.20	.14	.19	.04	–																
9. PA	.27	.25	.14	.11	.23	.20	-.04	.67	–															
10. IL	.13	.22	.05	.05	.00	.25	.12	.05	.06	–														
11. BFAS-I	.32	.41	.30	.27	.16	.17	.06	.24	.11	.07	–													
12. BFAS-O	.12	.29	.06	.19	.04	.22	.11	.14	.06	.29	.19	–												
13. NEO Fan.	.19	.21	.14	.22	-.02	.11	.02	.17	.06	.16	.18	.47	–											
14. NEO Aes	.10	.20	-.04	.11	.08	.24	.20	.12	.03	.21	.28	.72	.36	–										
15. NEO Feel.	.06	.13	.05	.16	.05	.20	.11	.20	.13	.14	.21	.50	.36	.49	–									
16. NEO Actions	.06	.11	.02	.13	-.03	.26	.13	.05	.01	.14	.22	.38	.18	.37	.38	–								
17. NEO Ideas	.42	.37	.30	.26	.12	.27	.18	.30	.13	.13	.71	.34	.31	.47	.33	.27	–							
18. NEO Values	.12	.24	.15	.17	.14	.15	-.04	.07	.02	.12	.21	.29	.20	.20	.22	.26	.19	–						
19. MBTI Int.	.16	.24	.12	.17	-.02	.14	.07	.12	-.06	.25	.17	.45	.39	.36	.16	.25	.34	.13	–					
20. REI Rat. F	.40	.31	.28	.27	.06	.20	.10	.24	.15	.16	.70	.20	.22	.27	.28	.23	.79	.22	.26	–				
21. UPPS Prem.	.00	-.09	.05	-.14	.09	.04	.02	.07	.07	-.23	.08	-.29	-.36	-.14	-.16	-.36	.05	-.19	-.32	.06	–			

22. UPPS Urg.	-.08	.02	-.01	.17	.07	-.10	-.07	.07	.04	.02	-.15	.20	.17	.14	.20	.05	-.09	-.01	.05	-.20	-.38	–		
23. UPPS Sens.	.02	.05	.23	.02	-.03	.23	.34	-.02	-.01	.16	.05	.17	.07	.23	.15	.40	.04	.02	.13	-.12	-.28	.08	–	
24. UPPS Pers.	.00	-.07	-.07	-.13	.03	.19	.07	.02	.13	-.06	.24	-.20	-.24	-.01	-.01	.01	.13	-.14	-.16	.26	.44	-.41	-.03	–
N	136	153	153	153	147	147	147	147	147	153	145	145	145	145	145	145	145	145	145	146	144	144	144	144
Mean	21.8	24.4	13.2	43.9	40.9	64.4	30.9	42.6	56.2	3.1	3.6	3.8	3.9	3.4	3.8	3.1	3.5	3.9	18.7	3.6	3.2	3.3	3.7	3.2
S.D.	5.4	5.9	5.3	8.4	9.3	10.2	4.3	21.4	19.2	1.5	.60	.60	.62	.82	.62	.54	.70	.49	5.2	.65	.65	.63	.68	.72
Reliability (α)	.80	.79	.78	.72	.65	.65	.65	.93	.96	.44	.78	.73	.78	.80	.77	.60	.80	.62	.84	.84	.87	.82	.84	.87

Note: Correlations > .16 in absolute value are significant at p < .05.

The latter two latent variables then served as markers for a latent AL variable, with the unstandardized paths from the AL factor to both 3-Term and PA constrained to be equal because two indicators do not provide enough information to determine a unique solution for their loading weights on a latent variable (Kline, 2005).

Correlations among the latent variables and with IL (which was an observed variable) appear in Table 4-2.

Table 4-2
Correlations among implicit learning and latent variables for g and ECTs (*N* = 153)

Measure	1	2	3	4	5
1. *g*	–				
2. WM	.55**	–			
3. GS	.38**	.19	–		
4. AL	.44**	.17	.18*	–	
5. IL	.16	.06	.24**	.08	–

Note. g = General intelligence; WM = Working Memory; Gs = Processing Speed; AL = Explicit Associative Learning; IL= Implicit Learning. *p < .05, **p < .01.

Consistent with my second hypotheses, the only ECT to which IL is significantly related is processing speed. IL is almost entirely uncorrelated with WMC and E-AL. Also in support of my hypotheses, *g* is significantly more strongly correlated with explicit associative learning than with implicit learning, according to a test of equality of correlations (Steiger, 1980), *t*(150) = 2.78, p < .01)

The correlation between *g* and IL, however, approaches significance (p = .08). To test whether this correlation is due to IL's relationship to DAT-V, I tested a

structural model in which g, all ECTs, and DAT-V simultaneously predict IL (see

Figure 4-2).

The model was analyzed using Amos 7.0 (Arbuckle, 2006) with maximum

likelihood estimation. When all the variables are entered together into a structural

model, only Gs and DAT-V independently predict IL. This suggests that g's zero-

order correlation with IL approaches significance only because of DAT-V's

correlation with IL. As an even more stringent test of the association of IL with DAT-

V independently of g, I created a broader g variable by allowing the latent E-AL, Gs,

and WM variables to load on g (instead of merely correlating with g). The results

remained substantively the same, with DAT-V but not g significantly predicting IL.

Also listed in Figure 4-2 is the χ^2 test for significant discrepancies between

the predicted and observed covariance matrices, as well as the Comparative Fit

Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of

Approximation (RMSEA). A significant χ^2 does not necessarily indicate poor fit

because the χ^2 value is sensitive to sample size (Kline, 2005). Other fit indices are

designed to surmount this limitation. CFI and TLI values over .90 indicate adequate

fit and values of .95 or higher indicate close fit (Kline, 2005). RMSEA values less than

0.08 indicate acceptable fit, while values of 0.05 or less indicate close fit (Kline,

2005). The $p_{(close)}$ statistic indicates whether the RMSEA value is significantly

greater than 0.05. The fit indices reported in Figure 4-2 reveal that the structural

model provides a good fit to the data.

Figure 4-2

Associative learning (AL), working memory (WM), processing speed (GS), and explicit cognitive ability (g), and verbal reasoning (DAT-V) predict implicit learning (IL) (N=153)
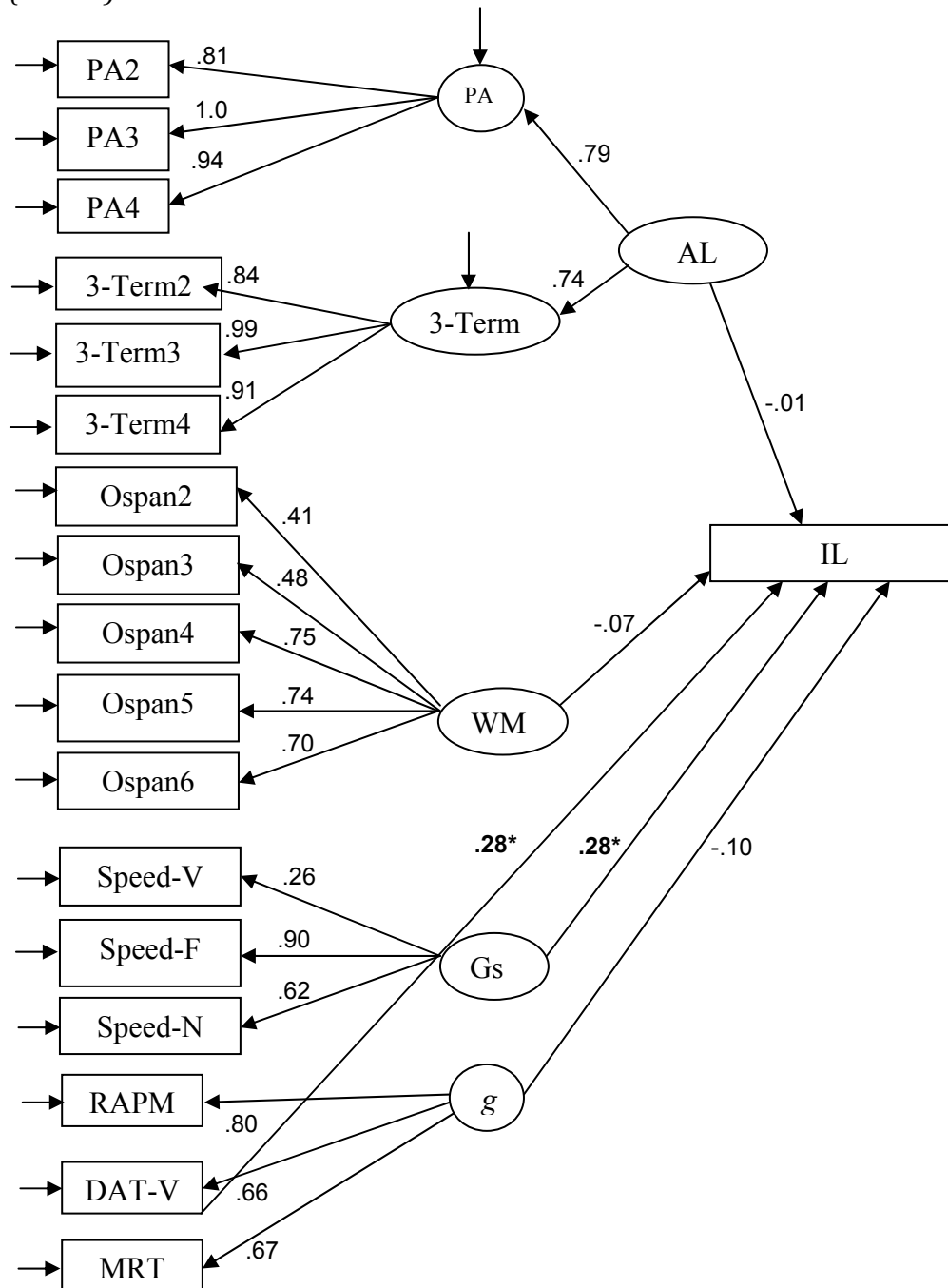
Notes: χ^2 = 189.13, df =124, p < .05, CFI = .96, TLI = .94, RMSEA = .06, p_{close} = .19; * p < .05. The latent predictors were allowed to correlate, but the correlations aren't shown for clarity of illustration

H2. Implicit learning is related to other measures of cognition independently of explicit cognitive ability and the elementary cognitive tasks associated with explicit cognitive ability.

GCSE scores were reported by the participants in this study. GCSE exams are national, subject-based exams taken by students in England at age 15-16 before entry to 6th form (eleventh year of schooling) and depending on the subject, involve some combination of coursework and written, listening, speaking and reading examinations. Based on prior reports of a correlation between implicit learning and Math and language achievement (Gebauer & Mackintosh, 2009; Pretz, et al., 2009), I focused my analysis just on Math and language-related courses. Using only those tests that displayed an adequate *N* for analysis (> 40), Table 4-3 shows the correlations of GCSE Math, English, French, and German scores with *g*, ECTs, and implicit learning.

Table 4-3

Correlations between GCSE scores and g, ECTs, and implicit learning

Measure	GCSE Math	GCSE English	GCSE French	GCSE German
g	.44**	.23*	.22*	.02
WM	.26**	.32**	.35**	.14
Gs	.32**	.33**	.12	.28
AL	.16	.20*	.24*	.16
IL	.21*	.15	.27**	.29
N	145	145	102	42

Note: The *N* for the correlation between Gs and Both Math and English is 144. GCSE English scores were calculated by taking the average of GCSE English Language and GCSE English Literature scores. *g* was calculated by assessing the common variance across RAPM, DAT-V, and MRT-A using Principal Axis Factoring (*N*= 153). The first PAF accounted for 67% of the total variance in the three tests. WM was calculated by summing the Ospan scores for all set sizes. E-AL was calculated by summing the 3-Term and PA learning scores. Gs was calculated by summing Speed-F, Speed-N, and Speed-F. *g* = General intelligence; WM = Working Memory; Gs = Processing Speed; AL = Explicit Associative Learning; IL= Implicit Learning. *$p < .05$, **$p < .01$.

Implicit learning is significantly correlated with Math and French scores. While the correlation between implicit learning and German scores wasn't significant, the effect size is close to that for the relation between implicit learning and French, suggesting that with a larger sample size the correlation would reach significance. Since *g* and some of the ECTs were also related to these scores, I assessed the partial correlation between IL and the GCSE scores, controlling for *g*, WM, E-AL, and Gs. After controlling for these variables, the correlation between Math and IL is no longer significant and the correlation between English and IL is still not significant, but the correlation between IL and French remains significant (*r*=.27, $p < .01$, *N*= 144), and the correlation between IL and German increases to reach significance (*r*=.35, $p < .05$, *N* = 42).

H3. Implicit learning is significantly associated with Openness and the related trait of Intuition but is not associated with Intellect

Whereas IL was not related to any of the three markers of Intellect (NEO Ideas, BFAS Intellect, REI Rational Favorability), IL was significantly related to three markers of Openness (BFAS Openness, NEO Aesthetics, and NEO Fantasy, see Table 4-1). Consistent with this pattern is the fact that NEO Aesthetics and NEO Fantasy were the two NEO facets that loaded mostly highly on the factor from which the BFAS Openness scale was derived (DeYoung, et al., 2007).

Using latent variables for Openness (consisting of BFAS Openness, NEO Aesthetics, NEO Fantasy, NEO Feelings, and NEO Actions) and Intellect (consisting of NEO Ideas, BFAS Intellect, and REI Rational Favorability), Openness was correlated with WM, Gs, and IL, and Intellect was associated with g, WM, Gs, and AL, but not IL (see Table 4-4).

As a consequence of the significant relationship of WM, Gs, and IL with the latent Openness factor, I ran an SEM model to assess the independent effects of IL on Openness, controlling for the other cognitive variables. With g, WMC, AL, Gs, and IL simultaneously predicting Openness, IL (β=.23, p < .01) remained a significant predictor of the BFAS Openness scale.

Table 4-4

Correlations between cognitive tasks, latent variables for Intellect and Openness, and Intuition

Measure	Intellect	Openness	MBTI Intuition
1. *g*	.55**	.20	.22*
2. WM	.35**	.25*	.20*
3. Gs	.27*	.30**	.14
4. AL	.30**	.17	.00
5. IL	.15	.30**	.25**

Note. N = 153 (with estimation for missing values in AMOS) *p* < .05, **p* < .01.

Table 3-4 also shows that *g*, WMC, and IL were significantly correlated with MBTI Intuition. I therefore ran another SEM model to assess the independent effects of IL on MBTI Intuition, controlling for the other cognitive variables. With *g*, WMC, AL, Gs, and IL entered simultaneously into a regression model, IL (β=.21, p < .05) remained a significant predictor of the MBTI Intuition scale.

H3. There is a double dissociation, with Intellect related to working memory and

Openness related to implicit learning

The pattern of correlations seen in Table 3 suggest a possible dissociation between Intellect and Openness, with measures of *g* and ECT's associated primarily with an intellectual cognitive style on the one hand, and IL independently associated with openness to experience on the other hand. Openness was associated with WM at the zero order (Table 3), but this might be due to the variance it shares with Intellect, as a previous study did not find any association between Openness and

WM (DeYoung, et al., in press). Because previous studies have suggested that WM is

a key cognitive correlate of Intellect (DeYoung, et al., 2005, DeYoung, et al., in press),

I contrasted IL with WM. To formally test the double dissociation of Openness and

Intellect with IL and WM, I used structural equation modeling (see Figure 4-3).

Figure 4-3
Double dissociation between Openness and Intellect in predicting working memory (WM) and implicit learning (IL) (N = 153)
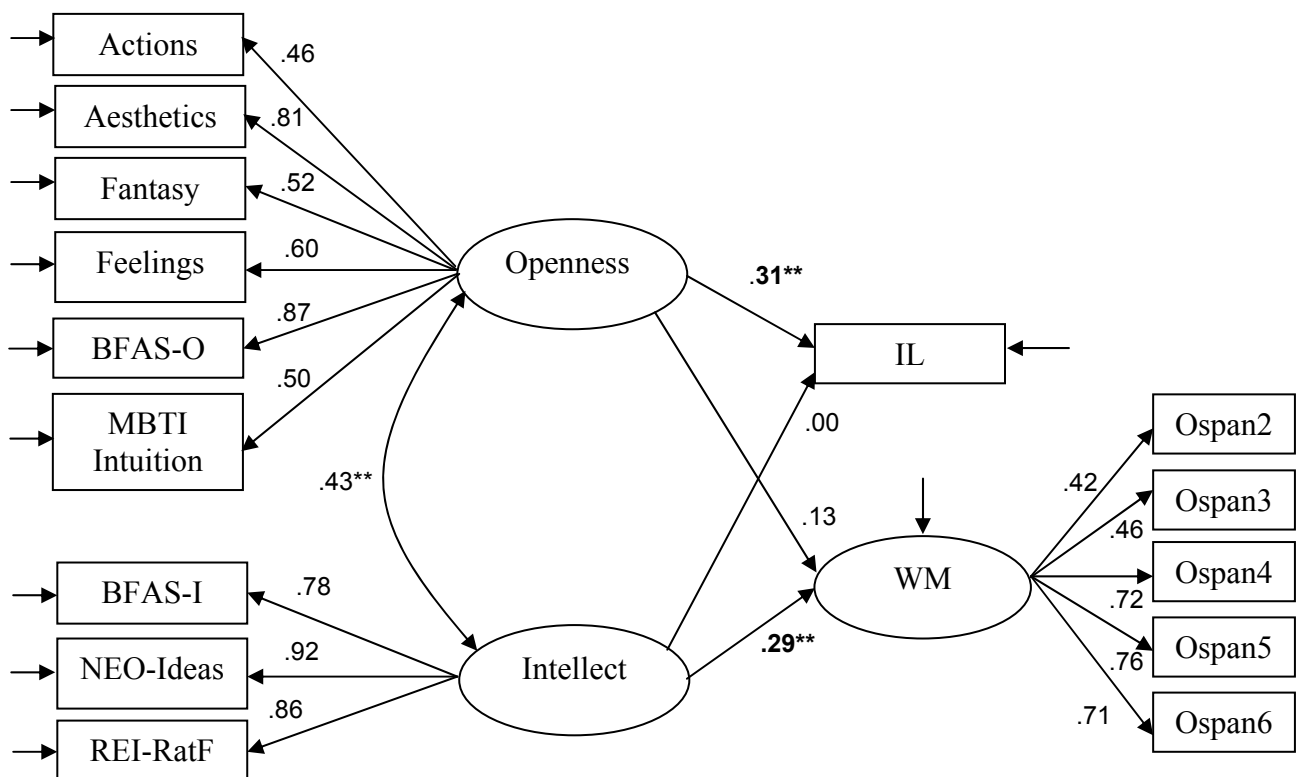
Notes: χ^2 = 118.07, *df* =86, p < .05, CFI = .96, TLI = .94, RMSEA = .05, p_{close} = .50; ** p < .01

The shared variance of NEO Actions, NEO Aesthetics, NEO Fantasy, NEO

Feelings, BFAS Openness, and MBTI Intuition scales formed the latent variable

"Openness". The shared variance of the Openness to Ideas facet of the NEO, as well

as the BFAS Intellect scale and the REI rational favorability scale formed the latent

variable "Intellect". The shared variance of Ospan trials of set size two, three, four, five, and six formed the latent variable "WM". While Openness significantly predicted implicit learning, Intellect did not. Further, while Intellect significantly predicted working memory, Openness did not, thereby indicating a double dissociation.

H4. Impulsivity—and particularly lack of premeditation—is positively correlated with implicit learning

Implicit learning is significantly correlated with a lack of premeditation (r)=.23, p < .01, suggesting that there is a tendency for those with higher implicit learning scores to deliberate less about decisions in their daily lives. Also, the relationship between implicit learning and sensation seeking is marginally significant (r)=.16, p = .05). Implicit learning is not related to either urgency or perseverance. Intellect is not related to premeditation, urgency, or sensation seeking, but is positively correlated with perseverance (r)=.24, p < .05, suggesting that those higher in Intellect have more self-discipline in their daily lives. Nonetheless, those scoring higher in Intellect do not tend have higher implicit learning scores (see Table 4-4).

Discussion

The current chapter conceptualized implicit learning as an ability and assessed the relationship of individual differences in implicit learning to explicit cognitive ability, elementary cognitive tasks commonly associated with explicit cognitive ability, and personality.

Implicit learning and intelligence

The current chapter found that explicit cognitive ability was significantly more related to explicit associative learning than implicit learning. This findings provide support for Reber's (1989; 1993) hypothesis that individual differences in explicit learning are more related to explicit cognitive ability than are individual differences in implicit learning. They are consistent with other empirical data (Gebauer & Mackintosh, 2007; McGeorge, et al., 1997; Reber, et al., 1991; Feldman, et al., 1995), and they are consistent with dual-process accounts of thinking and reasoning (e.g., Evans & Frankish, 2009; Sloman, 1996) as well as the Dual-Process (DP) Theory of Human Intelligence (see *Chapter 1: Introduction*).

Implicit learning was also unrelated to working memory or explicit associative learning. This suggests that explicit associative learning may indeed operate through a different cognitive pathway and further supports the distinction between explicit and implicit associative learning. Mackintosh (1998) argued for the existence of a general associative learning system that is largely independent of a cognitive learning system. Since Mackintosh was referring primarily to an implicit, automatic, associative learning system, the current study provides support for his

distinction, but also suggests caution in the use of the term "associative." One must distinguish between "explicit" and "implicit" associative processes.

The separation of implicit learning from working memory also lends support to the idea that the explicit and intelligent deployment of cognitive resources in an implicit learning task may be important in the initial stages of the task (in order to attend successfully to the information). However, as long as the attention is selectively directed to the relevant stimuli (as in the task by which we measured implicit learning), encoding and access to the incidentally learned structure appears to be no longer dependent on executive attentional resources (Jiménez & Mendez, 1999; Jiménez, 2003; Turke-Browne, et al., 2005). It would be interesting for future research to investigate the conditions in which individual differences in working memory are predictive of behavior compared to the conditions that individual differences in implicit learning are more predictive of behavior.

While implicit learning was unrelated to g, WM, and AL, implicit learning was significantly associated with processing speed and scores on the DAT verbal reasoning test. A link between implicit learning and processing speed is consistent with prior research (Salthouse, et al., 1999) and suggests the possibility that processing speed, like IL, relies in part on mechanisms that are phylogenetically older than the explicit cognitive mechanisms most strongly related to g. Future research should further investigate the nature of the link between processing speed and implicit learning.

The significant correlation between IL and DAT-V scores is more surprising. It represents an association between IL and the residual variance in DAT-V not attributable to explicit cognitive ability, which suggests that IL may contribute to a more specific language acquisition ability.

The relationship of implicit learning and language acquisition is evidenced by the independent association of implicit learning with educational attainment, in particular GCSE French and German results. Educational attainment has long been a yardstick for intelligence research to validate its claim that IQ is related to real-world cognition (Mackintosh, 1998). Moreover, this finding is convergent with the theoretical assertion that implicit learning is crucial to language acquisition (e.g. Chang, 2008; Ellis, 1994; Karmiloff-Smith, 1992; Perruchet, 2005, 2008 2008; Winter & Reber, 1994) and empirical findings of an association between measures of implicit learning and language acquisition (e.g. Conway & Pisoni, 2008; Destrebecqz & Cleeremans, 2008; Gómez & Gerken, 2000; Gebauer & Mackintosh, 2009; Krashen, 1992; Pacton, Fayol, & Perruchet, 2005; Pretz, et al., 2009; Robinson, 2001; Rohrmeier & Fu, 2008). Further, consistent with the findings of Gebauer and Mackintosh (2009), the relationship between implicit learning and second-language acquisition remained significant after controlling for g, while the relationship to Math scores was no longer significant after controlling for g.

Therefore, it is still an open question the extent to which implicit learning relates similarly to both first and second language acquisition. An intriguing possibility is that IL supports analogical reasoning, which is why a correlation with

DAT-V was evidenced, as well as achievement in learning a second-language, which presumably relies on analogical processes that allow the individual to bring their experiences with the first language to bear in learning the second language. These results suggest that a more complete understanding of language acquisition and perhaps other aspects of cognition could be had by further investigating individual differences in implicit learning.

The results of the current study have implications for intelligence research. Intelligence researchers in the psychometric tradition have predominantly focused on controlled, deliberate reasoning as the hallmark of intelligence (Jensen, 1998; Spearman, 1927; Chabris, 2006). Various researchers have posited additional 'intelligences' (e.g., Gardner, 1993b; Sternberg, 1997a), which have been criticized on the grounds either that these so-called 'intelligences' are poorly defined and/or measured or that they are not in fact separate intelligences because they are highly *g*-loaded (Gottfredson, 2003; Visser, et al., 2006).

Implicit learning may be related to the idea of "tacit knowledge", which forms the theoretical core of what Sternberg calls "Practical Intelligence" (Wagner & Sternberg, 1986; Sternberg, et al., 2000). As Mackintosh (1998) has pointed out, there are striking similarities between Reber's (1989; 1993) description of implicit learning and Wagner & Sternberg's (1986) description of tacit knowledge as knowledge that is "not openly expressed or stated...not directly taught... (p.54). Indeed, as suggested by Reber (1989), tacit knowledge and intuitive feelings may be the result of an implicit learning experience. It should be noted, however, that in

Wagner and Sternberg's conceptualization, tacit knowledge can be either conscious or nonconscious. Furthermore, an analysis of a battery of practical intelligence tests demonstrated that they were, in fact, significantly related to g (Cianciolo, et al., 2006). Implicit learning ability may come closer to operationalizing the idea of tacit knowledge than any of the "practical intelligence" tests that have been devised, as it seems to be at best only very weakly related to g.

Implicit Learning and Personality

The current study found that implicit learning was significantly related to the common variance across various self-report measures of the Openness aspect of the Big Five domain Openness/Intellect, as well as to the closely related measure of MBTI Intuition (the latter finding is consistent with results reported by Woolhouse & Bayne, 2000). Implicit learning was not related to the Intellect aspect of the domain, however. While the causal direction is unclear, these findings do raise the possibility that better unconscious detection and learning of covariance structures may be one of the cognitive mechanisms that support the trait of Openness, as distinct from Intellect. The engagement with the perceptual world that characterizes Openness may be facilitated by implicit learning. Of course, it is also possible that those high in Openness are better at implicit learning because they have a wider focus of attention. Future research could investigate the causal relationship between implicit learning and Openness to Experience.

To the best of my knowledge, few other studies have examined the relation between Openness to Experience and implicit learning. Norman, Price, & Duff

(2006) administered a deterministic SRT task (as opposed to the probabilistic version, like mine, which is thought to be a purer measure of implicit learning since it leads to less explicit knowledge of the sequence) and found a significant correlation between Openness to Feelings and the amount of decrease in RT throughout the training blocks, but did not find a correlation between Openness to Feelings and sequence learning scores, which were taken as the difference between RT to a sequential block and to a control block in which the training sequence was removed. Similarly, Norman, Price, Duff, & Mentzoni (2007) administered a probabilistic SRT task but still found no significant correlation between Openness to Feelings and learning scores. It should be noted that the current study also did not find a zero-order correlation between the NEO Openness to Feelings facet and SRT learning. Indeed, SRT learning was more related to Openness to Aesthetics, Openness to Fantasy, and a preference for imagination, patterns, possibility, and beauty, as measured by the MBTI Intuition and BFAS Openness scales. Therefore, it might be argued that the core component of Openness that is related to individual differences in implicit learning is not openness to affective information, but an openness to the experience of aesthetics, patterns, and possibilities. Consistent with this idea, Pretz and Totz (2007) have argued that the MBTI Intuition scale has less to do with affective intuition, and is uniquely related to the holistic nature of intuition.

The current study also found a significant correlation between implicit learning and lack of deliberation. These results suggest that those who deliberate less may be more open to implicit learning since their selective attention will focus

on a wider variety of stimuli, and thus be more likely to capture relevant associations. This idea is consistent with the reflective-impulsive model of Strack & Deutsch (2004), in which the reflective system is tied to explicit cognition whereas the impulsive system is related to the implicit system. Of course, it is also possible that good implicit learners deliberate less because they have more confidence in the implicit learning domain or good implicit learners deliberate less only when they are learning implicitly. Future research should attempt to investigate the relation between impulsivity and implicit processing more thoroughly in order to determine the causal direction of the association.

Broader Implications

The findings of the current study have implications for Reber's (1993) evolutionary theory of implicit learning, which predicts that because implicit learning ability is 'evolutionarily old', implicit processes should display tighter distributions and fewer individual differences in the general population than more 'evolutionarily recent' conscious processes. Even though it may indeed be the case that there is lower variability amongst humans in implicit learning than explicit learning, the current study suggests that individual differences in implicit learning are nonetheless meaningfully related to complex cognition and personality and deserve further study.

The results of the current study also have implications for skill acquisition research. Most theories of skill acquisition posit that the initial stages of learning draw strongly on explicit processes and general intelligence, which only later

become automated and implicit (Ackerman, 1988; J. Anderson, 1993; Guttman, 1954; Marshalek, Lohman, & Snow, 1983). The results of the current study suggest that the learning of a skill does not necessarily depend on deliberate processing in the initial stages. During interviews, none of the participants in the current study were able to articulate the underlying covariances in the implicit learning task, and a tendency for lack of deliberation was correlated with implicit learning, suggesting that they were building their tacit knowledge without deliberately trying to do so.

Limitations and Future Directions

A limitation of the current study was that it involved only one implicit learning task. While other measures of implicit learning were administered and also displayed significant learning at the group level (see *Appendix C: Additional Implicit Learning tasks*), the implicit learning task analyzed in the current chapter was the only one that proved informative at the individual differences level. Indeed, the measure of implicit learning in the current chapter is thought to be a 'pure' measure of implicit learning, since it leads to less explicit knowledge (see *Chapter 2: Methodology*).

Nonetheless, conclusions about the associations between implicit learning and other constructs would gain strength if they could be replicated using multiple implicit learning tasks and a latent implicit learning variable. In order to strengthen the status of implicit learning as an independent ability, it will be necessary to show that measures of implicit learning are not strongly related to g, and independently predict other important outcomes (Carroll, 1993). While prior research has shown

that various implicit learning paradigms do not correlate well with each other

(Gebauer & Mackintosh, 2007; Pretz, et al., 2009; Salthouse, et al., 1999), recent

work by Gebauer & Mackintosh (2009) suggests that if enough implicit learning

tasks are administered, a distinguishable factor, at least at the second-order level,

does emerge. Complicating the picture is the fact that implicit learning paradigms

differ in the ratio of explicit to implicit processes required for successful

performance on the tasks (Seger, 1994). Future research should administer a

variety of implicit learning tasks which vary the extent to which explicit encoding

during the learning phase is required. Additionally, Seger (1994) proposed that

there are both motor and judgment related forms of implicit learning. Some of the

results of the current study may only pertain to motor based implicit learning. It

therefore remains opens to further investigation the extent to which the current

study's findings are generalizable to other forms of implicit learning. The full range

of implicit learning paradigms that evince meaningful individual differences is also

an open question. Nonetheless, I see the investigation of individual differences in

implicit cognition a long neglected, but potentially fruitful line of research.

This chapter investigated individual differences in one widely administered

measure of implicit cognition. In the next chapter, I investigate the relation between

a different measure of implicit cognition—latent inhibition—that has received

attention in research on schizophrenia and creative achievement and has only just

begun investigations at the level of individual differences. In that chapter I will be

examining the relation between latent inhibition and explicit cognitive ability, as

well as linkages with rational and intuitive thinking dispositions, in order to further

our understanding of the separation of individual differences in Controlled and

Autonomous forms of Cognition.

In this chapter, I investigate individual differences in a measure of implicit processing called latent inhibition (LI; Lubow, Ingberg-Sachs, Zalstein-Orda, & Gewirtz, 1992). LI reflects the capacity of the brain to screen from current attentional focus stimuli previously tagged as irrelevant (Lubow, 1989). LI is often characterized as a pre-conscious gating mechanism that automatically inhibits stimuli that have been previously experienced as irrelevant from entering awareness, and those with *increased* LI show higher levels of this form of inhibition (Peterson, Smith, & Carson, 2002). Variation in LI has been documented across a variety of mammalian species, and, at least in other animals, has a known biological basis (Lubow & Gewirtz, 1995). LI surely is important in our everyday lives—if we had to consciously decide at all times what stimuli to ignore, we would quickly become over stimulated.

Indeed, prior research has documented an association between decreased LI and acute-phase schizophrenia (Baruch, Hemsley, & Gray, 1988a; 1988b; Lubow; Lubow, et al., 1992). It is known, however, that schizophrenia is also associated with low Central Executive Functioning (Barch, 2005). Recent research suggests that in *high-functioning* individuals (in this case, Harvard students) with high IQs, *decreased* LI is associated with increased self-reported creative achievement (Carson, et al., 2003). Therefore, decreased LI may make an individual more likely to perceive and make connections that others do not see, and in combination with high Central

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[h] Some of the content of the current chapter was taken from Kaufman, 2009.

Executive Functioning, may lead to the highest levels of creative achievement. Indeed, the link between low latent inhibition and creativity is part of Eysenck's (1995) model of creative potential, and Martindale (1999) has argued that a major contributor to creative thought is cognitive disinhibition.

A related concept to latent inhibition is intuition. Jung's original conception of intuition is "perception via the unconscious" (Jung, 1921/1971, p.538). Two of the most widely used measures of individual differences in the tendency to rely on an intuitive information processing style are Epstein's Rational-Experiential Inventory (REI; Pacini & Epstein, 1999) and the Myers-Briggs Type Indicator intuition/sensation subscale (MBTI, Myers, et al., 1998). Both of these measures have demonstrated correlations with Openness to Experience (Keller, Bohner, & Erb, 2000; McCrae, 1994; Pacini & Epstein, 1999), a construct that in turn has shown associations with a reduced LI (Peterson & Carson, 2000; Peterson, et al., 2002), as well as divergent thinking (McCrae, 1987), and creative achievement (Carson, Peterson, & Higgins, 2005; King, Walker, & Broyles, 1996).

Recent research, however, suggests that each of these intuition scales may be measuring different aspects of intuition, with MBTI Intuition relating more to a holistic type of intuition that is neutral in regards to affect, and REI Experiential being more affectively based, relying more on gut feelings and instinct (Pretz & Totz, 2007). To test whether individual differences in intuitive thinking relate to decreased latent inhibition, I administered a latent inhibition task along with the REI and two subscales of the MBTI. The main hypothesis was that intuitive cognitive

style is associated with decreased latent inhibition. It is an open question, however, whether different forms of intuition will show the same relationship.

Methodology

Measures

The following tests were included in the main analyses for this chapter (see *Chapter 2: Methodology* for a full description of each task): **Latent inhibition:** auditory task adapted from Carson, Peterson, & Higgins, 2003; **Intuition**: Myers-Briggs Type Indicator (MBTI), Rational-Experiential Inventory (REI).

Procedure

Because the preexposed condition was the condition of interest for individual differences, the first 121 participants who completed the LI task were assigned to the preexposed condition (but only 114 also completed the intuition scales) to ensure adequate power for detecting correlations with other variables. The remaining 48 participants who completed the LI task were assigned to the nonpreexposed condition simply to check for the presence of latent inhibition (i.e. as a validity check for the task).

Results

Table 5-1 shows the correlations among all of the intuition measures and LI scores in both the preexposed and nonpreexposed conditions, as well as the descriptive statistics for each of the tasks, and the reliabilities of the personality measures.

Since LI scores were bimodal rather than normally distributed (see Figure 5-1), all correlations with LI were conducted using Spearman's rho as the correlation coefficient. Also, all significance levels for correlations with LI were one-tailed.

Table 5-1
Correlations among REI and MBTI subscales and LI scores

	1	2	3	4	5	6	7	8
1. REI rational favorability	–							
2. REI rational ability	.46**	–						
3. REI experiential favorability	.02	-.23**	–					
4. REI experiential ability	-.13	.03	.67**	–				
5. MBTI Intuition	.26**	-.11	.21**	-.02	–			
6. MBTI feeling	-.28**	-.39**	.44**	.27**	.17*	–		
7. LI Preexposed	.03	-.02	-.18	-.22**	-.13	–	–	
8. LI Non Preexposed	-.13	-.14	.31*	.36*	-.28	.20	–	–
N	164	164	164	164	164	164	121	48
M	3.6	3.3	3.4	3.3	18.6	15	13.2	14.3
S.D.	.64	.59	.54	.59	5.4	5.8	11.6	11.6
Reliability (α)	.82	.80	.79	.82	.86	.88	–	–

Notes: Correlations among REI and MBTI scales have an *N* of 163. LI were calculated using Spearman's rho.   * = p < .05, ** = p < .01, one-tailed.

Lower LI scores in the preexposed condition were significantly correlated with higher scores on both REI Experiential subscales, as well as MBTI Feeling. Lower LI scores were not correlated with either REI rational subscales. The findings for those in the nonpreexposed condition showed the opposite trend: Participants with higher scores on the two REI Experiential scales required more trials to

correctly identify the rule during the test phase, and the correlation with MBTI

Feeling approached significance (*p* =.09). Interestingly, in the nonpreexposed

condition, those with higher MBTI Intuition scores required *fewer* trials to correctly

identify the rule during the test phase.

Figure 5-1
Bimodal distribution of latent inhibition scores in the preexposed condition (*N*= 121)
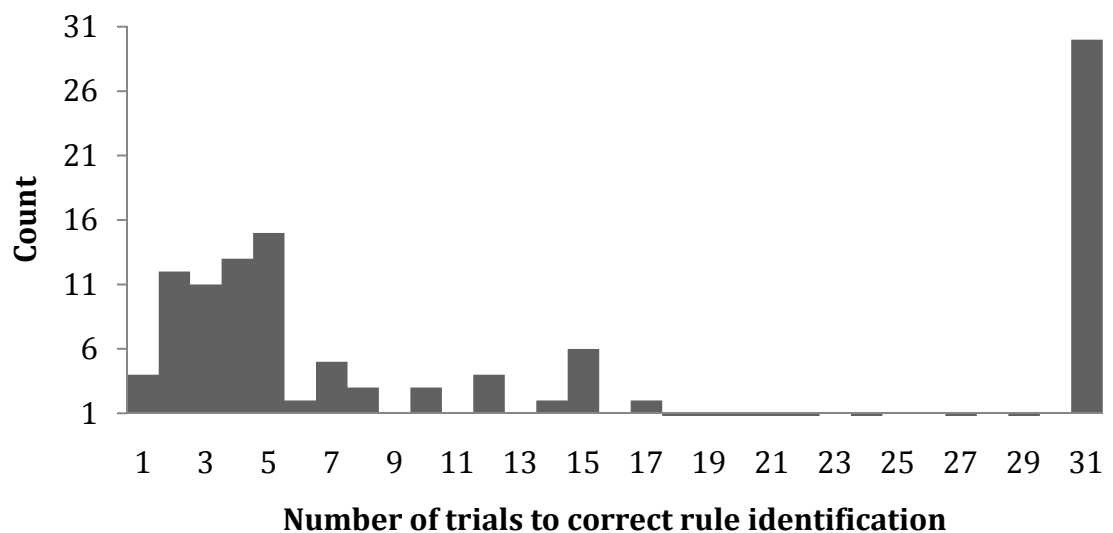
To assess LI's relationship to the different types of intuition as identified by

Pretz & Totz (2007), I first factor analyzed all the items included in the REI

experiential subscale using Principal Axis Factoring with a Direct Oblimin Rotation

(see Table 5-2).

Based on an examination of the scree plot and interpretability

considerations, two factors were extracted. The first REI experiential factor

consisted of items resembling a general "faith in intuition", such as "I like to rely on

my intuitive impressions." The items that loaded on to the second factor consisted

mostly of the subset of items on the REI experiential scale that related to a "faith in feeling", such as "I tend to use my heart as a guide for my actions." *Lower* LI scores in the preexposed condition significantly correlated with higher scores on *both* REI Experiential factors.

Table 5-2

Factor analysis of REI experiential items

Item	Faith in intuition	Faith in Feeling
33. Using my 'gut feelings' usually works well for me in figuring out problems in my life.	**.70**	**.49**
23. I don't like situations in which I have to rely on intuition. (R)	**.65**	.35
29. I don't have a very good sense of intuition. (R)	**.65**	.26
8. I like to rely on my intuitive impressions.	**.62**	.39
20. I often go by my instincts when deciding on a course of action.	**.60**	**.54**
6. When it comes to trusting people, I can usually rely on my gut feelings.	**.57**	**.44**
39. Intuition can be a very useful way to solve problems.	**.57**	.26
10. I believe in trusting my hunches.	**.56**	**.45**
37. I hardly ever go wrong when I listen to my deepest 'gut feelings' to find an answer.	**.56**	**.45**
13. I suspect my hunches are inaccurate as often as they are accurate. (R)	**.55**	.22
21. My snap judgments are probably not as good as most people's. (R)	**.52**	.21
19. I can usually feel when a person is right or wrong, even if I can't explain how I know.	**.51**	.20
2. If I were to rely on my gut feelings, I would often make mistakes. (R)	**.47**	.35
4. I generally don't depend on my feelings to help me make decisions. (R)	.31	**.67**

35. I tend to use my heart as a guide for my actions.	.28	**.65**
12. I think it is foolish to make important decisions based on feelings. (R)	.35	**.64**
27. I don't think it is a good idea to rely on one's intuition for important decisions. (R)	**.48**	**.50**
25. I trust my initial feelings about people.	**.41**	**.43**
16. I would not want to depend on anyone who described himself or herself as intuitive. (R)	.20	.32
31. I think there are times when one should rely on one's intuition.	.28	.28
Correlation with LI preexposed (N =114)	-.18*	-.24**
Correlation with LI nonpreexposed (N = 48)	.33*	.27*

Note: Factor loadings over .4 have been bolded. Reverse-scored items are marked (R). $\lambda1$ = 6.3 (31.5% Total Variance), $\lambda2$ = 1.7 (8.3% Total Variance). Total Variance Explained: 39.8%. Correlations with LI were calculated using the Spearman correlation coefficient. * = p < .05, ** = p < .01, one-tailed.

Again, the correlations with LI scores in the nonpreexposed condition

showed the reverse pattern: Those scoring higher on both REI Experiential factors

in the nonpreexposed condition required more trials to correctly identify the rule

during the test phase (see Table 5-2).

Table 5-3 shows the correlations among the two REI experiential factors and

the MBTI thinking/feeling, intuition/sensation, and REI rational favorability

subscales.

Table 5-3
Correlations among REI experiential factors and MBTI subscales

	1	2	3	4
1. REI Faith in Intuition Factor	–	164	163	163
2. REI Faith in Feeling Factor	.63**	–	163	163
3. MBTI Intuition	.07	.15	–	163
4. MBTI Feeling	.24**	.55*	.17*	–

Note: * = p < .05, ** = p < .01.

Consistent with Pretz and Totz (2007), MBTI Intuition is significantly

correlated with REI rational favorability, while the REI faith in feelings factor is

significantly correlated with MBTI feeling. As expected, the correlation between

MBTI Feeling is higher among the REI faith in feelings factor than the more general

REI faith in intuition factor. Even so, the REI faith in intuition factor is also

significantly correlated with MBTI Feeling.

Based on the methodology of Pretz and Totz (2007), the two REI experiential factors, the two MBTI subscales, and the REI rational favorability subscale were factor analyzed using Principal Axis Factoring with a Direct Oblimin Rotation to obtain multiple intuition factors (Table 5-4).

Table 5-4
Factor Analysis of REI experiential factors and MBTI subscales (N = 163)

	Faith in Intuition	Holistic Intuition	Affective Intuition
REI faith in feeling factor	**.89**	.12	**.53**
REI Faith in intuition factor	**.73**	.04	.20
MBTI feeling	**.43**	-.01	**.89**
REI rational favorability	-.07	**.62**	-.33
MBTI Intuition	.12	**.51**	.16
Correlation with LI PE (*N* = 113)	-.24**	-.07	-.21*
Corelation with LI non PE (*N*=48)	.32*	.19	-.17

Notes: Factor loadings over .4 have been bolded. $\lambda 1 = 2.0$ (40.9% Variance), $\lambda 2 = 1.3$ (25.5% Variance), $\lambda 3 = .90$ (17.5% Total Variance). Total Variance Explained: 83.9%. Correlations with LI were calculated using Spearman's rho. * = p < .05, ** = p < .01, one-tailed.

An examination of the scree plot and interpretability considerations led to an extraction of three factors. Loading on to the first factor were the two REI experiential factors, as well as MBTI feeling. This factor was labeled "faith in intuition." Loading on to the second factor was the REI faith in feeling factor and the MBTI feeling subscale. This factor was labeled "affective intuition."Loading on to the third factor was the REI rational favorability and MBTI intuition subscales. To be consistent with Pretz & Totz (2007), this factor was labeled "holistic intuition."

Lower LI scores in the preexposed condition were significantly correlated with higher scores on both the faith in intuition and affective intuition factors. LI was not related to the holistic intuition factor. Once again, the opposite pattern emerged for those in the nonpreexposed condition: Those scoring higher on the faith in intuition factor required significantly more trials to correctly identify the rule during the test phase and the correlation with the affective intuition factor approached significance (p = .10, see Table 5-4).

Prior research has demonstrated a higher mean in the preexposed condition than the nonpreexposed condition (Carson, Peterson, & Higgins, 2003; Peterson & Carson, 2000), suggesting intact LI at the group level of analysis. An Analysis of Covariance (ANCOVA) with the faith in intuition factor as a covariate showed no significant main effect of condition, but a significant interaction of condition with faith in intuition [$F(1,161)=8.2, p < .01$]. To further investigate the nature of this interaction, the faith in intuition factor was split into three equal groups (high, medium, low) and the interaction between level of faith in intuition and mean number of trials to correct rule identification was graphically analyzed for both the preexposed and nonpreexposed conditions (Figure 5-2).

Interestingly, those low in faith in intuition showed intact LI (i.e., did better in the preexposed condition than the nonpreexposed condition), whereas those high in faith in intuition demonstrated no LI (i.e., did worse in the preexposed condition than the nonpreexposed condition). Those in the medium group, also demonstrated no LI, but showed no difference between the conditions. (It should be noted that

these interaction effects as well as the latent inhibition correlations in this chapter are being driven by the females in the sample. This suggests that future research should keep in mind gender differences when investigating intuition and latent inhibition.)

Figure 5-2
Interaction between faith in intuition (FII) and mean number of trials to correct rule identification in the preexposed and nonpreexposed conditions
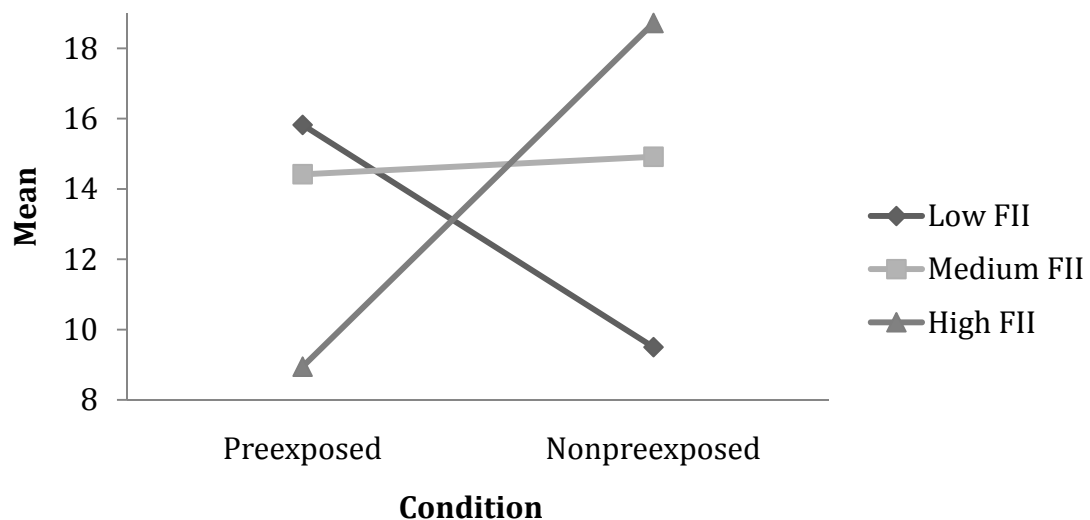
Notes: Preexposed-Low FII (*N*=34), Preexposed-Medium FII (*N*=43), Preexposed-High FII (*N*=36), Nonpreexposed-Low FII (*N*=18), Nonpreexposed-Medium FI (*N*=12), Nonpreexposed-High (*N*=18).

Because measures of general intelligence and working memory were acquired for all participants in the current study (see *Chapter 2: Methodology*), these variables were examined as additional covariates in the ANCOVA analysis. The effect of interest remained the same, when controlling for these variables. This is consistent with Peterson et al. (2002), who found that their effects were not the result of differences in IQ.

In fact, individual differences in latent inhibition were unrelated to general intelligence and the elementary cognitive tasks associated with general intelligence (see Table 5-5). Explicit Cognitive Ability (*g)* was calculated by assessing the common variance across RAPM, DAT-V, and MRT-A using Principal Axis Factoring (*N*= 177). The first PAF accounted for 67.2% of the total variance in the three tests. WM was calculated by summing the Ospan scores for all set sizes. E-AL was calculated by summing the 3-Term and PA learning scores. Gs was calculated by summing Speed-F, Speed-N, and Speed-F. Missing data was estimated following the same procedure as outlined in *Chapter 3: Explicit Cognitive Ability*.

Table 5-5
Correlations of g and associated ECTs with Latent Inhibition

	Latent Inhibition (*N*=121)
Explicit Cognitive Ability (*g*)	.02
Working Memory (WM)	-.04
Explicit Associative Learning (E-AL)	-.09
Processing Speed (Gs)	.10

Note: Correlations with LI were calculated using Spearman's rho, one-tailed.

Discussion

The results presented in this chapter suggest that faith in intuition, as assessed by Seymour Epstein's Rational-Experiential Inventory and the MBTI Feeling subscale, is associated with decreased latent inhibition. Furthermore, a factor consisting of abstract, conceptual, holistic thought is not related to latent inhibition. Consistent with Pretz and Totz (2007), exploratory factor analysis

revealed a distinction between a factor consisting of REI Experiential and MBTI Feeling, and a factor consisting of MBTI Intuition and REI Rational Favorability. This further supports Epstein's (1994) theory that the experiential system is directly tied to affect. The finding that MBTI Intuition and REI Rational Favorability loaded on the same factor supports the idea that the type of intuition that is being measured by these tasks is affect neutral, and more related to abstract, conceptual, holistic thought than the gut feelings that are part of the faith in intuition factor (Pretz & Totz, 2007).

Therefore, the association between faith in intuition and decreased latent inhibition may have to do with an openness to the affective cues that the participants built up through the first phase of the latent inhibition task. Those who tend to have faith in their gut feelings may have been more likely to trust their emotions relating to the white burst noise during the second phase, and therefore discover the underlying rule more rapidly than those who rely more on a rational cognitive style and disregard their gut feelings. That those with a high faith in intuition were aided by the preexposure whereas those low in faith in intuition were not is further suggested by the interaction analyses (see Figure 5-2), where it is clear that those high in faith in intuition were faster to identify the rule in the preexposed condition relative to those low and medium in faith in intuition.

Interestingly, the current study also found that those with a higher faith in intuition took *longer* to correctly identify the rule in the *nonpreexposed* condition. This suggests that it may require sufficient time for knowledge to be acquired

implicitly through extensive exposure to a pattern before the gut feelings can provide a guide to behavior. This possibility should be further investigated in future research.

The current study adds to a growing literature on the potential benefits of a decreased LI for creative cognition. Hopefully, with further research on the biological basis of LI, as well as its associated behaviors, including interactions with IQ and working memory, we can develop a more nuanced understanding of creative cognition. There is already promising theoretical progress in this direction (Peterson, et al., 2002).

Peterson et al. (2002) and Peterson and Carson (2000) found a significant relationship between low latent inhibition and three personality measures relating to an approach-oriented response and sensation seeking behavior: openness to experience, psychoticism, and extraversion. Peterson et al. (2002) found that a combined measure of openness and extraversion (which was referred to as 'plasticity') provided a more differentiated prediction of decreased LI.

Peterson et al. (2002) argued that individual differences in a tendency toward exploratory behavior and cognition may be related to the activity of the mesolimbic dopamine system and predispose an individual to perceive even preexposed stimuli as interesting and novel, resulting in low latent inhibition. Further, under stressful or novel conditions, the dopamine system in these individuals will become more activated and the individual will instigate exploratory behavior. Under such conditions, decreased LI could help the individual by allowing

him or her more options for reconsideration, and thereby more ways of resolving the incongruity. It could also be disadvantageous in that the stressed individual risks becoming overwhelmed with possibilities. Research shows that the combination of high IQ and reduced LI predicts self-reported creative achievement (Carson et al., 2003). Therefore, the individual predisposed to schizophrenia may suffer from an influx of experiential sensations and possess insufficient Central Executive Functioning to cope with the influx while the healthy individual low in latent inhibition and open to experience (particularly an openness and faith in his or her gut feelings), may be better able to use the information effectively while not becoming overwhelmed or stressed out by the incongruity of the situation. Clearly, further research will need to investigate these ideas, but an understanding of the biological basis of individual differences in different forms of implicit processing and their relationship to openness to experience and intuition, will surely increase our understanding of how it is certain individuals attain the highest levels of creative accomplishment.

Note that in the prior chapter (see *Chapter 4: Implicit Learning*), individual differences in implicit learning were correlated with a latent Openness construct that included MBTI Intuition as a marker. In the current chapter, a separate implicit process, latent inhibition, correlated with affective intuition. Since prior research has demonstrated an association between openness to experience and decreased latent inhibition and both measures of intuition administered in this dissertation have demonstrated correlations in the literature with openness to experience (e.g.,

Keller, et al., 2000; McCrae, 1994; Pacini & Epstein, 1999), this raises the intriguing

possibility that different forms of implicit processing may relate to different aspects

of the openness to experience construct. Indeed, Pacini and Epstein (1999) found

that even though both REI Rational and REI Experiential significantly correlated

with Openness to Experience, only REI Experiential significantly correlated with a

measure of emotional expressivity.

The idea that there may be at least two separable aspects of Openness to

Experience, each aspect associated with meaningful individual differences and

important correlates, is taken up in Part II of this dissertation.

PART II:

Engagement

In Part I of this dissertation I investigated the separability of individual

differences in Controlled and Autonomous Cognition. First I demonstrated that

working memory, explicit associative learning and processing speed each make

independent predictions to general intelligence (*Chapter 1*). I then investigated

individual differences in two measures of Autonomous Information Acquisition

Ability: implicit learning (*Chapter 4: Implicit Learning*) and latent inhibition

(*Chapter 5: Latent Inhibition*). I found that individual differences in each type of

autonomous cognition were unrelated to individual differences in Explicit Cognitive

Ability but were associated with different aspects of Openness to Experience and

intuitive thinking style. Reduced latent inhibition scores were related to the MBTI

Feeling scale and Seymour Epstein's Experiential Scale, suggesting that this form of

implicit processing is supported by affective processes. On the other hand, implicit

learning was related to an Openness to Experience latent factor, but most strongly

Openness to Aesthetics and Fantasy, and to the MBTI Intuition scale, which

measures the tendency for holistic processing (Pretz & Totz, 2007).

Part II will further explore the Controlled and Autonomous Cognitive ability

correlates of these thinking dispositions. Indeed, there is an emerging consensus

that cognitive capacities and thinking dispositions involve separable levels of

analysis and independently predict reasoning (Baron, 1985; Ennis, 1987; Kardash &

Scholes, 1996; Klaczynski, Gordon, & Fauth, 1997; Norris, 1992; Schommer, 1990;

Sternberg, 1997b). There is however, a much larger literature on the correlates of

thinking dispositions that are associated with Explicit Cognitive Ability (Stanovich & West, 2000), than on the correlates of thinking dispositions associated with Autonomous Cognition. Part II of my dissertation aims to correct that imbalance.

As a first step to get a better grasp on the structure of the correlation matrix of measures of thinking dispositions and their relations to Explicit Cognitive Ability, I followed Goldberg's (2006) methodology and started by doing it all "Bass-Ackwards", thereby developing the hierarchical factor structure from the top down. This technique involves calculating the factor scores of multiple varimax rotated solutions, starting with a one-factor solution, proceeding to two- and three-factor solutions, etc., and ending with a solution where the factors are still interpretable. Then the correlations among the orthogonal factor scores from adjoining levels are graphically represented as path coefficients in a hierarchical structure. This technique allows for a graphical representation of the relations between the different levels of the hierarchy, and also helps to clarify the core components of each factor at each level. Figure 6-1 shows a graphical representation of the varimax-rotated components derived from all measures of Explicit Cognitive Ability (with the exception of processing speed, since it is not clear that processing speed measures Explicit Cognitive Ability; see Mackintosh, 1998), Intellect, Openness to Experience, and intuition.

The first unrotated principal component involves the common variance across all the tests. Therefore, I labeled this component "Cognitive Traits". The first unrotated principal component breaks off into two latent variables. On the left hand

side is a latent variable that includes loadings from all measures of Explicit Cognitive

Ability as well as self-report measures of Intellectual Engagement. I therefore

labeled this latent variable "System 2 - Intellect", to represent a broad domain of

individual differences that consists of both an ability and disposition for

engagement in intellectual matters (DeYoung, et al., 2007; Stanovich & West, 2000;

Stanovich, 2009 Stanovich, 2009b), and is intimately tied to the Controlled

Cognition component of DP theory (see *Chapter 1: Introduction*).

Figure 6-1
Varimax-rotated components derived from all measures of g, Intellect, Openness, and Intuition (N = 146)
(Cognitive Traits, first unrotated principal component)
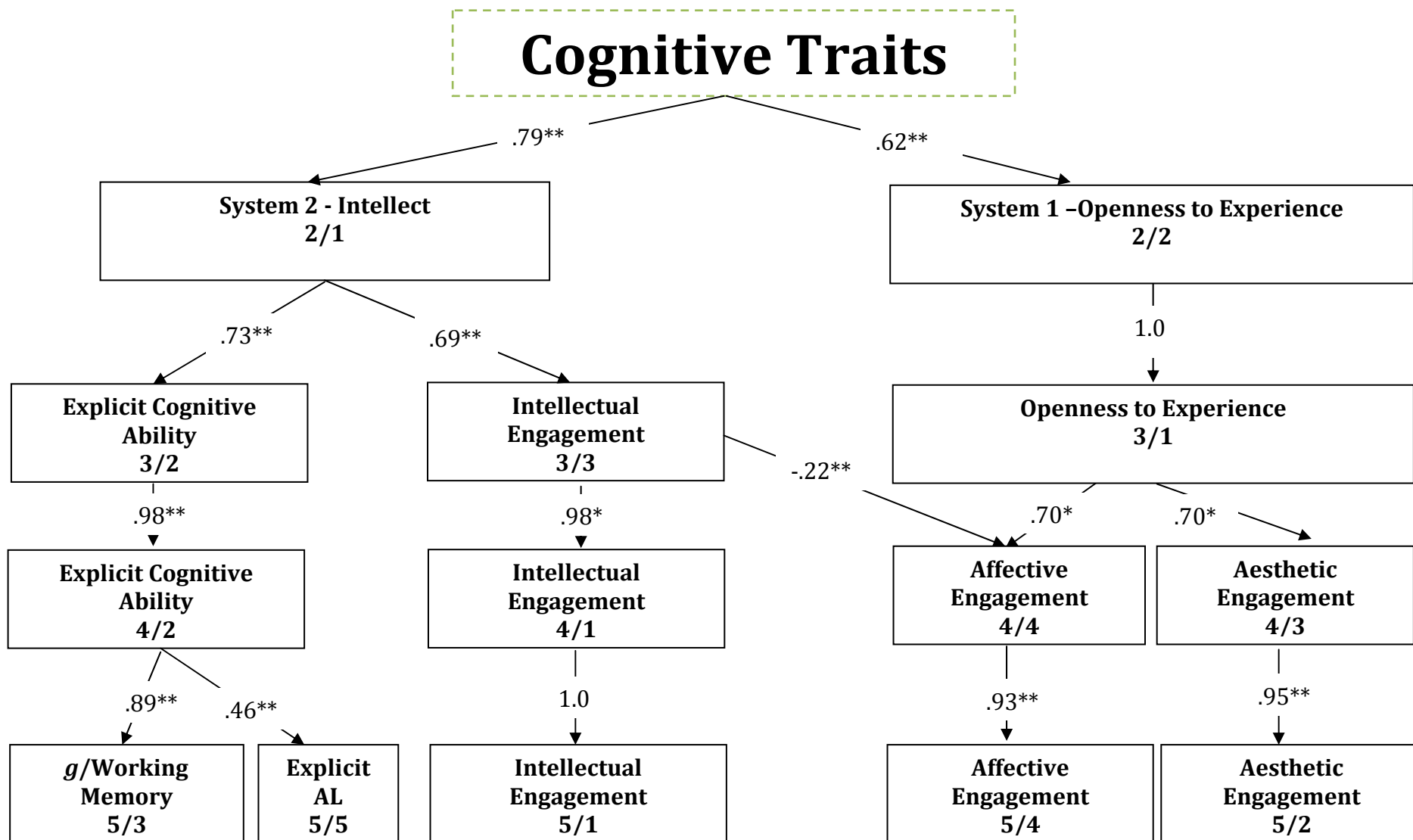
On the right hand side is a latent variable that includes loadings from all measures of Openness to Experience and intuition. I therefore labeled this latent variable "System 1 - Openness to Experience", to represent a broad domain of individual differences that consists of a desire for engagement in Autonomous forms of cognition such as aesthetics, imagination, behaviors, feelings, experiences, and sensations. Interestingly, both "Intellect" and "Openness to Experience" are substantially related to the first unrotated principal component, suggesting that these are two related yet distinguishable components of the overall construct here labeled "Cognitive Traits".

At the next level of the hierarchy, "Intellect" breaks off into two factors, while "Openness to Experience" remains unitary with the "Openness to Experience" factor in the prior level of the hierarchy. The second factor at this level has high loadings from the three markers of g: RAPM (.77), DAT-V (.75), and MRT (.72), as well as high loadings from two explicit measures of cognition that showed a relationship to g in *Chapter 1*: Working Memory (.57) and Explicit Associative Learning (.53). Since all the tests that have their primary loading on this factor relate to explicit, deliberate, intentional cognition, I decided to label this factor "Explicit Cognitive Ability". Other researchers may have labeled this "General Cognitive Ability" (e.g., Spearman, 1904), but I believe that "Explicit" is more appropriate than "General", considering that individual difference in implicit cognitive processes are unrelated to this factor (see *Chapter 4: Implicit Learning* and Chapter *5: Latent Inhibition*).

The third factor at this level is clearly related to the personality trait of Intellect, since the only three tests that loaded strongly on this factor were NEO Ideas (.76), REI Rational Favorability (.83), and BFAS Intellect (.83). Therefore, I labeled this factor "Intellectual Engagement" to distinguish this factor from "Explicit Cognitive Ability" which relates more to ability than a disposition toward Engagement in intellectual matters.

At the next level of the hierarchy, the two "Intellect" factors remain the same as the prior level, but "Openness to Experience" breaks off into two factors. The third factor at this level has strong loadings from MBTI Intuition (.80), BFAS Openness (.74), NEO Aesthetics (.63) and NEO Fantasy (.61). Therefore, these four tests appear to form the core of what I labeled "Aesthetic Engagement". The fourth factor at this level had high loadings from NEO Feelings (.72), REI Experiential (.71), and MBTI Feeling (.62), suggesting that these three tests form the core of what I labeled "Affective Engagement". Interestingly, the only other test that loaded on the Affective Engagement factor greater than .40 is NEO Aesthetics where the loading is .41. This is consistent with the idea that these two partially independent forms of Engagement are part of a larger "Openness to Experience" construct that is evident one level up in the hierarchy.

At the next level of the hierarchy, five factors are evident. It is at this level where we see two independent components of "Explicit Cognitive Ability". The first component (factor three in this hierarchy), has a loading of working memory (.70), as well as loadings of the three markers of g: RAPM (.70), DAT-V (.71), and MRT

(.74). I called this factor "*g*/Working Memory". The second component of "Explicit Cognitive Ability" (factor five in the hierarchy) only has a loading from Explicit Associative Learning (.78). Therefore, I call this factor "Explicit Associative Learning". Interestingly, "Explicit Cognitive Ability" is more strongly related to the "Working Memory" component (.89) than the Explicit Associative Learning component (.46), likely reflecting the importance of updating working memory for tests that are highly *g*-loaded (Friedman, et al., 2006). The components "Intellectual Engagement", "Affective Engagement", and "Aesthetic Engagement" remain the same as the prior level of the hierarchy. A six factor solution was extracted but wasn't interpretable. Five levels appear sufficient to meaningfully account for the covariance across all tests.

Overall then, the Bass Ackwards technique supports a distinction between two related but distinct aspects of Openness to Experience: Affective and Aesthetic Engagement, as well as two distinct dimensions of Intellect: Explicit Cognitive Ability and Intellectual Engagement. Below I directly test the hypothesis that Openness to Experience consists of both Ability and Engagement aspects.

Relationships to Autonomous Information Acquisition Ability

In order to assess the relationship of the two measures of Autonomous Information Acquisition Ability (latent inhibition and implicit learning) to the various dimensions of Intellect and Openness to Experience, I factor analyzed all the measures using Principal Axis Factoring with a Direct Oblimin Rotation in order to assess the relationship between the Autonomous Information Acquisition Ability

measures and the unique variance associated with each factor. The four-factor

solution is shown in Table 6-1 (see *Appendix B: Additional Covariance Analyses* for

full covariance matrix used to extract the four-factor solution).

Loading on the Explicit Cognitive Ability factor are all of the measures of

Explicit Cognitive Ability as well as the Intellectual Engagement items. The measure

with the highest loading on this factor is the Ravens Advanced Progressive Matrices,

which prior research has shown to be one of the best markers of g (Lohman, 2001).

Loading on the Intellectual Engagement factor are the three tests of intellect, and to

a lesser extent, the measures of Explicit Cognitive Ability. This is consistent with the

idea that the construct "Intellect" is a larger construct consisting of both ability and

propensity toward intellectual matters (DeYoung, et al., 2007; Stanovich & West,

2000; Stanovich, 2009b).

Table 6-1

Factor Analysis of all Explicit Cognitive Ability, Intellect, Openness to Experience and Intuition measures (N = 146)

	Intellectual Engagement	Affective Engagement	Explicit Cognitive Ability	Aesthetic Engagement
REI Rational Favorability	**.88**	-.02	**.44**	.31
NEO Ideas	**.86**	.11	**.48**	**.45**
BFAS Intellect	**.81**	-.09	**.43**	.29
NEO Feelings	.31	**.67**	.16	**.53**
MBTI Feeling	-.30	**.66**	-.11	.28
REI Experiential	-.05	**.57**	-.17	.21
RAPM	.36	-.16	**.77**	.16
DAT-V	.36	-.06	**.72**	.34
MRT-A	.27	-.20	**.66**	.07
WM	.26	.05	**.47**	.27
E-AL	.23	.09	**.42**	.14
BFAS Openness	.26	.43	.22	**.90**
NEO Aesthetics	.38	.44	.11	**.78**
MBTI Intuition	.24	.17	.24	**.54**
NEO Fantasy	.24	.33	.27	**.52**
NEO Action	.27	.34	.07	**.42**
r with Implicit Learning	.12	.12	.16	.31**
r Latent Inhibition	-.04	-.23*	-.07	-.10

Note: Factor loadings over .4 have been bolded. $\lambda 1$ = 4.68 (29.25% Variance), $\lambda 2$ = 2.77 (17.32% Variance), $\lambda 3$ = 1.40 (8.76% Variance), $\lambda 4$ = 1.04 (6.51% Variance). Correlations with Implicit Learning have an *N* of 143. Correlations with Latent Inhibition have an *N* of 97 and were calculated using Spearman's rho, one-tailed. * = p < .05, ** = p < .01; Total Variance Explained: 61.83%.

To get a better sense of which items this factor is most related to, Table 6-2

lists the top 10 loadings on a principal component consisting of all REI Rational

Favorability, NEO Ideas, and BFAS Intellect items. The specific item that loaded the

highest (.78), and is therefore most representative of the latent construct

"Intellectual Engagement" is the following: "I enjoy intellectual challenges". Also of

note in this list are items referring to an enjoyment of solving problems that

"require hard thinking", are "abstract", and "complex".

Table 6-2
Top 10 Loadings on a principal component consisting of all REI Rational Favorability,
NEO Ideas, and BFAS Intellect items

Test	Loading	Item
REI-RatF	.78	"I enjoy intellectual challenges."
REI-RatF	.77	"I enjoy solving problems that require hard thinking."
NEO-Ideas	.74	"I have a lot of intellectual curiosity."
NEO-Ideas	.72	"I often enjoy playing with theories or abstract ideas."
BFAS-I	.68	"Can handle a lot of information."
REI-RatF	.68	"I don't like to have to do a lot of thinking." (R)
NEO-Ideas	.67	"I have a wide range of intellectual interests."
REI-RatF	.66	"I prefer complex to simple problems."
BFAS-I	.64	"Learn things slowly." (R)
BFAS-I	.60	"Like to solve complex problems."

Loading on the "Affective Engagement" factor are NEO Feeling, MBTI Feeling,

REI Experiential, BFAS Openness, and NEO Aesthetics. Table 6-3 lists the top 10

loadings on a principal component consisting of the specific items from the tests that are most central to Affective Engagement: NEO Feeling, MBTI Feeling, and REI Experiential. The item that loaded the highest (.67), and is therefore most representative of the latent construct "Affective Engagement" is the following: "I tend to use my heart as a guide for my actions."

Table 6-3
Top 10 Loadings on a principal component consisting of all NEO Feeling, MBTI Feeling, and REI Experiential items

Test	Loading	Item
REI-Exp	.67	"I tend to use my heart as a guide for my actions."
MBTI-Fe	.62	sentimental (vs. practical)
MBTI-Fe	.60	sentimental (vs. analytical)
REI-Exp	.60	"I think it is foolish to make important decisions based on feelings." (R)
REI-Exp	.59	"I generally don't depend on my feelings to help me make decisions." (R)
REI-Exp	.57	"I often go by my instincts when deciding on a course of action."
MBTI-Fe	.57	bighearted (vs. firm-minded)
MBTI-Fe	.56	touching (vs. convincing)
REI-Exp	.55	"Using my 'gut feelings' usually works well for me in figuring out problems in my life."
MBTI-Fe	.55	feeling (vs. thinking)

Loading on the "Aesthetic Engagement" factor is NEO Ideas, NEO Feeling, BFAS Openness, NEO Aesthetics, MBTI Intuition, NEO Fantasy, and NEO Action. Table 6-4 lists the top 10 loadings on a principal component consisting of all NEO Aesthetics, NEO Fantasy, BFAS Openness, and MBTI Intuition items.

Table 6-4

Top 10 Loadings on a principal component consisting of all NEO Aesthetics, NEO Fantasy, BFAS Openness, and MBTI Intuition items

Test	Loading	Item
NEO-Aes	.62	"Sometimes when I am reading poetry or looking at a work of art, I feel a chill or wave of excitement."
NEO-Aes	.62	"I enjoy reading poetry that emphasizes feelings and images more than story lines."
MBTI-Int	.60	Answer a: "Do you usually get along better with (a) imaginative people, or (b) realistic people?
NEO-Fan	.60	"I try to keep all my thoughts directed along realistic lines and avoid flights of fancy." (R)
NEO-Aes	.57	"I am intrigued by the patterns I find in art and nature."
BFAS-O	.56	"Seldom notice the emotional aspects of paintings and pictures." (R)
BFAS-O	.54	"Believe in the importance of art."
NEO-Aes	.53	"I am sometimes completely absorbed in music I am listening to."
NEO-Aes	.52	"Poetry has little or no effect on me." (R)
NEO-Fan	.52	"I have a very active imagination."

The specific item that loaded the highest (.62), and is therefore most representative of the latent construct "Aesthetic Engagement" is the following: "Sometimes when I am reading poetry or looking at a work of art, I feel a chill or wave of excitement. This statement simultaneously reflects an interest in poetry and art, as well as the capacity to be fully engaged with the aesthetic stimuli.

Table 6-1 also shows the correlation of both measures of Autonomous Cognition (Latent Inhibition and Implicit Learning) with each of the four factors. Both measures of autonomous cognition are unrelated to the two components of Intellect, providing support for the idea that Autonomous Cognition is primarily part of System 1. Furthermore, in line with the results of *Chapter 4: Implicit learning* and *Chapter 5: Latent Inhibition*, implicit learning was significantly correlated with Aesthetic Engagement but not related to Affective Engagement, whereas a reduced latent inhibition was significantly correlated with Affective Engagement but not correlated with Aesthetic Engagement. This lends support to the idea that both Affective and Aesthetic Engagement represent a broad phenotype that consists of both ability and a disposition for engaging in Autonomous forms of cognition.

Relations among the four factors

Table 6-5 shows the correlations among the four factors.

Table 6-5
Correlations among the four factors (N = 146)

	1	2	3	4
1. Explicit Cognitive Ability	–			
2. Intellectual Engagement	.43	–		
3. Affective Engagement	-.08	.01	–	
4. Aesthetic Engagement	.27	.36	.45	–

It should be noted that while separable, the three factors "Explicit Cognitive Ability", "Intellectual Engagement", and "Aesthetic Engagement" are all moderately inter correlated with one another. Therefore, there indeed is a tendency for those with higher Explicit Cognitive Ability to also engage in intellectual pursuits that can be either of the abstract, cognitively complex variety, or the deeply associative, fantasy and sensory based aesthetic variety. Indeed, Explicit Cognitive Ability may support such pursuits. However, there seems to be no relation between Affective Engagement and either Explicit Cognitive Ability or Intellectual Engagement. Therefore, while the individual high in Aesthetic Engagement tends to also be of higher Explicit Cognitive Ability and Affective Engagement, the individual high in Explicit Cognitive Ability or Intellectual Engagement is not more likely to engage with Affect.

Now that these four factors have been identified and explicated, the next three chapters will flesh out the implications of these four factors for understanding

personality (*Chapter 7*), creative achievement (*Chapter 8*), and deductive reasoning

(*Chapter 9*). The data presented in the next three chapters suggest that the four

factors presented in this chapter are each uniquely associated with each of these

major domains of human psychological functioning.

This chapter will further explore each of the four factors that make up the four-factor model of cognitive traits (see *Chapter 6: Four-Factor Model*)—Explicit Cognitive Ability, Intellectual Engagement, Affective Engagement, and Aesthetic Engagement— by assessing each factor's relation to three sets of personality variables: The Five Factor Model (FFM), Impulsivity, and Need for Uniqueness.

The Big Five

The five factor model (FFM) or Big Five is the most widely used and best validated taxonomy of personality traits (Goldberg, 1990; Markon, et al., 2005). Table 7-1 shows the correlation between each of the four factors of the four-factor model of cognitive traits (see *Chapter 6: Four-Factor Model*) and all of the domains of The Big Five measured by the Big Five Aspect Scales (DeYoung, et al., 2007; see *Chapter 2: Methodology*) except for Intellect/Openness—Neuroticism, Agreeableness, Conscientiousness, and Extraversion. Intellect/Openness was not included in the analysis since this domain was part of the four-factor model of cognitive traits.

Explicit Cognitive Ability is not correlated with Neuroticism, Agreeableness, Conscientiousness, or Extraversion. This suggests that out of the Big Five domains, only Intellectual and Aesthetic Engagement are related to Explicit Cognitive Ability (see *Chapter 6: Four-Factor Model*). This is consistent with prior research that has found that Dorsolateral PFC function as well as measures of fluid and crystallized cognitive abilities are related only to the Intellect/Openness domain of the Big Five

(DeYoung, et al., 2005). Intellectual Engagement was significantly correlated with Conscientiousness and Extraversion, Affective Engagement was correlated with Neuroticism, Agreeableness, and Extraversion, and Aesthetic Engagement was correlated with Agreeableness, negatively correlated with Conscientiousness, and positively correlated with Extraversion. The finding that Affective Engagement was only correlated with Neuroticism, Agreeableness, and Extraversion provides validity for the Affective Engagement construct, since these three Big Five domains are the ones that have emotional content.

Table 7-1
Correlations between the four-factor model of cognitive traits and Neuroticism, Agreeableness, Conscientiousness, and Extraversion (N= 143)

Factor	N	A	C	E
Explicit Cognitive Ability	-.03	.00	-.09	.02
Intellectual Engagement	-.07	-.02	.19*	.22**
Affective Engagement	.21*	.43**	-.13	.43**
Aesthetic Engagement	.11	.21*	-.27**	.23**

Notes: *N*=Neuroticism; *A*=Agreeableness, *C*=Conscientiousness; *E*=Extraversion. *p < .05, **p < .01.

To further investigate the particular aspects of each Big Five domain that are related to the four factors, I assessed the correlation between each of the four factors and 8 aspects of personality as measured by the Big Five Aspect Scales (BFAS; DeYoung, et al., 2007; see Table 7-2).

Table 7-2

Correlations among the four-factor model of cognitive traits and the aspects of Neuroticism, Agreeableness, Conscientiousness, and Extraversion (N= 143)

Factor	N-V	N-W	A-C	A-P	C-I	C-O	E-E	E-A
Explicit Cognitive Ability	-.09	.05	.06	-.06	-.04	-.10	.10	.13
Intellectual Engagement	-.06	-.06	.09	-.11	.25**	.08	.01	.36**
Affective Engagement	.24*	.13	.65**	.07	-.11	-.11	.51**	.24**
Aesthetic Engagement	.09	.12	.36**	-.02	-.24**	-.22*	.20*	.20*

Notes: N-V= Neuroticism Volatility; N-W-Neuroticism Withdrawal; A-C=Agreeableness Compassion; A-P=Agreeableness Politeness; Conscientiousness Industriousness; Conscientiousness Orderliness; Extraversion Enthusiasm; Extraversion Assertiveness; *p < .05, **p < .01.

Explicit Cognitive Ability is not related to any of the aspects of Neuroticism, Agreeableness, Conscientiousness or Extraversion. While Intellectual Engagement is significantly correlated with Conscientiousness and Extraversion (see Table 7-1), these correlations appear to be due to Intellectual Engagement's relation to the Industriousness aspect of Conscientiousness and the Assertive aspect of Extraversion.

Furthermore, while Affective Engagement is positively related to Neuroticism, Agreeableness, and Extraversion (see Table 7-1), these correlations seem to be due to Affective Engagement's relation to the Volatility aspect of Neuroticism, the Compassion aspect of Agreeableness, and both aspects of Extraversion. Interestingly, latent inhibition (LI), which is associated with Affective Engagement, was also negatively related to the Compassion aspect of Conscientiousness (Spearman's rho=.-19, p < .05) and positively related to the Assertiveness aspect of Extraversion (Spearman's rho=.-.19, p < .05). The former finding is interesting in light of Affective Engagement's high correlation with Compassion (r=.65). The latter finding is consistent with prior research demonstrating a link between reduced LI and Extraversion (Peterson, et al., 2002; Peterson & Carson, 2000). LI was not related to any of the other aspects of Neuroticism, Agreeableness, or Conscientiousness. Finally, while Aesthetic Engagement was positively related to Conscientiousness (see Table 7-1), these correlations appear to be due to Aesthetic Engagement's positive relation to the Compassion aspect of Agreeableness, Aesthetic Engagement's negative relation to both the Industriousness and Orderliness aspects of Conscientiousness, and Aesthetic Engagement's positive relation to both aspects of Extraversion (Enthusiasm and Assertiveness).

In sum, the four factors Explicit Cognitive Ability, Intellectual Engagement, Affective Engagement and Aesthetic Engagement show different patterns of correlations with Neuroticism, Agreeableness, Conscientiousness, and Extraversion.

Investigation of the aspects of each of these Big Five domains further clarified each of the four factors relation to these Big Five domains. Three findings are particularly noteworthy. The first is the finding that Affective Engagement is related to the three Big Five domains that have emotional content: Neuroticism, Agreeableness, and Extraversion. The second noteworthy finding is the dissociation found between Intellectual Engagement and Aesthetic Engagement: Intellectual Engagement was positively correlated with the Industriousness aspect of Conscientiousness, while Aesthetic Engagement was negatively correlated with this aspect. The third finding that is particularly noteworthy is that while Intellectual, Affective, and Aesthetic forms of Engagement all correlate with the Extraversion domain of the Big Five, the correlation with Intellectual Engagement is primarily through the Assertiveness aspect of Extraversion, showing no relation to the Enthusiasm aspect of Extraversion, in contrast with both Affective and Aesthetic Engagement which both show a significant relation to both Extraversion aspects. This suggests that while all three forms of Engagement are related to the latent Extraversion construct, Aesthetic and Affective forms of Engagement tend to be associated with positive emotions in the form of Enthusiasm whereas those higher in Intellectual Engagement do not tend to be more enthusiastic.

The latter correlation between all three forms of Engagement and Extraversion is consistent with recent theorizing about the meta-traits of the Big Five. Factor analyses on multiple datasets have consistently revealed two higher-order factors that explain much of the shared variance among the five domains

(DeYoung, 2006; DeYoung, et al., 2002; Digman, 1997; Olson, 2005). DeYoung, Peterson, & Higgins (2002) labeled these two factors "Stability" and "Plasticity". Stability consists of the shared variance of Emotional Stability, Agreeableness, and Conscientiousness and "is thought to relate to the need to maintain a stable organization of behavioral and psychological function (Hirsch, DeYoung, & Peterson, 2009; p. 3)". Plasticity consists of the shared variance of Extraversion with Openness/Intellect, and relates to "an individual's basic need to incorporate novel information from the environment."

DeYoung, Peterson, & Higgins (2002) relate Stability to functioning in the ascending rostral serotonergic system, a system that plays an important role in behavioral and emotional constraint and control (Gray & McNaughton, 2000; Spoont, 1992). They relate Plasticity to functioning in the central dopaminergic (DA) system, a system which plays an important role in mediating approach behavior, positive affect, incentive reward sensitivity, and mental flexibility (Berridge & Robinson, 1998; Depue & Collins, 1999; DeYoung, et al., 2005; Harris, et al., 2005; Panksepp, 1998 Panksepp, 1998).

The finding that all three forms of Engagement: Intellectual, Affective, and Aesthetic were significantly correlated with Extraversion (see Table 7-1) is consistent with DeYoung, Peterson, and Higgins's (2002) finding that the Intellect/Openness domain is correlated with the Extraversion domain of the Big Five, and raises the further possibility that all three forms of Engagement are tied to the dopaminergic system.

Impulsivity

The umbrella term "impulsivity" makes an appearance in almost every major system of personality (Barratt, 1993; Buss & Plomin, 1975; Cloninger, Svrakic, & Przybeck, 1993; Dickman, 1990; Eysenck & Eysenck, 1975; Jackson, 1984; McCrae & Costa, 1990; Newman & Wallace, 1993; Tellegen, 1985; Zuckerman, 1994). However, these different researchers have sometimes used the term "impulsivity" to refer to very different phenomena. Additionally, researchers have also used different labels to refer to the same phenomenon (Whiteside & Lynam, 2001).

To attempt to bring some order to this state of affairs, Whiteside & Lynam (2001) administered a wide range of self-report impulsivity measures that have been used in the literature along with a well validated measure of the Big Five (the NEO-PI-R) to 437 undergraduates. Factor analyses revealed a robust four-factor solution. The primary factor consisted of tests relating to "(Lack of) Premeditation". According to the researchers, this factor assesses the tendency to delay action in favor of careful thinking and planning. Their second factor consisted of tests relating to impulsiveness and inhibitory control, and they labeled this factor "Urgency". According to the researchers, this factor reflects a tendency to commit rash or regrettable actions as a result of intense negative affect. Their third factor consisted of tests relating to sensation seeking and venturesomeness. They appropriately labeled this factor "Sensation Seeking." Finally, their fourth factor consisted of items relating to "(Lack of) Perseverance", including scales relating to self-discipline, persistence, and boredom susceptibility. Based on this factor identification, they

created the UPPS Impulsive Behavior scale to measure each of the four facets of impulsivity.

How does the four-factor model of cognitive traits relate to the four-factor model of impulsivity? I predicted that both Affective and Aesthetic Engagement would be related to the sensation seeking component of impulsivity, since these aspects are part of a more general Openness to Experience construct (see *Chapter 6: Four-Factor Model*). Furthermore, since prior research has shown a relation between Explicit Cognitive Ability and both ADHD and delay discounting (Kuntsi, et al., 2004; Shamosh & Gray, 2007; Shamosh, et al., 2008), I predicted that those higher in Explicit Cognitive Ability and Intellectual Engagement would be less impulsive on all aspects of impulsivity that relate to inhibitory control and premeditation.

Table 7-3 mostly confirms these hypotheses.

Table 7-3
Correlations between the four-factor model of cognitive traits and four-factor model of impulsivity (N= 145)

Measure	Lack of Premeditation	Urgency	Sensation Seeking	Lack of Pers.
Explicit Cognitive Ability	.03	.01	.05	.06
Intellectual Engagement	-.07	-.16	.00	-.23**
Affective Engagement	.30**	.24**	.21*	.11
Aesthetic Engagement	.33**	.18*	.22**	.18*

Note: *p* < .05, **p* < .01.

Both Affective and Aesthetic Engagement were positively related to Lack of Premeditation, Urgency and Sensation Seeking. Additionally, Aesthetic Engagement

was positively related to Lack of Perseverance. Unexpectedly, however, Explicit

Cognitive Ability was not related to any of the facets of impulsivity. On first blush,

this finding seems to counter prior research that has demonstrated a relation

between g and impulsivity (Kuntsi, et al., 2004; Shamosh & Gray, 2007; Shamosh, et

al., 2008;). The methods used in those studies, however, were quite different than

the self-report measures employed in the current study. Indeed, Whiteside & Lynam

(2001) found that their UPPS dimensions related to different domains of the Big

Five- Conscientiousness (the Self-Discipline and Deliberation facets), Neuroticism

(the Impulsiveness facet), and Extraversion (the Sensation Seeking facet)-

personality domains that do not normally show relations to IQ. (See *Appendix B:*

Additional Covariance Analyses for a replication in the current dataset of the Big Five

correlations with the 4 UPPS Impulsivity dimensions).

Another explanation for the discrepancy may be that Explicit Cognitive

Ability relates less to the UPPS dimensions than to distinct Central Executive

processes. Friedman et al. (2006) found that the ability to update working memory

was significantly correlated with g, which is in line with the findings of *Chapter 3:*

Explicit Cognitive Ability. Nonetheless, they found that the functioning of two other

Central Executive processes: inhibiting prepotent reposnses and shifting mental

sets, were not related to fluid or crystallized intelligence, even though all three

Central Executive Functions were significantly correlated with each other. This

finding is consistent with a more recent genetic analysis of these three different

Central Executive Functions (Friedman, et al., 2008), in which it was found that all

three functions significantly correlate with each other because they are influenced by a highly heritable (99%) common factor that goes beyond *g* and perceptual speed. Their study also suggests that the Central Executive Functions are separable due to additional genetic influences unique to each function, which is consistent with prior research showing that, though correlated, Central Executive Functions are separable (Miyake, et al., 2000). Taken together, these research reports raise the intriguing possibility that Explicit Cognitive Ability was not correlated with the UPPS impulsivity aspects since Explicit Cognitive Ability is mainly tied to the updating function of executive control, and other forms of Central Executive Functioning may make a more important contribution to the manifestation of impulsive behavior that is being measured by the UPPS impulsivity scale.

Indeed, the UPPS impulsivity dimensions may be more related to Openness to Experience than the type of impulsivity as conceived in other literatures. As Table 7-3 shows, Aesthetic Engagement was related to all four UPPS aspects. Since Aesthetic Engagement and Explicit Cognitive Ability are moderately correlated (see *Chapter 6: Four-Factor Model*), a simple "higher *g*=better impulse control" model does not seem warranted. Indeed, DeYoung et al. (DeYoung, et al., 2006) found that among individuals lacking a 7-repeat allele of the dopamine D4 receptor gene, those with higher IQ's showed higher impulsivity whereas IQ and externalizing behavior (a broad category encompassing aggression, impulsivity, antisocial behavior, hyperactivity, and drug abuse) was uncorrelated for those having at least 1 copy of the allele. Future research should further explore interactions between *g*, multiple

Central Executive Functions, self-reported impulsivity and Engagement, actual measures of impulsivity such as delay discounting (Shamosh & Gray, 2007; Shamosh, et al., 2008), and genes that predispose an individual to produce less efficient dopaminergic receptors.

Intellectual Engagement was only related to the Lack of Perseverance facet of impulsivity, in that those higher in Intellectual Engagement also reported higher perseverance, planning and organizational skills. This is consistent with Intellectual Engagement's correlation with the Industriousness aspect of Conscientiousness (see Table 7-2). Intellectual Engagement was not related to the other components of impulsivity. Taken together, these results suggest that Affective and Aesthetic forms of Engagement are positively related to more impulsivity facets than Intellectual Engagement, which was negatively related to only one of the impulsivity facets: Lack of Perseverance.

The correlations of impulsivity with Affective and Aesthetic Engagement are consistent with recent research. Hypothesizing that Stability would be related to restraining behavior and Plasticity would be related to engagement of behavior, Hirsch, DeYoung, and Peterson (Hirsch, et al., 2009) had 307 adults rate the frequency with which they engage in 400 behaviors. They also collected multi-informant reports of the metatraits. Consistent with their hypotheses, they found that the extent to which participants engaged in a wide variety of behaviors was positively correlated with Plasticity and negatively correlated with Stability. For instance, the top three behavioral cluster predictors of Stability all were *negative*

predictors: Anger (-.32), Nervousness (-.28), and Overeating (.24), whereas the top

three behavioral cluster predictors of Plasticity all were *positive* predictors:

Interpersonal Warmth (.31), Parties (.30), and Laughter (.29). They also

hypothesized that the behaviors restrained by those high in Stability would be

primarily those associated with strong disruptive impulses, whereas the behaviors

engaged by those high in Plasticity would be those associated with social or mental

exploration. They therefore argue that at the broadest level of description, variation

in human personality reflects both engagement and restraint of behavior.

The current result that Affective and Aesthetic Engagement were positively

related to these impulsivity aspects and additionally were related to Sensation

Seeking supports the idea that Affective and Aesthetic Engagement are related to

the engagement of new and varied Experiences. The finding that Intellectual

Engagement was not related to impulsivity, but was positively related to

Perseverance supports the Controlled / Autonomous distinction made between the

different forms of Engagement (see *Chapter 1: Introduction*). Consistent with my

hypothesis, Intellectual Engagement related more to an exploration of Controlled

Cognition (intellectual ideas), whereas Affective and Aesthetic forms of Engagement

related more to an exploration and Engagement in Autonomous Cognition

(experiences and sensations).

Need for Uniqueness

According to Snyder & Fromkin (1977, 1980), while everyone has a need or

desire to be moderately dissimilar to one another, individual differences exist in the

strength of this motivation. In other words, some people seek uniqueness and distinctiveness more so than others. Snyder & Fromkin (1977) developed a scale to measure this construct. High scorers on this scale are hypothesized to be nonconformists who are independent, inventive, and emotionally stable, whereas low scorers are thought to be the opposite. Through factor analysis, Snyder & Fromkin identified three main components of need for uniqueness which they described as (a) a lack of concern about others' reactions to one's different ideas or actions (NFU-Concern), (b) desire to not always follow rules (NFU-Rules), and (c) willingness to defend one's beliefs publicly (NFU-Defend). As Table 7-4 shows, using Principal Axis Factoring with a Direct Oblimin rotation, I replicated these three factors.

Theorizing that conformists should be stable but rigid, DeYoung, Peterson, & Higgins (2002) predicted a strong positive association between stability and conformity, and a negative correlation between plasticity and conformity. Their results confirmed their prediction: those scoring highest in two measures of self-reported conformity (drawn from the literature on socially desirable responding) were those highest in stability and lowest in plasticity.

Based on these findings, and given its connection to concepts such as independence from societal pressures and nonconformity, it is expected that the need for uniqueness scale will correlate positively with both Affective and Aesthetic Engagement.

Table 7-4
Factor analysis of Need for Uniqueness items (N=113)

Item	Defend	Rules	Concern
11. I tend to express my opinions publicly, regardless of what others say.	**.70**	.34	.36
15. As a rule, I strongly defend my own opinions.	**.63**	.19	.25
10. When I am with a group of people, I agree with their ideas so that no arguments will arise. (R)	**.62**	.11	.60
32. I speak up in meetings in order to oppose those whom I feel are wrong.	**.61**	.15	.16
26. I tend to keep quiet in the presence of persons of higher rank, experience, etc. (R)	**.54**	.12	.30
28. If I disagree with a superior on his or her views, I usually do not keep it to myself.	**.51**	.53	.30
17. When I am in a group of strangers, I am not reluctant to express my opinion publicly.	**.49**	.28	.24
31. People frequently succeed in changing my mind. (R)	.38	.28	.39
7. I always try to follow rules. (R)	.21	**.63**	.29
24. It is better to break rules than always to conform with an impersonal society.	-.04	**.63**	.30
16. I find it sometimes amusing to upset the dignity of teachers, judges, and "cultured" people.	.07	**.62**	.08
8. I would rather be known for always trying new ideas than for employing well trusted methods.	.18	**.52**	.12
25. I must admit I find it hard to work under strict rules and regulations.	-.14	**.52**	.10
13. I do not always need to live by the rules and standards of society.	.00	**.45**	.12
4. Whenever I take part in group activities, I am somewhat of a nonconformist. (R)	.08	**.44**	.41
29. If I must die, let it be an unusual death rather than an ordinary death in bed.	.02	.38	.19

20. I think society should let reason lead it to new customs and throw aside old habits or mere traditions.	.05	.36	.02
22. I like wearing a uniform because it makes me proud to be a member of the organization it represents. (R)	-.14	.34	.28
30. I have been quite independent and free from family rule.	.14	.32	.11
23. Feeling 'different' in a crowd of people makes me feel uncomfortable. (R)	.05	.21	**.69**
12. I would rather be just like everyone else than be called a 'freak'. (R)	.24	.32	**.68**
18. Others' disagreements make me uncomfortable. (R)	.34	.12	**.57**
14. It bothers me if people think I am being too unconventional. (R)	.25	.25	**.47**
27. It is better always to agree with the opinions of others than to be considered a disagreeable person. (R)	.30	.35	**.45**
19. I find that criticism affects my self-esteem. (R)	.32	.03	**.40**
9. I do not like to go my own way. (R)	.26	.37	.37
6. I sometimes hesitate to use my own ideas for fear they might be impractical. (R)	.19	-.17	.32
3. I am unable to express my feelings if they result in undesirable consequences. (R)	.37	.02	.20
1. I do not like to say unusual things to people. (R)	.17	.30	.21
5. In most things in life, I believe in playing it safe rather than taking a gamble. (R)	.22	.38	.18
21. Being a success in one's career means making a contribution that no one else has made.	.21	.26	.07
2. People have sometimes called me 'stuck-up'.	.18	-.05	.04

Notes: Factor loadings over .4 have been bolded. Reverse-scored items are marked (R). $\lambda 1 = 6.44$ (20.14% Total Variance), $\lambda 2 = 2.91$ (9.10% Total Variance), $\lambda 3 = 1.91$ (5.98% Total Variance). *Defend*=A person's willingness to defend his or her beliefs; *Rules*= A person's desire to not always follow rules; *Concern*=A lack of concern regarding others' reactions to one's different idea, actions, etc.

This is what was found. Table 7-5 shows the correlations between the four-factor model of cognitive traits and need for uniqueness.

Table 7-5

Correlations between four-factor model of cognitive traits (N=112) and need for uniqueness

Factor	Defend	Rules	Concern	Total
Explicit Cognitive Ability	.04	-.10	-.04	.07
Intellectual Engagement	.34**	-.09	-.21*	.30**
Affective Engagement	.12	-.11	-.04	.14
Aesthetic Engagement	-.02	-.33**	-.25*	.28**

Notes: *Defend*=Willingness to defend one's beliefs; *Rules*=Desire to not always follow rules (Reverse); *Concern*= lack of concern about others' reactions to one's different ideas or actions (Reverse). *$p < .05$, **$p < .01$.

Explicit Cognitive Ability was not related to need for uniqueness. Intellectual Engagement was positively related to need for uniqueness, but this relation was a result of Intellectual Engagement's correlation with the factor relating to a lack of concern about others' reactions to one's different ideas or actions, and a factor relating to a willingness to defend one's beliefs. This is consistent with Intellectual Engagement's relation to the Assertiveness aspect of Extraversion (see Table 7-2). Affective Engagement wasn't related to a need for uniqueness. Finally, Aesthetic Engagement was correlated with the factor relating to a desire to not always follow rules, as well the factor relating to a lack of concern about other's reaction to one's different ideas or actions. Unlike Intellectual Engagement, Aesthetic Engagement scores weren't correlated with the factor relating to a willingness to defend one's beliefs publicly.

Summary

Taken together, some general trends can be found in linking the four-factor model of cognitive traits to personality. Explicit Cognitive Ability shows no relation to any of the Big Five dimensions (except for the Intellect aspect of Openness/Intellect), any of the UPPS impulsivity dimensions, or need for uniqueness.

Those scoring high in Intellectual Engagement, however, tended to be industrious, assertive, and persevering. Furthermore, they tended to lack concern over public criticism and possessed a willingness to defend their beliefs publicly. The lack of correlation between Intellectual Engagement and sensation and excitement seeking, as well as the lack of correlation with the Enthusiasm aspect of Extraversion suggests that Intellectual Engagement is distinct from Engagement in Autonomous Cognition. This supports my decision to link Controlled Cognition with Intellect and autonomous cognition with Openness to Experience (see *Chapter 6: Four-Factor Model*).

Those scoring high in Affective Engagement tended to be more volatile, compassionate, enthusiastic, and assertive. They tended to deliberate less about decisions, have greater urgency, and tended to be sensation and excitement seekers. Affective Engagement, however, did not predict need for uniqueness. Taken together, Affective Engagement appears to be primarily related to engagement in the full range of human emotions, both positive and negative. This is supported by Affective Engagement's relation to both positive (Enthusiasm) and negative affect

(Neuroticism and Urgency) (see Cyders & Smith, 2008). Put simply, those high in Affective Engagement are "emotional" people.

Finally, those scoring high in Aesthetic Engagement tended to be more compassionate, enthusiastic, and assertive. They tended to be less industrious, orderly, and persevering. Furthermore, they tended to be less deliberative, and, like those high in Affective Engagement, tended to be sensation seekers and possess greater urgency. In terms of a need for uniqueness, those scoring high in Aesthetic Engagement desire to not always follow rules and lack concern about others' criticisms. They are no more willing, however, to defend their beliefs publicly. This contrasts with those high in Intellectual Engagement, who were more willing to defend their beliefs publicly.

These findings suggest that each of these four traits display different patterns of correlations with a wide variety of personality variables. Furthermore, while Affective and Aesthetic Engagement are tied to engagement in experiences, and therefore System 1 processes, Intellectual Engagement is more related to engagement in controlled, conscientious thinking and behavior, and therefore tied to System 2 processes. All three forms of Engagement—Intellectual, Affective, and Aesthetic—most likely are tied to the dopaminergic system. Nonetheless, they may differ in terms of other neurotransmitter functions.

Now that these four factors have been identified (*Chapter 6: Four-Factor Model*) and the personality correlates of these fourfactors have been further elucidated (this chapter), the next two chapters investigate the implications of these

four factors for two important domains of human psychological functioning: creative achievement (*Chapter 8: Creative Achievement*) and deductive reasoning (*Chapter 9: Deductive Reasoning*).

Creative achievement is the confluence of various intrapersonal and interpersonal dimensions (Amabile, 1996; Carson, et al., 2005; Eysenck, 1995; Ludwig, 1995; Simonton, 1994). As noted by Carson, Peterson & Higgins (Carson, et al., 2005), intrapersonal factors include cognitive abilities, personality characteristics, intrinsic motivation, and talent and relevant interpersonal factors may include financial resources, socioeconomic status, societal factors (e.g., the field's receptivity to an individual's novel and useful ideas), and sufficient environmental stability (Csikzentmihalyi, 1988; Ludwig, 1995; Simonton, 1975). As Simonton (1999, 2005) has noted, while each intrapersonal factor may be normally distributed in the general population, creative achievement results from the interaction of many individual traits, producing a non-Gaussian, inverted "J" distribution. Therefore, it is theoretically predicted that only a minority of individuals within any given population will exhibit high levels of creative achievement (Eysenck, 1995; Simonton, 1999, Simonton, 2005).

Various methodologies have been used to assess creative achievement, such as specific markers of eminence (Colangelo, Kerr, Hallowell, Huesman, & Gaeth, 1992; Ellis, 1926; Simonton, 1980), and expert and nonexpert ratings of eminence (Ludwig, 1992; Mackinnon, 1962; Richards, Kinney, Benet, & Merzel, 1988). Hocevar and Bachelor (1989) suggested that the self-report inventory is the most justifiable method of assessing creative achievement and creative talent. Such inventories require the participant to check off achievements across a variety of domains. Researchers who have utilized this technique include Torrance (1972), Holland and

Nichols (Holland & Nichols, 1964), and Hocevar (1979). Carson, Peterson, & Higgins (2005) argue however that all of these existing methodologies suffer from various limitations. One limitation is that many of these methodologies apply to those who are deceased or publicly eminent. Another limitation is that many of these measures are subjective in that they rely on ratings from external judges. A third limitation mentioned by Carson, Peterson & Higgins is that these measures do not carefully discriminate among different levels of accomplishment and mix achievement related items with items relating to attitudes and other traits. According to Carson, Peterson, & Higgins (Carson, et al., 2005), "This confounds the assessment of actual achievement with cognitive ability, motivation, and personality (p. 39)."

Creative Achievement Questionnaire (CAQ)

In order to overcome the various limitations inherent in prior methods of assessing creative achievement, Carson, Peterson, & Higgins (2005) developed a new scale that measures self-reported levels of achievement across nine separate domains of creative achievement in the arts and sciences that have received attention in previous research (Colangelo, et al., 1992; Hocevar, 1979; Mackinnon, 1962; Taylor & Ellison, 1967 Taylor & Ellison, 1967; Torrance, 1972). The additional domain of Culinary Arts was added by the researchers.

The result was the production of the Creative Achievement Questionnaire (CAQ; Carson, et al., 2005). The CAQ consists of three sections. In Part One, participants are asked to select from among 13 areas in which they feel they have more talent, ability or training than the average person. 10 of the areas are later

assessed in the second section, and there are an additional three areas: individual sports, team sports, and entrepreneurial ventures. In Part Two, participants are asked to select items that describe their achievements in 10 domains of artistic and scientific endeavor: Visual Arts, Music, Dance, Architecture Design, Creative Writing, Humor, Inventions, Scientific Discovery, Theater/Film, and Culinary Arts. In Part Three, participants are asked to indicate which of three sentences apply to them: *One of the first things people mention when introducing me to others is my creative ability in the above areas*, *People regularly accuse me of having an "artistic" temperament*, and *People regularly accuse me of being an "absent-minded professor" type.*

Before I present analysis of the relations between the four-factor model and Creative Achievement, I will make a few predictions.

Creative Achievement and the Four-Factor Model

The investigation of the relationship between general intelligence and creativity has taken two main approaches. In one set of approaches, researchers have investigated the relationship between IQ and the judged creativity of creative products as well as scores on tests of divergent thinking. Some researchers in this tradition have found support for a "threshold effect", in which divergent thinking ability and Explicit Cognitive Ability are positively correlated up until an IQ of approximately 120, after which the two constructs are no longer related (Fuchs-Beauchamp, Karnes, & Johnson, 1993; Getzels & Jackson, 1962; Sternberg & O'Hara, 2000). Others have found small to modest correlations across all levels of IQ

(Preckel, Holling, & Wiese, 2006; Kim, 2005), and others still have found that crystallized intelligence shows a positive and moderate relationship to the generation of creative inventions, whereas fluid intelligence is only significantly correlated with the generation of creative inventions in the high end of the IQ spectrum, but not for those with average IQs (Sligh, Conners, & Roskos-Ewoldsen, 2005). Additionally, Park, Lubinski, & Benbow, 2007 have argued that the contribution of IQ and domain-specific abilities (e.g., verbal and spatial) to creativity occurs over the full range of IQs and domain-specific abilities.

Another research tradition, and the one adopted in this chapter, is the investigation of the determinants of creative achievement. Consistent with the "threshold effect" idea, various research studies have found that above an IQ of approximately 120, there are low correlations between general intelligence and creative achievement across a variety of domains (Mackinnon, 1978; Barron, 1969). Sternberg & O'Hara (2000) posit that the correlation of creativity to IQ is variable depending on domain of achievement, ranging from weak to moderate. Consistent with this view, Roe (Roe, 1952) found that the strength of the IQ-Creative Achievement correlation varied depending on the field of science. Based on these findings, I predicted that Explicit Cognitive Ability will have variable relations to Creative Achievement depending on the domain's requirement for Controlled vs. Autonomous Cognitive processes. In particular, I predicted that the domains relating to the Arts would demonstrate lower correlations with Explicit Cognitive Ability than achievement in the Sciences. In terms of total CAQ Score, I predicted a weak

relation with Explicit Cognitive Ability, in line with Carson, Peterson, & Higgin's (2005) finding of a weak relation between total CAQ score and IQ in a sample of participants with above average Explicit Cognitive Ability.

Prior research has demonstrated substantial correlations between both Intellect and Openness to Experience with a variety of creativity measures and creative achievement (Costa & McCrae, 1992; King, et al., 1996; McCrae, 1987; Goldberg, 1992; Carson, et al., 2005). Further, the MBTI Intuition scale, which loaded highly on to the Aesthetic Engagement factor (see *Chapter 6: Four-Factor Model*) has also demonstrated substantial correlations with a variety of measures of creative potential, self-reported creative personality, self-reported creative behavior, and self-reported creative achievement (Carne & Kirton, 1982; Dollinger, Palaskonis, & Pearson, 2004; Fleenor, 1997; Fleenor & Taylor, 1994; Gryskiewicz & Tullar, 1995; Hall & MacKinnon, 1969; Jacobson, 1993; Myers, et al., 1998; Mackinnon, 1962; Richter & Winter, 1966; Sundstrom, Koenigs, & Huet-Cox, 1994; Van Rooyen, 1994; Whittemore & Heimann, 1965; but see Ohnmacht, 1970). Additionally, Dollinger, et al., 2004 found that those scoring high on both the MBTI Intuition and the MBTI Feeling scale (which loaded highly on to the Affective Engagement factor, see *Chapter 6: Four-Factor Model*) displayed the most creative potential.

Most of these studies, however, have not assessed the independent differential relation of these personality traits to achievement in different domains of creativity controlling for Explicit Cognitive Ability. Based on this prior research, I

predicted that Intellectual, Affective, and Aesthetic Engagement would be related to CAQ Total score, but that each form of Engagement would have differing correlations with specific domains of creative Achievement. In particular, I predicted that Intellectual Engagement would be more associated with domains that require higher levels of Explicit Cognitive Ability (such as the Sciences), whereas Affective and Aesthetic forms of Engagement would be related to domains that required higher levels of Autonomous Information Acquisition Ability (such as the Arts). I will now present the results of my analysis, divided into three sections that correspond to the three parts of the CAQ.

Part I

Table 8-1 shows the Spearman's rho correlation among each of the four factors and the checklist items in part one of the CAQ. I used Spearman's rho since the scores weren't normally distributed. Explicit Cognitive Ability was significantly correlated with self-perceived talent in Music and Scientific Discovery. Intellectual Engagement was significantly correlated with self-perceived talent in Creative Writing, Inventions, and Scientific Inquiry. Affective Engagement was positively correlated with self-perceived talent in Art, Music, Dance, and Theatre and Film. Affective Engagement was negatively correlated with self-perceived talent in Scientific Inquiry and Individual Sports. Aesthetic Engagement was positively correlated with self-perceived talent in Art, Music, Creative Writing, and Theatre and Film. Aesthetic Engagement was negatively correlated with self-perceived talent in Individual Sports and Entrepreneurial Ventures. These results suggest differential

relations between the four factors and self-perceived talent across a variety of

creative domains.

Table 8-1

Spearman's rho correlation among four-factor model of cognitive traits and self-perceived talent in 13 domains (N= 146)

Factor	Art	Music	Dance	ADes	Cwri	Humor	Inv.	Sci.	ThFi	Cul.	Isports	Tsports	EntVen
Explicit Cognitive Ability	-.04	.17*	-.06	.08	.13	.05	.15	.28**	-.07	.16	.10	-.08	-.05
Intellectual Engagement	.07	.13	-.09	.08	.26**	.00	.19*	.38**	-.04	.14	.01	-.10	.00
Affective Engagement	.18*	.22**	.30**	.06	.06	-.02	-.07	.27**	.17*	.01	.17*	-.10	-.09
Aesthetic Engagement	.29**	.33**	.10	.03	.27**	.06	.02	-.11	.23**	-.03	-.21*	-.20*	-.17*

Notes: *Art*=Visual Arts (painting, sculpture); *Music*=Music; *Dance*=Dance, *Ades*=Architectural design; *Cwri*=Creative Writing; *Humor*=Humor; *Inv*=Inventions; *Sci*=Scientific inquiry; *ThFi*=Theater and Film; *Cul*=Culinary Arts; *ISports*=Individual sports (tennis, golf); *TSports*=Team sports; *EntVen*=Entrepreneurial ventures. *p < .05, **p < .01.

Part II

The mean CAQ score of all participants who took the CAQ (*N*=177) is 16.4,

(*SD* = 13.2, minimum=0, maximum=74), and the scale has an overall reliability of

.74, which is acceptable. Consistent with prior theory and research (Carson,

Peterson, & Higgins, 2005; Eysenck, 1995; Simonton, 1999, 2005), CAQ scores

weren't normally distributed, but were skewed to the left (see Figure 8-1), with

87% of the participants obtaining a total CAQ score of less than 29. Indeed, this

finding relates to one of Carson, Peterson, & Higgin's (2005) underlying

assumptions about the nature of creative achievement: "Fewer individuals attain

higher levels of achievement. The CAQ was therefore designed so that the levels of

achievement acknowledged by the fewest individuals received the most weight (p.

39)".

Figure 8-1
Distribution of Creative Achievement Questionnaire (CAQ) scores (N=177)
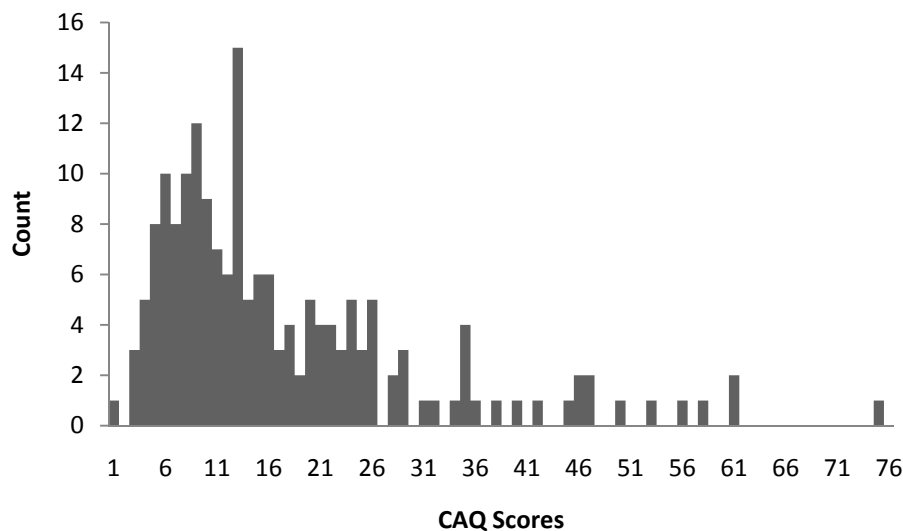
Table 8-2 shows the Spearman's rho correlation among the four factors and levels of self-reported log-transformed creative achievement among the 10 domains of creativity, as well as total creative achievement.

Table 8-2

Spearman's rho correlation among the four-factor model of cognitive traits, 10 domains of achievement, and total creative achievement (N= 146)

Factor	Art	Music	Dance	ADes	CWri	Humor	Inv	Sci	ThFi	Cul	CAQ Total
Explicit Cognitive Ability	.02	.10	-.24**	-.06	-.04	-.00	.22**	.31**	.01	-.10	.02
Intellectual Engagement	.00	.11	-.09	-.05	.22**	.04	.20*	.50**	.06	.00	.14
Affective Engagement	.13	.27**	.28**	-.12	.06	.22**	-.04	-.24**	.20*	.10	.31**
Aesthetic Engagement	.27**	.31**	.10	-.08	-.02	.15	.12	-.03	.21*	-.06	.35**
Reliability (α)	.52	.63	.76	.14	.34	.19	.43	.41	.72	.35	.74

Notes: Art=Visual Arts (painting, sculpture); Music=General Music; Dance=Dance, ADes=Architectural design; CWri=Creative Writing; Humor=Humor; Inv=Inventions; Sci=Scientific discovery; ThFi=Theater and Film; Cul=Culinary Arts. *$p < .05$, **$p < .01$.

Both Explicit Cognitive Ability and Intellectual Engagement weren't correlated with total CAQ score. The former finding is consistent with Carson, Peterson, & Higgins (2005). The lack of correlation between Intellectual Engagement and total CAQ score conflicts with Carson, Peterson, & Higgins finding of a significant correlation between Intellect and total CAQ score. This difference could either be due to a difference in sample (they had a more restricted range), or in measurement (I included a broader Intellectual Engagement latent factor whereas they just included a single measure of Intellect).

Both Affective Engagement and Aesthetic Engagement were correlated with total CAQ score. This is consistent with Carson, Peterson, & Higgins (2005) finding of a significant correlation between Openness to Experience and total CAQ score. Explicit Cognitive Ability was negatively correlated with self-reported achievement in Dance, and positively correlated with self-reported achievement in Inventions and Scientific Discovery. Intellectual Engagement was significantly correlated with self-reported achievement in Creative Writing, Inventions, and Scientific Discovery. Affective Engagement was positively correlated with self-reported achievement in Music, Dance, and Humor and was negatively correlated with self-reported achievement in Scientific Discovery. Aesthetic Engagement was positively correlated with self-reported achievement in Art, Music, and Theatre/Film.

Since Dance and Scientific Discovery displayed a double dissociation between Explicit Cognitive Ability and Aesthetic Engagement, I assessed the independent contribution of these factors for both of these domains. Entering Explicit Cognitive Ability and Affective Engagement into a stepwise regression

model, Explicit Cognitive Ability was not a significantly independent predictor of self-reported Dance achievement, but Affective Engagement was a significantly independent positive predictor of self-reported Dance achievement (β=.31, p < .01). For self-reported achievement in Scientific Discovery, Explicit Cognitive Ability was a significantly independent positive predictor (β=.27, p < .01), and Affective Engagement was a significantly independent negative predictor (β=-.18, p < .05). This suggests that given two people with the same levels of Explicit Cognitive Ability, the person with higher Affective Engagement will tend to score higher in self-reported Dance achievement whereas those with the highest levels of self-reported Scientific Discovery will tend to score higher in Explicit Cognitive Ability and lower in Affective Engagement.

Arts and Sciences Achievement

Since the domains varied considerably in their reliability (see Table 8-2), ranging from .14 (Architectural Design) to .76 (Dance), I ran a factor analysis on all ten domains in order to assess the common variance among the scales and thereby correct for the unreliability unique to each particular domain (see Table 8-3).

To investigate whether an Arts and Sciences found would emerge, I conducted a factor analysis. To be consistent with Carson, Peterson, & Higgins (2005), I assessed a 2-factor solution using principal components analysis, with varimax rotation on all participants with CAQ scores (*N*=177). Two factors accounted for 37.1% of the total variance in the 10 domains, which is close to Carson, Peterson, & Higgins 33.5%. Loading on Factor 1 was self-reported

achievement in Theatre/Film, Humor, Music, Visual Arts, and Creative Writing. I
labeled this factor "Arts". Loading on Factor 2 was Inventions, Scientific Discovery,
and Architectural Design. Theatre/Film and Dance loaded negatively on Factor 2. I
labeled this factor "Sciences".

Table 8-3
Factor Analysis of REI experiential factors and MBTI subscales (N = 177)

	Arts	Sciences
Theatre/Film	**.68**	**-.42**
Humor	**.63**	.24
Music	**.58**	.02
Visual Arts	**.43**	.00
Creative Writing	**.41**	.28
Culinary Arts	.36	.02
Inventions	.20	**.72**
Dance	.39	**-.59**
Scientific Discovery	-.04	**.56**
Architectural Design	.20	**.55**

Note: Loadings greater than .40 (in absolute terms) were bolded.

Table 8-4 shows the correlations among the four factors and self-reported
achievement in the Arts and Sciences.

Table 8-4

Spearman's rho correlations among the four-factor model of cognitive traits, and self-reported achievement in the Arts and Sciences (N=146)

Factor	Arts	Sciences
Explicit Cognitive Ability	-.03	.24*
Intellectual Engagement	.09	28**
Affective Engagement	.33**	-.25**
Aesthetic Engagement	.30**	-.05

Explicit Cognitive Ability and Intellectual Engagement weren't correlated with the Arts factors, but were positively correlated with the Sciences factor. Both Affective and Aesthetic Engagement significantly correlated with the Arts factor, but Aesthetic Engagement did not correlate with the Sciences factor, and Affective Engagement was negatively correlated with the Sciences factor. Furthermore, putting all four factors into a regression model, Affective Engagement remained the only independent predictor of the Arts (β=.20, p < .05), whereas Intellectual Engagement remained the only independent predictor of the Sciences (β=.20, p < .05). In terms of Explicit Cognitive Ability, this suggests that for self-reported achievement in the Arts, Explicit Cognitive Ability shows no incremental validity above and beyond Affective Engagement, whereas for self-reported achievement in the Sciences, Explicit Cognitive Ability shows no incremental validity above and beyond Intellectual Engagement. These results have implications for the threshold effect. That Explicit Cognitive Ability wasn't correlated with self-reported achievement in the Arts, but was correlated with self-reported achievement in the

Sciences may reflect differential Explicit Cognitive Ability thresholds for creative achievement in the Arts and Sciences. In other words, creative achievement in the Arts may require a lower Explicit Cognitive Ability threshold than achievement in the Sciences. For the Arts, Autonomous forms of Cognition may be a more important contributor to Arts Achievement across the full range of Autonomous Cognition scores. For Sciences Achievement, Intellectual Engagement predicted achievement above and beyond Explicit Cognitive Ability, suggesting that Intellectual Engagement is an important predictor of Science Achievement in its own right, consistent with the DP model. In total, the results suggest that investigating Arts and Sciences achievement separately proves useful in determining the Controlled and Autonomous Cognition contributors to achievement.

Latent Inhibition and Creative Achievement

Since Affective Engagement was the sole independent predictor of self-reported achievement in the Arts (see above), and reduced latent inhibition is associated with Affective Engagement (see *Chapters 5 and 6*), I predicted an association between reduced latent inhibition and self-reported achievement in the Arts. Indeed, prior research has demonstrated a relation between reduced latent inhibition and total CAQ score (Carson, et al., 2003, see *Chapter 5: Latent Inhibition*). Prior research, however, hasn't specifically investigated the relation between latent inhibition and self-reported Arts achievement. Consistent with my prediction, latent inhibition was negatively correlated with the Arts factor (Spearman's rho=-.21, p < .05, one tailed; *N*=121), as well as self-reported achievement in Music (Spearman's

rho=-.19, p < .05, one tailed; *N*=121), Humor (Spearman's rho=-.24, p < .01, one tailed; *N*=121), and Culinary Arts (Spearman's rho=-.29, p < .01, one tailed; *N*=121). Interestingly, implicit learning was also significantly correlated with self- reported Music achievement (Spearman's rho=.19, p < .05, *N*=153). This suggests that both System 1 processes may contribute to Music achievement above and beyond Explicit Cognitive Ability and Intellectual Engagement. Latent inhibition was not related to the Sciences factor, or total CAQ score. All of the associations between LI and self-reported creative achievement held after controlling for Explicit Cognitive Ability.

The fact that these results held after controlling for Explicit Cognitive Ability is interesting in light of the theory put forth by Carson, et al., 2003. In trying to reconcile prior findings of an association between reduced LI and psychosis with their finding of a correlation between reduced LI and self-reported creative achievement, Carson, Peterson, & Higgins argue that high IQ may serve as a beneficial moderating factor in the expression of LI. In support of this idea, they found that within their population (Harvard students with an average IQ of 129), the highest levels of total self-reported creative achievement were those with a combination of high IQ with reduced LI. According to the researchers, "These results also support the theory that highly creative individuals and psychotic-prone individuals may possess neurobiological similarities, perhaps genetically determined, that present either a psychotic predisposition on the one hand or as unusual creative potential on the other on the basis of the presence of moderating cognitive factors such as high IQ…These moderating factors may allow an individual

to override a 'deficit' in early selective attentional processing with a high-functioning mechanism at a later, more controlled level of selective processing (p.505)." The results of this chapter suggest that for achievement in the Arts, the important combination for creativity may not necessarily be a high-IQ, but at least a normal level of IQ. Within the average range of Explicit Cognitive Ability scores in the current sample, Explicit Cognitive Ability did not predict creative achievement in the Arts. Further research should investigate Arts domains particularly in relation to the schizophrenia-creativity link.

Indeed, it has been noted that creative thought and schizophrenic thought both seem to evidence activations in the right hemisphere (see Bakan, 1976) which is often associated with images and spatial thought (Sperry, 1968) . Indeed, Hines and Martindale (1974) found improved performance on the Remote Associations Test (RAT; Mednick, 1962), a measure of the ability to access remote associations as well as verbal intelligence, when they required that participants turn their eyes left (reflecting right-hemispheric activation) while engaging in the task. This is consistent with other research showing that the right hemisphere is important for Autonomous Cognition. In one study, individuals who produced left-eye movements during concentration experienced more vivid and frequent daydreaming activity than those who moved their eyes to the right during concentration (Meskin & Singer, 1974; Singer, 1974). Additional research has found that in a sample of males, those who moved their eyes to the left during concentration tended to sleep longer than males who moved their eyes to the right during concentration, suggesting that

left-eye moving males may have more REM sleep and therefore dream more than right-eye moving males (Bakan, 1978). Future research should replicate this finding and see whether it can be extended to females.

Therefore, people with schizophrenia may have enhanced levels of Autonomous Cognition without the Controlled Cognitive resources to cope with the influx of ideas, sensations, and feelings. Recent research suggests that people with schizophrenia evidence a "functionally overactive" default network, a brain network also linked to Autonomous Cognition (Garrity, et al., 2007; Zhou, et al., 2007). These results suggest that the boundary between imagination and reality may be disrupted in individuals with schizophrenia. Buckner, Andrews-Hanna Schacter (2008) note that "The complex symptoms of schizophrenia could arise from a disruption in this control system resulting in an overactive (or inappropriately active) default network (p. 27)." Along similar lines, Bakan, 1978 suggested that the difference between creative individuals without schizophrenia and people with schizophrenia may be due to the presence of the left-hemisphere operating on the products of the right hemisphere in creative individuals without schizophrenia. The proper balance of the hemispheric lateralization would allow the left-hemisphere's analysis and explanation functions to keep the Autonomous Cognitions of the right-hemisphere from controlling too much of behavior (see also Bogen & Bogen, 1969).

In sum, all the research taken together is in support of the idea that people with schizophrenia and creative individuals without schizophrenia both possess enhanced levels of Autonomous Cognition. The findings of this chapter further suggest though that high levels of Autonomous Cognition can lead to high levels of Arts achievement in individuals with at least an average level of Explicit Cognitive Ability.

To investigate whether the highest creative achievers in the current sample were those with the low LI/high g combination, I followed the same procedure employed by Carson, Peterson, & Higgins (2003). First I formed two Explicit Cognitive Ability groups (high/low) as well as two Latent Inhibition (LI) groups (high/low) on the basis of the naturally occurring split in bimodal LI scores in the preexposed condition (split at 5, see *Chapter 5: Latent Inhibition*). A 2 x 2 factorial ANOVA examined total CAQ scores using high LI/low LI and high Explicit Cognitive Ability/low Explicit Cognitive Ability as factors (for clarity of graphical presentation, the CAQ total scores in this analysis weren't log transformed. Conducting the same analyses with log transformed scores yielded the same pattern of results). The results showed no main effect of Explicit Cognitive Ability or LI, but a significant interaction between the two variables $F(1, 97) = 8.2$, $p < .01$, with the low LI/low Explicit Cognitive Ability group and the high LI/high Explicit Cognitive Ability group outperforming the other two groups.

Also of interest was the prediction of self-reported achievement in the Arts and Sciences separately. A 2 x 2 factorial ANOVA examined self-reported

achievement in the Arts and Sciences using high LI/low LI and high Explicit Cognitive Ability/low Explicit Cognitive Ability as factors (for clarity of graphical presentation, the Arts scores were calculated by summing the non log transformed scores for Theatre/Film, Humor, Music, Visual Arts, Creative Writing, and Dance. Sciences scores were calculated by summing the non log transformed scores for Inventions, Scientific Discovery, and Architectural Design. Conducting the same analyses with the Arts and Sciences factor scores derived from the log transformed scores yielded the same pattern of results). Figure 8-2 shows the graphs of the results. For self-reported achievement in the Arts, the results echoes the result for the CAQ total score: there was no main effect of Explicit Cognitive Ability or LI, but there was a significant interaction between the two variables $F(1,97)=8.0$, $p < .01$, with the low LI/low Explicit Cognitive Ability group and the high LI/high Explicit Cognitive Ability group outperforming the other two groups.

Figure 8-2
*Self-reported Arts and Sciences Achievement scores of high-low latent inhibition (LI)
and high-low Explicit Cognitive Ability groups (N= 97)*

Arts

Sciences
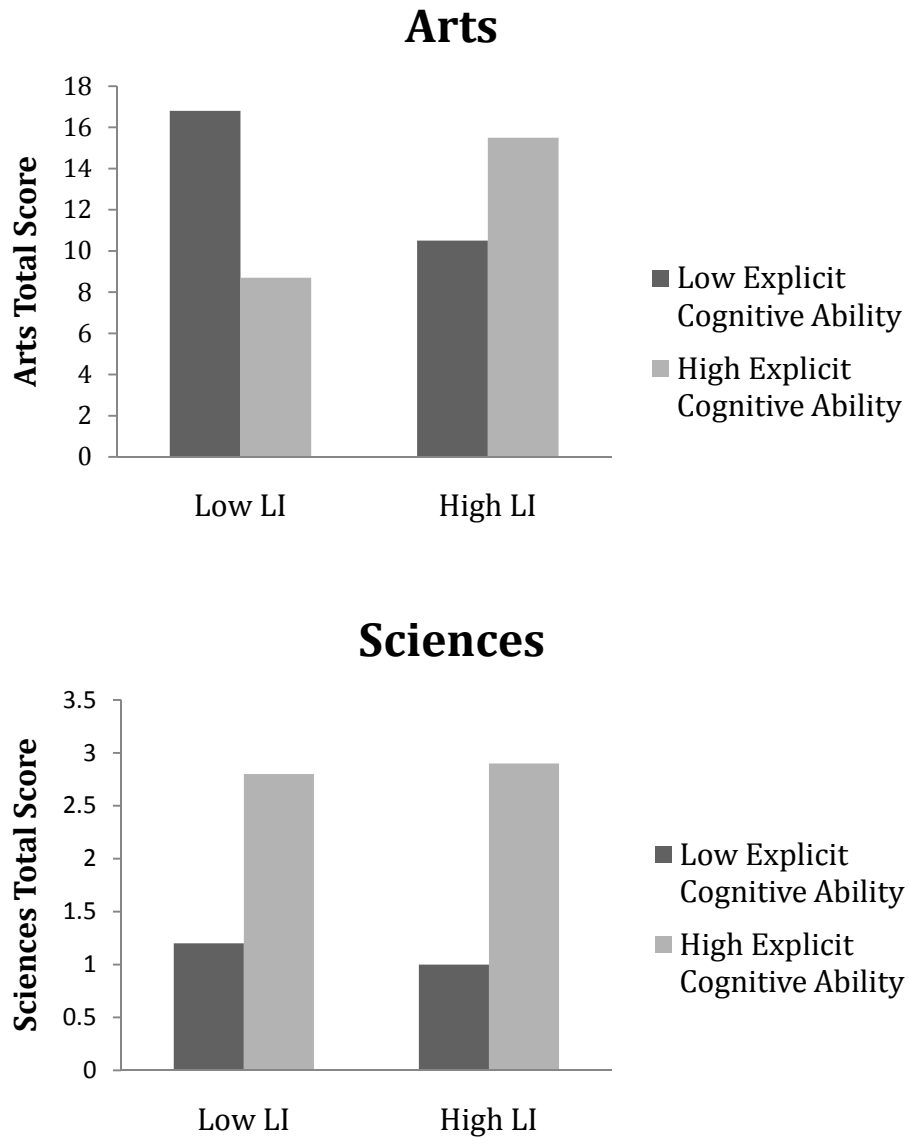
Note: Low LI-Low Explicit Cognitive Ability (*N*=22), Low LI-High Explicit Cognitive Ability (*N*=26),
High LI-Low Explicit Cognitive Ability (*N*=23), High LI-High Explicit Cognitive Ability (*N*=26)

The pattern of results was different for self-reported achievement in the

Sciences, however. For self-reported sciences achievement, there was a main effect

of Explicit Cognitive Ability F(1, 97)=72.2, p < .01, but no main effect of LI or interaction between the two variables. Therefore, there appeared to be no significant LI differences between those scoring high vs. low in self-reported Scientific achievement. Indeed, these results are intriguing, and further research should investigate why both low LI/low Explicit Cognitive Ability and high LI/high Explicit Cognitive Ability groups outperformed the other groups in predicting self-reported Arts achievement and why latent inhibition did not predict self-reported Sciences achievement.

These results differ from those of Carson, Peterson & Higgins (2003) who found that those with the highest CAQ total scores were those with a combination of low LI and high *g.* There are multiple reasons why the results of the current study may be more representative of the general population as whole than the Carson, Peterson & Higgins study. For one, the participants in their sample (Harvard students) were a more restricted range than the participants in the current sample. Secondly, the current study employed a better measure of *g,* which consisted of multiple indicators of *g* as well as two ECTs that are related to *g* (working memory and explicit associative learning, see *Chapter 3: Explicit Cognitive Ability*). Further, since the CAQ is weighted more toward self-reported achievement in the arts, the total CAQ score may reflect self-reported achievement in the arts more than self-reported achievement in the sciences. Indeed, the pattern of results was the same using CAQ Total scores or Arts scores. Carson, Peterson & Higgins (2003) did not

investigate the interaction between latent inhibition and Explicit Cognitive Ability in predicting self-reported achievement in the Arts and Sciences specifically.

Another issue for both the current dissertation and the study conducted by Carson, Peterson, & Higgins (2003) is that most of the participants haven't really come into their own yet in regards to creative achievement. It will be important to conduct studies predicting lifetime creative achievement among those who are at the end, not the beginning of their careers. A fuller age range (and career age range) will allow for a better assessment of the role of Controlled and Autonomous Cognition in predicting different levels of creativity. Kaufman & Beghetto (2009) offer a useful framework for distinguishing between four different levels of creativity. They include "Big-C" creativity (examples of clear-cut eminent creative contributions), "little-c" creativity (everday creativity found in nearly everyone), "mini-c" creativity that is part of the learning process and isn't necessarily evidenced by a final creative product, and "Pro-c", which consists of professional-level expertise in any creative area (for applications of this model to giftedness, also see Kaufman, Kaufman, Beghetto, Burgess, & Persson, 2009). In sum, the results presented in the current chapter are intriguing, and the conflicts with the work by Carson, Peterson & Higgins (2003) suggest new avenues for research investigating creative achievement in both the Arts and Sciences, using samples with a larger range of Explicit Cognitive Ability, a wider age range (as well as career age range), employing multiple measures of LI, proneness for psychosis, and a variety of so-called "moderating factors".

Need for Uniqueness

Dollinger (2003) made the case that two important variables have been neglected in explaining creativity: need for uniqueness and need for cognition, which is closely related to the Big Five trait Intellect (Cacioppo & Petty, 1982). Consistent with this idea, Dollinger found that both variables independently predicted multiple measures of creativity, including an inventory of creative accomplishments, preference for complex visual figures, unconventional word associations, and expert rated creative drawings, stories, richness of photo essays about the self, and vividness of a recent dream.

Dollinger's study suffers from some limitations, however. He did not include a measure of g in his study, so he did not control for Explicit Cognitive Ability. Further, he only looked at domain-general creativity, not investigating particular types of creative accomplishments. The current study was able to overcome these various limitations.

Table 8-5 presents the Spearman's rho correlations among need for uniqueness and self-reported achievement in the Arts and Sciences.

Table 8-5
*Spearman's rho correlations among need for uniqueness, and self-reported
achievement in the Arts and Sciences (N=113)*

Factor	Arts	Sciences
NFU-Concern	-.30**	-.11
NFU-Rules	-.14	-.27**
NFU-Defend	.11	.05
NFU-Total	.19*	.20*

High scorers on the Arts achievement factor tended to show a lack of concern for other's reaction. In contrast, high scorers on the Sciences achievement factor were more likely to not always follow rules. Controlling for Explicit Cognitive Ability and Intellectual Engagement, the correlation between NFU-Concern and Arts remained significant [r(109)=.23, p < .05)], Similarly, controlling for Explicit Cognitive Ability and Intellectual Engagement, NFU-Rules remained significantly correlated with self-reported achievement in the sciences [r(108)=-.24, p < .01]. Vice versa, Intellectual Engagement remained significantly correlated with self-reported achievement in the sciences, even while controlling for NFU-R [r(109)=.29, p < .01]. The correlation between NFU-Total and the Arts and Science factor no longer remained significant, controlling for Explicit Cognitive Ability and Intellectual Engagement. Taken together, these results suggest that need for uniqueness and Intellectual Engagement make independent predictions on self-reported creative achievement, but at different levels of analysis. Intellectual Engagement and a desire to follow rules are independently related to self-reported achievement in the

Sciences, whereas a lack of concern for other's reactions is independently correlated with self-reported achievement in the Arts.

Part III

Table 8-6 shows the correlation between the four factors and how others perceive the participant in terms of creative characteristics.

Table 8-6
Correlations between the four-factor model of cognitive traits and four-factor model of impulsivity (N= 146)

Factor	People Mention Creativity	Artistic Temperament	Absent-Minded
Explicit Cognitive Ability	-.01	-.06	.16
Intellectual Engagement	.13	.01	.10
Affective Engagement	.24**	.16*	-.19*
Aesthetic Engagement	.26**	.33**	-.01

Notes: People Mention Creativity=One of the first things people mention about me when introducing me to others is my creative ability in the above areas; Artistic Temperament=People regularly accuse me of having an "artistic" temperament; Absent-Minded=People regularly accuse me of being an "absent-minded professor" type. *$p < .05$, **$p < .01$.

Explicit Cognitive Ability and Intellectual Engagement weren't correlated with any of the statements. Affective Engagement was positively correlated with the statement "One of the first things people mention about me when introducing me to others is my creative ability in the above areas" and "People regularly accuse me of having an 'artistic' temperament", and negatively correlated with the statement "People regularly accuse me of being an "absent-minded professor". Aesthetic Engagement was positively correlated with "One of the first things people mention

about me when introducing me to others is my creative ability in the above areas" and "People regularly accuse me of having an "artistic" temperament".

Summary

Taken together, these results suggest that Controlled Cognition (Explicit Cognitive Ability and Intellectual Engagement) relate more to self-reported achievement in the Sciences than the Arts, and that Autonomous Cognition (Affective and Aesthetic Engagement and latent inhibition) relate more to self-reported achievement in the Arts than the Sciences. In the next chapter, I explore the implications of the four-factor model for predicting deductive reasoning.

Dual-process theories of reasoning posit that two distinct cognitive systems underlie reason and decision making (Evans, 2003). System 1 is often characterized by a set of automatic, unintentional, and nonconscious processes, whereas System 2 is often characterized by a set of conscious, deliberate, and reflective processes thought to be associated with Central Executive Functioning and Explicit Cognitive Ability (e.g., Barrett, et al., 2004).

One particularly active area of reasoning that has received attention from dual-process theorists is deductive reasoning. Wason set off the study of the psychology of deductive reasoning in the 60's and 70's (Wason & Johnson-Laird, 1972). One of Wason's most studied tasks is the Card Selection Task (Wason, 1968). More recently, the application of dual-process theory to understanding performance on this task has been an active area of research (Evans, 2002; Wason & Evans, 1975).

Wason Card Selection Task

A large literature exists on the Wason four-card selection task. This task provides a helpful way to investigate the contribution of dual-processes since it is sensitive to the content and context of presentation (Evans, 2003). On this task, participants must decide which of four cards are necessary to turn over in order to confirm a truth. Research has shown that abstract, indicative forms of this task are very difficult for participants to solve, whereas concrete and deontic forms that are placed in a context (and involve determining whether a rule or obligation is violated) are solved by a higher proportion of participants.

It has been argued that performance on the abstract version is strongly influenced by automatic System 1 processes, either through the automatic activation of heuristics that produce a "matching bias" (Evans, 1998) and guide the particiants' focus of attention to cards that match the lexical content of the instructions, or through preconscious heuristic processing of the kind described by Reber's (1993) implicit learning system (Evans & Over, 1996). Taking a more modular approach, Cosmides (1989) and Cosmides & Tooby (2004) argue that Social Exchange and Precautionary reasoning are supported by dedicated information processing modules that are a result of evolution by natural selection. According to Stanovich & West (2000), the ability to solve the Wason selection task under abstract conditions involves the ability to resist the automatic contextualization of problems that involves the activation of automatic prior belief and knowledge.

Individual differences in abstract deductive reasoning

While the search for the underlying cognitive processes involved in performance on the Wason task has been an active program of research, the investigation of individual differences in the cognitive processes underlying performance on this task has only recently begun to receive attention. Indeed Newstead, Handley, Harley, Wright, & Farelly, 2004 argued that an individual differences approach can make an important contribution to the field by providing support for the existence of different systems of thought, as well as informing the human rationality debate.

According to Stanovich & West (2000), for most people, most of the time, System 1 and System 2 operate simultaneously and in coordination. Sometimes however, especially in situations where cognition must be decoupled and decontextualized from prior belief and experience, the two systems may come into conflict. It is under these conditions, argue Stanovich & West, when cognitive ability is most important to override the automatic processing of System 1. In particular, they argue that "in order to observe large cognitive ability differences in a problem situation, the two systems must strongly cue *different* responses. It is not enough simply that both systems are engaged. If both cue the same response, then this could have the effect of severely diluting any difference in cognitive ability (p. 659)." Further, they suggest that "Individuals of higher cognitive ability may be more likely to override evolutionarily optimized computations in order to pursue a normative solution." (Stanovich & West, 1998a, p. 227). Along similar lines, Newstead et al., (2004) argue that contextualized version of the Wason selection task are easier to solve by most participants because they can mostly be solved by pragmatic, belief-based System 1 processes without invoking System 2 processes.

Perhaps due to the focus of these theories on the importance of decontexualization, the majority of the research on this topic has focused on predicting performance on abstract versions of the section task. Stanovich & West (1998a) found that participants with higher SAT scores tended to perform better on abstract versions of the Wason selection task, whereas the correlation between Wason selection task performance and SAT scores were much weaker for concrete

forms of the task. Other research has also found a correlation between general cognitive ability and logically correct performance on the standard, abstract version of the Wason selection task (Dominowski & Dallob, 1991; Klaczynski, 2001; Stanovich & West, 1998a, Stanovich & West, 1998b; Valentine, 1975).

In fact, across a variety of studies, researchers have demonstrated that individual differences in g are associated with the ability to find normatively correct solutions across a range of decisions making tasks (Stanovich & West, 2000; Stanovich, 1999; Stanovich & West, 2003; Kokis, Macpherson, Toplak, West, & Stanovich, 2002). In these studies, the precise mechanism by which g is exerting its effect on reasoning is not explicated. Therefore, these results may just be further evidence for the positive manifold (positive correlations) found across diverse measures of abstract cognitive ability (Hunt, 2000).

It is often assumed (e.g., Stanovich & West, 2000) that those with higher working memory capacity are better able to inhibit the prepotent response cued by System 1 and to reason through the abstract formal rules of logic. Since most researchers have not actually administered a measure of working memory along with measures of g, this conclusion remains speculative. Furthermore, just because a correlation is found between g and abstract deductive reasoning does not suggest that the inhibiting aspect of Central Executive Functioning is involved. Indeed, research shows that only the updating Central Executive Function is related to measures of g, with a much weaker relation between the ability to inhibit prepotent responses and g (Friedman, et al., 2006).

Individual differences in contextualized reasoning

While the majority of research on individual differences in deductive

reasoning has focused on explaining individual differences on abstract versions of

the selection task, there is evidence that individual differences also exist in

contextualized reasoning. Various intelligence researchers (e.g., Ceci, 1996,

Sternberg, 1997a) argue for the importance of context in understanding individual

differences in intellectual performance.

A major limitation of some of the prior studies demonstrating that

individuals with average or even low IQ can still reason complexly on "practical"

problems is that "task complexity" is poorly defined in these studies and not

controlled or matched to the complexity on IQ tests. The Wason selection task can

overcome this limitation since the underlying logic system remains constant while

task content (abstract vs. contextual) can vary across items.

Evidence for the relation between g and performance on the contextualized

version of the Wason selection task is variable. On the one hand, Stanovich & West

(1998a) found SAT score differences to be greater on the abstract version than the

deontic version of the Wason selection task. However, Dominowski & Dallob (1991)

found that performance on abstract and thematic tasks were correlated and that

performance on both was related to several general reasoning tasks. Furthermore,

Klaczynski (2001) found correlations between ability and performance on a deontic

task, and Dominowski and Dallob (1991) found that these were just as high as those

with abstract tasks. Indeed, both Dominowski and Dallob (1991) and Wetherick

(1995) suggest that both types of tasks call on the same mental processes.

All of these studies suffer from a few limitations that might be adding to the

inconsistencies found across the studies, and may be limiting our knowledge of the

true contributions of System 1 and System 2 processes to deductive reasoning

performance. Firstly, reliability of reasoning is difficult to assess in these studies,

since only one or two scenarios are typically administered. The lack of the

relationship between g and deontic reasoning demonstrated by Stanovich & West

(1998a) may be due to the low reliability of the task.

Secondly, prior studies have not assessed the relation between a latent g

factor and a latent deductive reasoning factor. Indeed, this has not been possible

since these researchers have typically only administered a few items at a time, and

have only administered one marker of g.

Thirdly, while studies of individual differences in reasoning have focused on

accuracy of reasoning, very few studies have looked at the role of System 1 on *speed*

of reasoning. Recently, Reis et al. (2007) provided evidence that measures of

emotional intelligence predict the speed of Social Exchange reasoning. This suggests

that individual differences in the ability to use emotions to guide reasoning may be

related to speed, in addition to, or in place of, accuracy.

While Reis et al. employed a measure of emotional intelligence, g was not

controlled for. It is therefore an open question the extent to which emotional

intelligence predicts contextualized deductive reasoning above and beyond the

effects of g and the ECTs associated with g. If it does not, then emotional intelligence might be better conceptualized as a subset of g, and be considered part of System 2.

A fourth major limitation of prior studies has been the limited use of measures that assess a tendency for Engagement in System 1 processes (Epstein, et al., 1996; Klaczynski, 2001; Newstead, et al., 2004, Pacini & Epstein, 1999). Indeed, this is partly due to the focus in this literature on the importance of a "rational thinking disposition" (Stanovich & West, 2000). For instance, according to Stanovich's (2009b) "tri-process theory", both the "reflective mind" and the "algorithmic" mind are part of a larger construct called "rationality" which is exclusively tied to System 2 processes. In the words of Stanovich: "To be rational, an organism must have well calibrated beliefs (reflective level) and must act appropriately on those beliefs to achieve its goals (reflective level). The organism must, of course, have the algorithmic-level machinery that enables it to carry out the actions and to process the environment in a way that enables the correct beliefs to be fixed and the correct actions to be taken" (pp. 6-7). Therefore, Stanovich argues that individual differences in "rational thought and action" can arise due to individual differences in "intelligence" or individual differences in "thinking disposition". Stanovich sees thinking dispositions as indexing an individual's goals and epistemic values at the intentional level of analysis and functioning of the algorithmic mind as relating to "cognitive capacity" that can be measured by measures of g.

Stanovich makes clear however, that these rational thinking dispositions are part and parcel of System 2, and are distinguishable from the "Autonomous Mind" which must be suppressed under conditions of System 1 and System 2 conflict. Stanovich refers to such instances of System 2 not overriding System 1 as instances of an "override failure". Further, Stanovich explicitly states that there are minimal individual differences in the Autonomous Mind that predict reasoning performance. According to Stanovich (2009b), "Disruptions in algorithmic-level functioning are apparent in general impairments in intellectual ability of the type that cause mental retardation... And these disruptions vary continuously. In contrast, *continuous individual differences in the autonomous mind are few*. The individual differences that do exist largely reflect damage to cognitive modules that result in very discontinuous cognitive dysfunction such as autism or the agnosias and alexias. (p. 6, italics added for emphasis). This statement is directly contradicted, however, by evidence presented in *Chapter 4: Implicit Learning & Chapter 5: Latent Inhibition,* in which it was demonstrated that there indeed exist meaningful individual differences in processes related to the Autonomous Mind (implicit learning and latent inhibition) that aren't completely modular but instead are to a large degree domain-general and are at least partially independent of the functioning of what Stanovich refers to as the "Algorithmic Mind".

Current Study

In the current study, I adopted the computerized Wason selection task constructed and employed by Reis et al. (2007). This version of the task is time-limited, involves a card-by-card presentation, and records both accuracy and reaction time. The purpose of administering this task was to investigate the relation between contextualized deductive reasoning and individual differences in Explicit Cognitive Ability, Intellectual Engagement, Affective Engagement, and Aesthetic Engagement (see *Chapter 6: Four-Factor Model*). The benefits of administering this version of the task for the current purposes are threefold. First, the time limited nature of this task allows for the minimizing of explicit processes that contribute to the task, maximizing System 1 processes, and therefore increasing the likelihood that associations with individual differences in System 1 thinking will be discovered if they exist. Second, the card-by-card presentation allows for an assessment of reaction time for each card. Prior research on the Wason selection task has mostly assessed accuracy, whereas the results of Reis et al. (2007) suggest that System 1 processes may play an important role in speeding up responses by facilitating the reasoning of contextual information. Third, the task involves multiple trials across multiple forms of contextualized reasoning that have been employed in the literature (Descriptive, Precautionary, and Social Exchange), allowing for a proper assessment of the common variance across multiple deductive reasoning items. Prior research has suffered from the administration of only a few items measuring

contextualized reasoning, and therefore lack analysis involving a latent contextualized deductive reasoning factor.

According to Stanovich's (2009b) model, the "Algorithmic" and "Reflective" mind should not relate to individual differences in contextualized reasoning. Therefore it is predicted that Explicit Cognitive Ability and Intellectual Engagement (which are part of System 2) will not relate to accuracy or speed of performance on this version of the task. Based on Reis et al.'s (2007) finding of a relation between emotional intelligence and speed of Social Exchange reasoning, it is predicted that Affective Engagement will relate to performance on deductive reasoning items relating to Social Exchange, and that this effect will hold after controlling for Explicit Cognitive Ability. Further, Aesthetic Engagement is also predicted to relate to both the speed and accuracy of deductive reasoning since Aesthetic Engagement is related to implicit learning (see *Chapter 6: Four-Factor Model*), and according to Evans & Over (1996), implicit learning facilitates reasoning during contextualized reasoning.

Methodology

Participants

112 Participants (40 males, 72 females) were included in the analyses presented in this chapter. Out of the total sample of 177 (see *Chapter 2: Methodology*), 112 participants successfully completed the computerized Wason card selection Task. The Wason selection task was offered as an option at the end of the third test session for participants who completed all the other tests and had time remaining. Since this was the case, a legitimate concern may be that somehow this

subset of the total sample is not representative of the sample as a whole. Analysis

suggests this isn't the case. *g* factor scores calculated among the participants who

completed the Wason selection task correlated .99 with *g* factor scores calculated on

the sample as a whole (*N*=177). Furthermore, the mean RAPM score of the total

sample was almost identical (21.7, *S.D.*=5.4) with the mean RAPM score of those

participants completing the Wason task (22.0, *S.D.*=5.8). Therefore, the subsample

analyzed in this chapter appears to be representative of the total sample.

Measures

The focus of this chapter is the computerized Wason card selection task (see

Chapter 2: Methodology for a full description of the task). This task involves

deductive reasoning on three types of content: Descriptive, Precautionary, and

Social Exchange. Descriptive problems had arbitrary rules (e.g., "If the container is

red, then it must contain sugar"). Precautionary problems involve rules related to

avoiding potential danger (e.g., If you work in the virus lab, then you have to wear

rubber gloves"). Social exchange problems involved detecting if one party might be

taking a benefit without fulfilling an obligation (e.g., If you order beer at dinner, then

you have to buy me a drink at the bar"; see Figure 9-1 for an actual Social Exchange

Scenario used in the task). This type of reasoning concerns the mutual exchange of

goods or services between individuals and are characteristic of human societies and

found in only a few other species (Cosmides & Tooby, 2004). Such interactions

involve the ability to determine other's motive and intentions since it is necessary

for individuals to be able to detect those who receive benefits but fail to meet their

obligations (Reis, et al., 2007). It has been argued that reasoning about social

exchanges have been an important problem over evolutionary time and the ability

to reason about social exchanges develops without requiring effort or

understanding of formal logic (Cosmides & Tooby, 2004; Fehr & Gachter, 2002).

Analysis

g was calculated by assessing the common variance across RAPM, DAT-V, and

MRT-A from the entire sample (N=177) using Principal Axis Factoring. The first PAF

accounted for 67.2% of the total variance in the three tests. WM was calculated by

summing the Ospan scores for all set sizes. E-AL was calculated by summing the 3-

Term and PA learning scores. Gs was calculated by summing Speed-F, Speed-N, and

Speed-F. Missing data was estimated following the same procedure as outlined in

Chapter 3: Explicit Cognitive Ability.

Figure 9-1
Social Exchange Scenario

Joe often goes out to dinner with friends from work, and they go to a bar afterwards. Joe always pays the dinner check with his credit card and his friends pay him back with cash. He notices that people usually don't consider how much their beer costs when paying him back. So Joe announces a rule, "If you order beer at dinner, then you have to buy me a drink at the bar."

You want to see whether any of Joe's friends cheat on this rule.

The following cards represent five of Joe's friends that joined him for dinner. Each card represents one friend. One side of the card tells what type of drink that person ordered at dinner and the other side tells whether that person bought Joe a drink at the bar.

Please decide if you would definitely need to turn each card over to see if any of the friends cheated on the rule:

"If you order beer at dinner, then you have to buy me a drink at the bar."

Do not turn over any more cards than are absolutely necessary.

Results

Figure 9-2 shows the mean proportion correct and mean response time for each trial type (Descriptive, Precautionary, and Social Exchange). In terms of accuracy, proportion correct on the Descriptive trials was significantly less than proportion correct on both Precautionary [t(111)=17.4, p < 01] and Social Exchange [t(111)=17.1, p < .01] reasoning trials. There was no significant difference between proportion correct on Precautionary and Social Exchange reasoning trials. In terms of speed, the same pattern emerged: mean reaction time to arrive at the correct answer was significantly higher for Descriptive trials than either Precautionary [t(111)=6.1, p < .01] or Social Exchange [t(111)=5.3] trials. There was no significant difference between mean RT for Precautionary and Social Exchange trials. This pattern of results is consistent with Reis et al. (2007), although the accuracy rates were lower and the responses were slower than their sample. This is most likely due to their restricted range of participants and the administration of fewer items in the current dissertation than they administered (see *Chapter 2: Methodology*). Nonetheless, the results are consistent with prior research showing that at the group level of analysis, Precautionary and Social Exchange reasoning is easier for participants than reasoning that is less contextualized (Evans, 2008).

Figure 9-2
(a) Mean proportion correct and (b) mean response time by condition with bars representing S.E. of the mean. (N= 112)

a)

b)
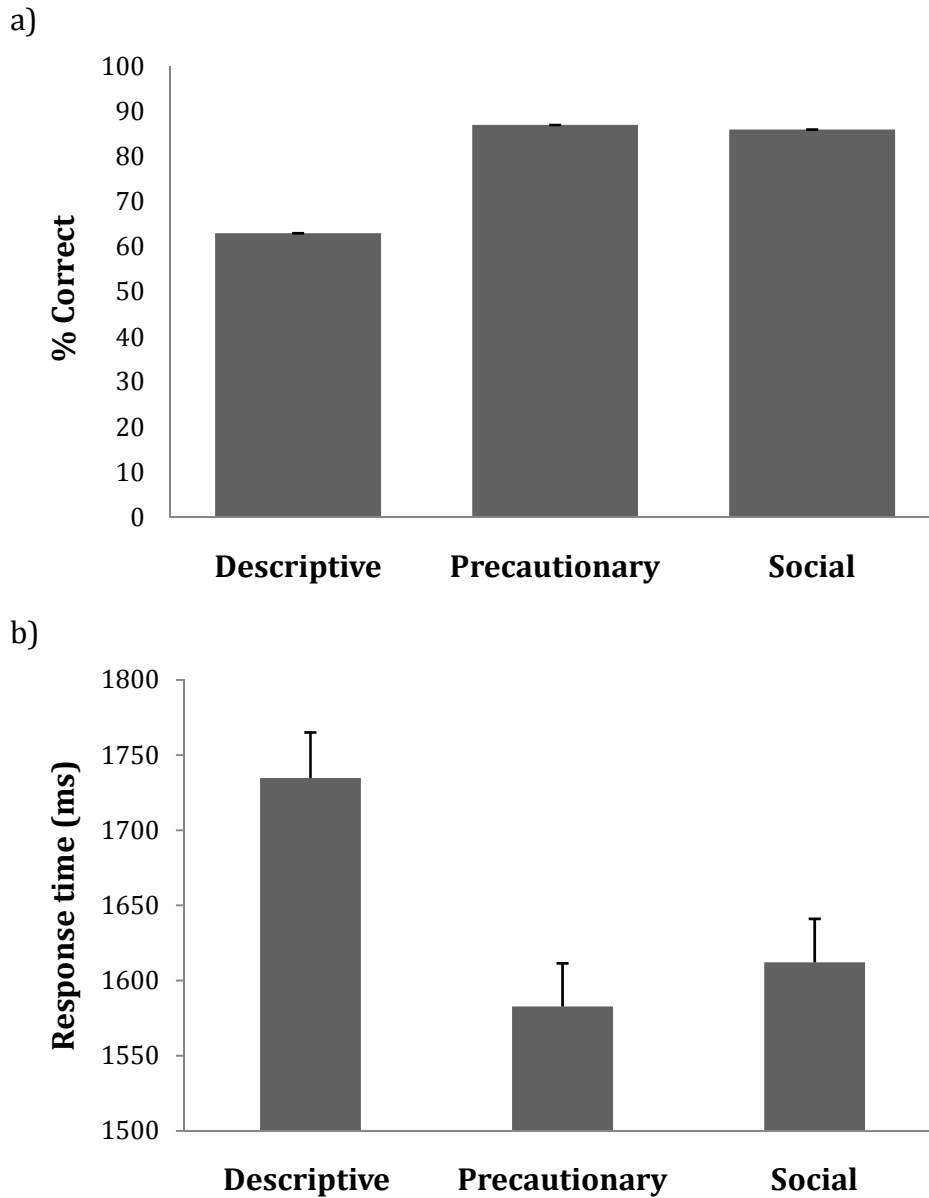
Notes: (a) Descriptive: 63% correct, S.D.=.12, Range=28% to 88% correct; Precautionary: 87%, S.D.=.12, Range=55% to 100%; correct, Social: 86% correct, S.D.=.15, Range=36% to 100%. (b) Descriptive: RT (ms) mean=1734.8 ms, S.D.=320.6, Range=660.2 to 2526.8; Precautionary: RT (ms) mean=1582.8, S.D.=303.6, Range=860.4 to 2268.3; Social: RT(ms) mean=1612.1, S.D.=305.6, Range=777.8 to 2782.6.

Reliability

The alpha reliability of all 70 trials on the task is .84. Therefore, collapsing across trial type, there is a lot of variability that is common among all the trials. In fact, such a high alpha suggests that all of the items, regardless of content (Descriptive, Precautionary, or Social Exchange), tap into a more general deductive reasoning factor. Therefore, this gave me justification to create a latent reasoning factor for both accuracy and speed that represents the common variance across the total scores for the three types of reasoning. Using Principal Axis Factoring (PAF), the first factor (consisting of the common variance across mean proportion correct on the three tests) accounted for 63.4% of the total variance. The three loadings on this factor were: Descriptive (.43), Precautionary (.65), and Social (.97). These loadings appear to mirror the strength of the reliability of each type of reasoning (see Table 9-1). Also using Principal Axis Factoring (PAF), the first factor consisting of the common variance across mean reaction time on the three tests accounted for 80.5% of the total variance. In fact, all three tests loaded extremely high on this factor: Descriptive (.76), Precautionary (.86), and Social (.91).

Accuracy

Table 9-1 lists the correlations between accuracy in deductive reasoning and *g*, ECTs, and the four factors. *g,* Intellectual Engagement, and Aesthetic Engagement were the only tests that significantly correlated with accuracy of deductive reasoning with descriptive content. *g*, WM, AL, Gs, and Explicit Cognitive Ability were significantly correlated with accuracy of Precautionary deductive reasoning. *g*,

WM, AL, Gs, Explicit Cognitive Ability, and Aesthetic Engagement were significantly

correlated with accuracy of Social deductive reasoning. All measures were

associated with the Accuracy Factor except for Affective Engagement. It should be

noted that Affective Engagement did not correlate with accuracy of deductive

reasoning in any of the analyses just presented, suggesting that Affective

Engagement does not relate to accuracy of contextualized deductive reasoning.

Table 9-1

Correlations between Accuracy of Deductive Reasoning and g, ECT's, Intellectual Engagement, Affective Engagement, and Aesthetic Engagement

Measure	Descriptive	Precautionary	Social	Accuracy Factor
g	.23*	.33**	.40**	.41**
WM	.18	.25**	.28**	.28**
AL	.08	.21*	.26**	.26**
Gs	.18	.21*	.26**	.26**
Explicit Cognitive Ability	.21	.37**	.43**	.43**
Intellectual Engagement	.22*	.16	.20	.21*
Affective Engagement	.08	-.17	.00	-.01
Aesthetic Engagement	.28**	.12	.28**	.28**
α	.56	.69	.83	

Notes: Correlations with *g*, WM, and Gs had an *N* of 112. Correlations with AL had an *N* of 111. Correlations with Explicit Cognitive Ability, Intellectual Engagement, Affective Engagement, and Aesthetic Engagement had an *N* of 92. *$p < .05$, **$p < .01$.

In order to determine the best Engagement predictor(s) of the accuracy

factor, I assessed the correlation between each of the scales that have their primary

loadings on the Intellectual and Aesthetic Engagement factors (*Intellectual*

Engagement: NEO Ideas, BFAS Intellect, REI Rational Favorability; *Aesthetic*

Engagement: NEO Aesthetics, NEO Fantasy, BFAS Openness, MBTI Intuition; see

Chapter 6: Four-Factor Model) and the accuracy factor. NEO Fantasy [r(93)=.37, p <

.01], NEO Ideas [r(93)=.21, p < .05], BFAS Intellect [r(108)=.22, p < .05], and BFAS

Openness [r(108)=.22, p < .05] were significantly correlated with the accuracy

factor (Interestingly, NEO Fantasy also significantly correlated with accuracy on all

three types of reasoning problems: Descriptive [r(93)=.24, p < .05], Precautionary

[r(93)=.34, p < .01], and Social Exchange [r(93)=.36, p < .01]). Singling out these four

tests, I put NEO Fantasy, NEO Ideas, BFAS Intellect, and BFAS Openness along with *g*,

WM, AL, and Gs into a regression model predicting the accuracy factor. With all of

these factors entered into the same regression model, *g* remained the sole

independent predictor of the accuracy factor (β=.24, p < .05). However, NEO Fantasy

approached significance (p=.06). Since NEO Fantasy shares a lot of variance with the

other NEO Openness measures, I put just *g* and NEO Fantasy into the same

regression model. Both variables independently predicted the accuracy factor

(β=.31, p < .01 and β=.29, p < .01, respectively), jointly explaining 22.2% of the total

variance in the accuracy factor. Therefore, the best predictors of accuracy across all

of the deductive reasoning items are a combination of *g* and NEO Fantasy.

Additionally, when *g* is substituted by the Explicit Cognitive Ability factor, both

Explicit Cognitive ability (β=.34, p < .01) and NEO Fantasy (β =.23, p < .05)

independently predict the accuracy factor. This suggests that the reason why the

ECTs did not independently predict the accuracy factor above and beyond *g* is

because the ECTs share so much variance with *g* that is also shared with variance in

the speed factor.

Table 9-2 lists the correlations between speed in deductive reasoning and *g*,

ECTs, and the four factors.

Table 9-2
*Correlations between speed of deductive reasoning and g, ECT's, Intellectual
Engagement, Affective Engagement, and Aesthetic Engagement*

Measure	Descriptive	Precautionary	Social	Speed Factor
g	.12	-.11	-.05	-.04
WM	.03	-.26**	-.16	-.17
AL	-.05	-.21*	-.14	-.16
Gs	-.10	-.19*	-.23*	-.22*
Explicit Cognitive Ability	.22*	-.09	-.01	.00
Intellectual Engagement	.16	-.04	-.03	.00
Affective Engagement	-.20	-.16	-.23*	-.22*
Aesthetic Engagement	-.03	-.22*	-.18	-.18

Notes: Correlations with *g*, WM, and Gs had an *N* of 112. Correlations with AL had an *N* of 111.
Correlations with Explicit Cognitive Ability, Intellectual Engagement, Affective Engagement, and
Aesthetic Engagement had an *N* of 92. *$p < .05$, **$p < .01$.

Here, almost the opposite pattern emerged. For Descriptive deductive

reasoning, only Explicit Cognitive Ability positively predicted speed, suggesting the

higher the *g*, the slower the deductive reasoning on the Descriptive problems. For

Precautionary deductive reasoning, WM, AL, Gs, and Aesthetic Engagement were all

negatively correlated with speed, suggesting that these variables contribute to faster

Precautionary reasoning. For Social Exchange reasoning as well as scores on the

Speed Factor, only Gs and Affective Engagement negatively predicted speed. Putting both Gs and Affective Engagement into a regression model predicting the Speed Factor, Gs does not predict the speed factor, but Affective Engagement marginally predicts the speed factor (β=-.21, p =.05). (It is interesting to note that while Aesthetic Engagement wasn't correlated with performance on the Descriptive trials, it was significantly correlated with Precautionary trials, and its relation to both Social Exchange and the speed factor approached significance. Further, the correlation between Aesthetic Engagement and the average speed of Precautionary and Social Exchange reasoning was significant [r(92)=-.21, p < .05].)

To further investigate the particular aspect(s) of Aesthetic Engagement that may be contributing to Precautionary and Social Exchange reasoning, I assessed the relation between the tests that have their primary loading on the Aesthetic Engagement factor (NEO Aesthetics, NEO Fantasy, MBTI Intuition, and BFAS Openness; see *Chapter 6: Four-Factor Model*) and speed of deductive reasoning. Interestingly, only NEO Fantasy significantly correlated with any of the measures of speed of deductive reasoning, correlating with Precautionary [r(93)=-.32, p < .01], Social Exchange [r(93)=-.24, p < .05] deductive reasoning, and the speed factor [r(93)=-.26, p < .05]. NEO Fantasy was not correlated with speed on the Descriptive problems. This suggests that engagement in Fantasy facilitates deductive reasoning that is more contextualized than the content presented in the Descriptive scenarios.

Since NEO Fantasy and Affective Engagement are significantly correlated [r(92)=.37, p < .01], I assessed the independent prediction of both on speed of

deductive reasoning. Putting both NEO Fantasy and Affective Engagement into the same regression model, neither variable independently predicted speed of Descriptive or Social Exchange deductive reasoning. NEO Fantasy did independently predict speed of Precautionary deductive reasoning (β=-.31, p<.01) and marginally independently predicted the speed factor (β=-.21, p=.05).

In sum, the results suggest that the best predictors of accuracy of deductive reasoning are *g,* the Explicit Cognitive Ability factor, and NEO Fantasy whereas the best predictors of speed of deductive reasoning are Affective Engagement and NEO Fantasy. NEO Fantasy was the only marker of Engagement that was related to both accuracy and speed of deductive reasoning. Explicit Cognitive Ability did not contribute to the speed factor (although those scoring higher on the Explicit Cognitive Ability factor tended to be slower arriving at the correct answer on the Descriptive deductive reasoning problems).

Discussion

One of the main findings of this chapter is that Affective Engagement significantly correlated with a general contextualized deductive reasoning speed factor. Even so, it should be noted that Affective Engagement was most strongly related to Social Exchange reasoning (see Table 9-2). This is consistent with Reis et. al (2007), who found that emotional intelligence significantly correlated with Social Exchange reasoning. Since one of the main components of emotional intelligence is the ability to use emotions to guide thinking (e.g., Mayer, Salovey, et al., 2008), and one of the main components of Affective Engagement is the tendency to engage

affect in the service of cognition (see Chapter 6: *Four-Factor Model*), some of the same mechanisms may be underlying the results of both studies. Reis et al. also found distinct patterns of hemodynamic brain activity during social vs. Precautionary reasoning, consistent with prior theorizing that Social Exchange reasoning is at least partially separable from Precautionary reasoning (Cosmides, 1989; Fiddick, Cosmides, & Tooby, 2000; Fiddick, 2004; Gigerenzer & Hug, 1992; Stone, Cosmides, Tooby, Kroll, & Knight, 2002; Cosmides & Tooby, 2004; Ermer, Guerin, Cosmides, Tooby, & Miller, 2006).

The findings presented in this chapter have implications for other areas of study. Here I will discuss the implications for the great rationality debate, evolutionary psychology, intelligence, and for understanding the role of fantasy and imagination in contextualized reasoning.

Rationality

Human rationality research shows that humans often deviate from the response considered normative (by the psychologists constructing the task) on many reasoning tasks. The reason for this discrepancy, however, is the subject of intense debate (Baron, 1994; Cosmides & Tooby, 1996; Gigerenzer, 1993, 1996; Kahneman & Tversky, 1996; Koehler, 1996; Piattelli-Palmarini, 1994; Stein, 1996 Stein, 1996). According to Stanovich (1999), researchers contributing to this debate can be characterized by three different positions, and he labels researchers within each camp as either "Apologists", "Panglossians", or "Meliorists".

According to Stanovich, the "Apologist" position argues that human rationality is bounded by cognitive constraints (e.g., Cohen, 1981, Gigerenzer, 1991, 1996). The Apologist views errors as real, but does not refer to such errors as acts of irrationality. According to the Apologist, humans are constrained by limited cognitive capacities and are therefore limited in their ability to sustain the serial reasoning operations needed to reason logically and probabilistically (e.g., Stanovich, 2004). They argue that in many cases, the computational limitations of the human brain prevent humans from thinking rationally, so it is unfair to call their thinking "irrational."

Another view, which Stanovich refers to as the "Panglossian" view, argues that all behavior is rational. According to this view, performance errors are not systematic, but the result of random lapses of attention (e.g., Stein, 1996). Panglossians argue that people reason very well, in fact as good as can be in this best of all possible worlds. According to Stanovich & West (2000), "The strong form of this hypothesis has the implication that there should be virtually no correlations among nonnormative processing biases across tasks. If each departure from normative responding represents a momentary processing lapse due to distraction, carelessness, or temporary confusion, then there is no reason to expect covariance among biases across tasks (or covariance among items within tasks, for that matter) because error variances should be uncorrelated (p. 2)".

Stanovich and West (1998b) argue against both these views by demonstrating a positive manifold among a variety of tests of "rational thinking"

that exist in the heuristics and biases literature. Calling himself a "Meliorist", Stanovich argues that the gap between the descriptive (how most participants actually perform) and the normative (what experts decide is the rational choice) is characterized by *systematic irrationalities* but can be moderated by education and training. The Meliorist thinks that sometimes people do not reason well and but they could reason better with training and education.

Indeed, Stanovich & West (2000) argue that the positive correlation between *g* and reasoning implies that the normative model *is* being applied to evaluate performance, and that individual differences in performance are a result of differences in the "algorithmic" and "reflective" mind (that in the view of Stanovich together comprise human rationality) and that those with fewer algorithmic limitations would be assumed to be closer to the "rational response."

As I see it, a major limitation of each of the above views is the exclusive emphasis on one type of process over another for explaining "rational" behavior. By "cognitive capacity constraints", the Apologists are referring to System 2 processes such as working memory and processing speed. The Meliorists' focus on System 2 processes and their role in inhibiting pragmatic, automatic processes that lead to cognitive biases under conditions in which there is a conflict between the two systems. Finally, the Panglossian view tends to emphasize System 1 processes, suggesting that we have been "evolutionarily optimized" so all our thinking is rational.

In the current chapter, data was presented that showed two thinking dispositions that I posit are intimately tied to System 1 (Affective and Aesthetic Engagement) also contributed to deductive reasoning. Affective Engagement contributed to speed of deductive reasoning, while the NEO Fantasy aspect of Aesthetic Engagement contributed strongly to both accuracy and speed of deductive reasoning. In fact, controlling for Explicit Cognitive Ability, Intellectual Engagement did not independently predict contextualized reasoning performance above and beyond g. This suggests that although Stanovich may be correct that both the "algorithmic mind" and the "reflective mind" are important contributors to reasoning, individual differences in System 1 thinking dispositions (and most likely also the associated System 1 processes) independently contribute to the accuracy and speed of the normative rational response on a deductive reasoning items with contextualized content.

Furthermore, another aspect that is missing from these perspectives is the investigation of thinking dispositions that predict contextualized reasoning. Most of the focus has been on "the importance of decontextualized reasoning styles that foster the tendency to evaluate argument and evidence in a way that is not contaminated by one's prior beliefs (Stanovich & West, 1997, p. 342)." Indeed, Stanovich & West, (1997) draw heavily on Baron's (1985, 1988, 1993) construct "actively open-minded thinking", in which a major component is the cultivation of reflectiveness rather than impulsivity.

To measure the construct "actively open-minded thinking", they administered a variety of scales that mix together Intellect and Openness aspects of the Intellect/Openness domain. For instance, two items on their "Flexible Thinking scale" are "If I think longer about a problem I will be more likely to solve it" and "Intuition is the best guide in making decisions.", items that clearly conflate explicit from implicit thinking styles. They also administered the NEO Ideas and NEO Values facets along with self-report measures of Absolutism, Dogmatism, and Categorical Thinking. They calculated composite "Actively Open-Minded Thinking" scores by taking the difference between the sum of scores on the Flexible Thinking, NEO Ideas and NEO Values tests, and the sum of scores on the tests of Absolutism, Dogmatism, and Categorical Thinking. The researchers found that individual differences in the ability to evaluate objective argument quality independent of prior belief was associated with individual differences in cognitive ability (SAT scores and vocabulary) and their actively-open minded thinking disposition composite. They also found that actively open-minded thinking predicted variance in reasoning after controlling for cognitive ability.

One main limitation of the study, however, is the lumping together of items relating to Intellect and items related to Openness and calling the overall score an index of variation at the "rational level". The results of this chapter (and the rest of this dissertation) suggests that both Intellect and Openness may be differentially associated with explicit vs implicit cognition (see Chapter 6: *Four-Factor Model*), as well differentially related to reflection vs. impulsivity (see *Chapter 7: Personality*),

making the justification for lumping together both aspects of Intellect/Openness and referring to the overall construct as a tendency toward reflective, rational thinking unwarranted.

Further, such an exclusive focus on decontextualized reasoning may unintentionally neglect important *contextualized* reasoning styles that are important for *contextualized* reasoning. The results of the current chapter suggest that under highly contextualized situations with limited time constraints and minimal System 1 and System 2 conflicts, both g and NEO Fantasy independently predicted accuracy of reasoning, and NEO Fantasy and Affective Engagement facilitated speed of arriving at the correct answer. Therefore, while Stanovich (2004) may be correct that g contributes to performance under situations of conflict between the two systems, g also seems to be an important contributor to the reliable covariance in contextual reasoning when there is no conflict between the systems. Also, on such problems, thinking dispositions relating more to impulsivity (Affective Engagement) than reflection *facilitated*, not inhibited, deductive reasoning. Impulsivity may have made the difference between those who used their affective intuitions to guide their choice under the timed conditions versus those who ignored their gut feelings and consequently acted by choosing the wrong answer. The extent to which the interaction of g with contextualized thinking dispositions facilitate contextualized reasoning should be further investigated.

Evolutionary Psychology

Various optimization theorists look through an evolutionary lens and emphasize the evolutionary adaptiveness of human cognition, including many of the reasoning biases found in the literature (J. Anderson, 1990, 1991; Campbell, 1987; Cooper, 1989; , Cosmides & Tooby, 1994, 1996; Oaksford & Chater, 1993, 1994, 1995; Payne, Bettman, Coupey, & Johnson, 1992; Schoemaker, 1991; Shanks, 1995a). Evolutionary psychologists' massive modularity account, however, seems to counter dual-process theory, as it implies that all reasoning takes place in System 1, leaving little room for System 2 processes. Indeed, Stanovich (2004) argues that evolutionary theorists disregard System 2 processes (mainly *g*) in their accounts of reasoning and rationality. Stanovich makes the distinction between System 2 goals which are tied to the vehicle, and System 1 goals which are rigidly tied to the genes, and accuses evolutionary psychologists of ignoring this important distinction.

The results presented in this chapter actually suggest a piece of the puzzle that both camps might have missed. The findings of the current chapter suggest that *individual differences* in evolutionarily optimized functions contribute to the variance in reasoning performance above and beyond the effects of Explicit Cognitive Ability differences. Evolutionary psychologists have tended to focus on modular, domain-specific adaptations that are species-typical and display few individual differences (Barkow, Cosmides, & Tooby, 1992; Pinker, 1999), while Stanovich's research program focuses on individual differences, in explicit reasoning processes which he sees as "rational". The results of the current study suggest that

both camps may be missing an important aspect of individual differences: individual differences in implicit cognition.

Middle Ground

To me, the most reasonable interpretation of the data presented in this chapter is that for the type of contextualized reasoning that most people engage in *most of the time*, the functioning of both System 1 and System 2 processes are important. While it is certainly possible to construct abstract reasoning tasks that minimize the operation of automatic processes and maximize the role of g, it does not appear to be the case that g plays little or no role in contextualized reasoning. In fact, the results of the current study suggest that individual differences in both systems play complementary roles in contextual reasoning—System 2 processes relating to accuracy and System 1 processes relating to accuracy and speed. Also, contextualized deductive reasoning appears to be a reliable ability. While *at the group level*, humans may find tasks that are more contextualized (such as Precautionary and Social Exchange) easier to solve, since they have more facilitation from System 1 processes, it appears that at the *individual level*, individual differences in both System 1 and System 2 processes contribute to reasoning on various deductive reasoning problems that have the same underlying formal logic and only differ in their context.

Intelligence

The results of the current chapter also have implications for intelligence research. Recently, Cianciolo et al., (2006) assessed the structural relation between

a latent construct they labeled "Practical Intelligence" [consisting of the common variance across three everyday tacit-knowledge inventories and the common variance across the quantitative, verbal, and figural content composites of the Sternberg Triarchic Abiltities Test (STAT; Sternberg and the Rainbow Project Collaborators, 2006) Practical subscale and g (consisting of the common variance across one measure of gf and one measure of gc)]. They found that all of the indicators of practical intelligence loaded substantially on the Practical Intelligence latent factor. Further, they found a correlation of .48 between their latent Practical Intelligence factor and g. They conclude that practical intelligence is not the same construct as general intelligence, but do admit that the constructs overlap. According to the researchers, "The high-moderate correlation between Practical Intelligence and g reflects common variance that may be due to shared demand for neurological functioning and/or shared performance requirements (i.e., test-taking versus other types of performance) (p.249)". Further, they describe their "Practical Intelligence" latent variable as representing a "general ability to learn from everyday experience (p.237)."

The results presented in the current chapter are consistent with the finding that there is more to practical (i.e., contextual) reasoning than g. Two distinct aspects of Openness to Experience-Affective Engagement and NEO Fantasy—related to reasoning above and beyond the effects of g. Since NEO Fantasy is significantly correlated with implicit learning (see *Chapter 4: Implicit Learning*), this is consistent with Sternberg and colleagues' theoretical link between practical intelligence and a

generalized ability to learn from experience. Perhaps the current findings can help to inform the mechanisms underlying the Practical Intelligence construct. Future research should attempt to separate unique sources of variance in explicit and implicit cognitive functions and dispositions that are associated with g vs. those that are associated with Sternberg's measures of Practical Intelligence. Indeed, such a study is currently underway by my colleague Jamie Brown at the University of Cambridge.

Fantasy Engagement

"Imagination is more important than knowledge." – Albert Einstein

One particularly intriguing finding in the current study is that NEO Fantasy, which assesses the extent to which participants have a vivid imagination and an active fantasy life, significantly correlated with both speed and accuracy of deductive reasoning independent of Explicit Cognitive Ability. Stanovich (2004) refers to the fundamental computational bias as a form of cognition that is the default in humans and includes contextualization, socialization, and a preference for narrative form. The results of the current chapter suggest that individual differences in preference for narrative form significantly correlates with both accuracy and speed of contextualized deductive reasoning.

These results are interesting in light of recent brain research. Buckner, Andrews-Hanna and Schacter (2008) proposed that a single core network of brain regions (medial prefrontal, medial-temporal, and medial and lateral parietal regions) underlies a number of cognitive domains previously seen in the literature

as distinct, such as remembering, prospection, spatial navigation, and theory of mind and may support the ability to mentally project oneself from the present moment into a simulation of another perspective (Buckner, et al., 2008) as well as construct scenes in one's mind (Hassabis & Maguire, 2007).

Spreng, Mar, and Kim (in press) link this network to recent research on the default-mode network, a set of brain areas associated with stimulus-independent thought and imagination (Mason, et al., 2007; Buckner, et al., 2008). The default network is highly active when individuals imagine fictitious circumstances. Employing quantitative meta-analyses of a variety of neuroimaging studies on autobiographical memory, navigation, theory of mind, and default mode thinking, Spreng et al. found a high correspondence in the set of brain regions within the default network that underlie remembering, prospection, navigation, and theory of mind.

Stanovich's idea of a "fundamental computational bias" is therefore both conceptually and empirically linked to the "default mode" of brain regions. An important future line of research would be to investigate individual differences in functioning of the default network and contextual reasoning performance. The current study suggests that default mode of processing may facilitate contextual reasoning above and beyond the role of prefrontal cortex regions associated with g.

"Psychologists have to deal with persons, not atoms. It is a person who comes into the laboratory: a person with his or her own ideas, emotions, prejudices, bits of knowledge and information; a person with a specific position on the major dimensions of personality; a person with his or her special IQ and specific abilities. All of this must interact in diverse ways with performance on most, if not all experimental conditions; it must affect memory, learning, perception, conditioning, emotional reactions, psychophysiology—indeed, anything he or she does. The evidence for such large-scale interaction is now conclusive (Eysenck & Eysenck, 1985) and makes it imperative for the relevant personality factors to be included in any experimental design (Hans J. Eysenck, 1997, p. 1234)."

      Taken together, the data in the current dissertation lends support to the Dual-Process (DP) Theory of Human Intelligence (see *Chapter 1: Introduction*). *Chapter 3: Explicit Cognitive Ability* presented evidence that explicit associative learning, working memory, and processing speed each make independent contributions to the variance in g, supporting the Explicit Cognitive Ability (ECA) construct. *Chapter 4: Implicit Learning* directly compared the variance in Explicit Cognitive Ability with the variance in Implicit Learning and found that the two sources of variance are not correlated. Further, while implicit learning was not related to Explicit Cognitive Ability, implicit learning was independently related to verbal analogical reasoning, processing speed, and language learning achievement, as well as a latent Openness to Experience construct that consisted of MBTI

Intuition, NEO Aesthetics, NEO Fantasy, NEO Feelings, and the BFAS Openness scale. Interestingly, a double dissociation was evidenced, with working memory relating to Intellect and implicit learning ability relating to Openness to Experience. This finding supports the central tenet of the DP theory that Controlled Cognition is related to Central Executive Functioning, whereas Autonomous Cognition is not restricted by the same limited capacity constraints. *Chapter 5: Latent Inhibition* investigated latent inhibition—the ability to screen from awareness stimuli previously tagged as irrelevant. The data presented in that chapter suggested that latent inhibition is uncorrelated with Explicit Cognitive Ability, as well as a rational thinking style, but that a reduced latent inhibition (an inability to screen) was related to affective intuition but not holistic intuition. Taken together, the results of Part I suggest that the variance in various Autonomous Information Acquisition Abilities are unrelated to individual differences in Explicit Cognitive Ability, and are associated with distinct forms of Autonomous Engagement (but not Controlled Engagement).

Part II further investigated the Engagement aspects of the DP model. Factor analyzing all the measures of Intuition, Intellect, Openness, and Explicit Cognitive Ability revealed a four-factor model that explained 61.8% of the total variance among the tests (see *Chapter 6: Four-Factor Model*). Based on the loadings, the four factors were labeled *Explicit Cognitive Ability*, *Intellectual Engagement*, *Affective Engagement*, and *Aesthetic Engagement*. Consistent with the findings in Part I, implicit learning was related to Aesthetic Engagement but not Affective

Engagement, while reduced latent inhibition was related to Affective Engagement and not Aesthetic Engagement. Neither measure of Autonomous Information Acquisition Ability was related to Explicit Cognitive Ability or Intellectual Engagement.

The next three chapters explored the differential correlates of each of the four factors. In particular, I investigated the relation of the four factors to Personality, looking at relations to the other Big Five domains, impulsivity, and need for uniqueness (see *Chapter 7: Personality*). Then I assessed each factor's relation to self-reported creative achievement, including self-reported achievement in the Arts and Sciences (see *Chapter 8: Creative Achievement*), and relations to deductive reasoning with contextualized content (see *Chapter 9: Deductive Reasoning*). The results mostly supported the DP model, demonstrating that the different forms of Autonomous Engagement were related to impulsivity whereas Intellectual Engagement was not, and showing that the different forms of Engagement differentially predicted Arts and Sciences achievement as well as deductive reasoning above and beyond Explicit Cognitive Ability.

Implications and Future Research Directions

Below I will discuss implications of the DP model and also propose future directions.

Controlled Cognition and Autonomous Cognition Interactions

In his review of dual-process accounts of reasoning, judgment, and social cognition, Evans (2008) notes two distinct kinds of dual-process theories. One kind,

which he refers to as "Parallel-competitive" forms of dual-process theory, state that there are two forms of learning that lead to two forms of knowledge (explicit and implicit) that compete for the control of behavior. Evans refers to another category of dual-process researchers as the "Default-Interventionists" who assume that rapid preconscious processes supply content for conscious processing, and that the explicit system can intervene with the application of controlled processes.

Both seem right. The evidence suggests that that two systems are independent—under processing conditions that favor automatic processing, Autonomous Cognitive processes and the brain regions supporting those processes are more active than the brain regions supporting Controlled Cognition, and vice-versa, under conditions that favor controlled processing, controlled cognitive processes and the brain regions supporting those processes are more active than the brain regions supporting Autonomous Cognitive processes (Lieberman, 2007).

But the default-interventionists are most certainly right that humans on average have a tendency to contextualize information (i.e., Autonomous Cognition is the default mode in most humans), and that in some instances it is important for Controlled Cognition to reflect on that contextualization and potentially override the outputs of Autonomous Cognition (Stanovich, 1999; Kahneman & Frederick, 2002). Nonetheless, the DP model assumes that there are also situations in which the output of the Autonomous System is beneficial for intelligent behavior, and Controlled Cognition is not necessary, or can even get in the way. Interestingly, a number of neuroimaging studies in humans and lesion studies on rodents have

found that the basal ganglia and Medial Temporal Lobe function (mTL) competitively (Poldrack & Packard, 2003; Packard, Hirsh, & White, 1989). In an interesting study, Packard, Hirsh, & White (1989) found that rats with basal ganglia lesions performed better than normal rats on a mTL-specific task, and rats with mTL lesions performed better than normal on the basal-ganglia-specific task. These results suggest that the presence of a normally functioning Medial Temporal Lobe may interfere with performance on tasks that strongly recruit basal ganglia functions, and performance is thus improved on these tasks when the Medial Temporal lobe is removed (Lieberman, 2007).

Therefore, a main tenet of the DP theory is that Controlled Cognition and Autonomous Cognition mostly work in concert with each other during our daily lives, but in some situations they may be competitive—and depending on the situation, either Controlled Cognition or Autonomous Cognition is the more important contributor to intelligent behavior. And it is possible for one form of cognition to get in the way of the other.

Therefore, measuring individual differences in the ability and desire for Engagement in each form of cognition can help explain variations in intelligent behavior across a wide variety of situations. While in general, Autonomous Cognition may be the default mode of cognition, there may be individual differences in the extent to which it is the default mode. Further, it may be that some of the sub-components of the DP model are more predictive of some situations than others. The DP model is agnostic as to which component is best overall. Instead, the aim of

the DP model is to separate sources of variance in Controlled Cognition and Autonomous Cognition with the aim of looking at how interactions between the various sources of variance differently predict intelligent behavior across a variety of situations that vary in the ratio of Controlled and Autonomous Cognitive processes required for intelligent performance.

<div align="center">Social Cognition</div>

A major tenet of the DP theory is that meaningful individual differences exist in Autonomous Cognition. This tenet has strong implications for research on social cognition. As already mentioned in *Chapter 1: Introduction*, there is an emerging consensus in the social cognition literature that most of our behaviors and judgments are made automatically, without intention, effort, or awareness (Bargh, 1994, 2006; Bargh & Chartrand, 1999; Greenwald & Banaji, 1995). Research on automatic evaluation (Bargh, et al., 1996; Fazio, et al., 1986), impression formation (Albright, et al., 1988), and automatic characterization (Devine, 1989) all demonstrate the prevalence of automaticity in social life. Indeed, until the 1980s attitudes were mostly assumed to rely on consciously available information (Greenwald & Banaji, 1995; Nosek, Greenwald, & Banaji, 2007).

Recently, a variety of measures have been employed "that avoid requiring introspective access, decrease the mental control available to produce the response, reduce the role of conscious intention, and reduce the role of self-reflective, deliberative processes (Nosek, et al., 2007; p. 267)." Greenwald and Banaji (1995) have been among the most active researchers investigating the role of implicit

cognition in various social psychology constructs such as attitudes, stereotypes, and self-esteem. In their research, they attempt to "reveal traces of past experience that people might explicitly reject because it conflicts with values or beliefs, or might avoid revealing because the expression could have negative social consequences. Even more likely, implicit cognition can reveal information that is not available to introspective access even if people were motivated to retrieve and express it" (Nosek, et al., 2007, p. 266; see Wilson, Lindsey, & Schooler, 2000 for related ideas about attitudes).

One of the most well validated measures of social implicit cognition is the Implicit Association Test (IAT; Greenwald, McGhee, & Schwartz, 1998). The IAT requires the participant to categorize various stimulus exemplars representing four concepts (e.g., men, women, good, bad) using two response options. When concepts that share a response are strongly associated, it is expected that the sorting task will be easier for the participant (as indexed by faster responses and fewer errors) than when the concepts are weekly associated. Thus, the IAT affords insight into automatic associative processes that are introspectively inaccessible. Over the last decade, the IAT has been adapted for use in various disciplines (see Nosek, et al., 2007 for a review), and to assess implicit attitudes related to categories such as race, gender, and even insects. In studies that involve some measure of discrimination toward a social group, both explicit and IAT measures predict behavior, with the IAT offering superior prediction (Greenwald, Poehlman, Uhlmann, & Banaji, in press). Further, it has been demonstrated that people with the

strongest automatic racial biases are most likely to engage in a wide variety of discriminatory behavior, including overt behavior (Rudman & Ashmore, 2007).

Therefore, research on individual differences in automatic stereotyping and attitude formation is of both theoretical and practical interest. One question of particular interest is whether individual differences in various implicit social cognition measures correlate with each other. Bosson, Swann, and Pennebaker (2000) observed weak relations among seven implicit measures of self-esteem, including the IAT. However, when unreliability is accounted for, stronger relations emerge (Cunningham, Preacher, & Banaji, 2001). Therefore, just as there may be a coherent implicit learning factor, there may also be a coherent implicit social cognition factor. If this is indeed the case, it would be interesting to investigate relations between individual differences in implicit learning as well as other forms of Autonomous Cognition and individual differences in measures of implicit social cognition. It may be that high implicit learners are most prone to stereotyping since they are faster at extracting statistical regularities in the environment. If this does turn out to be the case, then an important question would be to determine the role of individual differences in Controlled Cognition in modulating inhibitory mechanisms. There are a few studies, utilizing fMRI, that offer some insight into these issues.

Chee, Sriram, Soon, & Lee, 2000 used fMRI while participants were taking the IAT. They found that the left dorsolateral prefrontal cortex and to a lesser degree the anterior cingulate were most active during conditions in which items from

incongruent categories (e..g, insect + pleasant) shared a key than when items from congruent categories (e.g., flower + pleasant) shared a response key. According to the researchers, this suggests that greater Controlled Cognition was required in conditions in which it was necessary to overcome the prepotent tendency to map emotionally congruent items to the same response key. In another study, Phelps et al. (2000) had White participants view faces of unfamiliar Black and White males. Participants who showed greater activation of the amygdala (a region of the brain associated with fear and negative emotions) while viewing Black faces relative to White faces tended to score higher on two measures of unconscious race evaluation: the IAT and eyeblink response. In a second experiment, the researchers did not find the same pattern of brain activation when the faces were familiar and the participants regarded the Black and White individuals positively. In a related study, Cunningham et al. (2004) had participants view Black and White faces either subliminally or supraliminally during fMRI. When presented subliminally, the amygdala was more active for Black faces relative to White faces. This effect was reduced when the faces were presented supraliminally. Further, control regions in the prefrontal cortex showed greater activation for Black faces than White faces when presented supraliminally. Race bias as assessed by the IAT was related to a greater difference in amygdala activation for Black faces relative to White faces, and activity in the prefrontal cortex predicted a reduction in amygdala activation from the subliminal to the supraliminal condition. According to the researchers, this provides evidence for neural distinctions between automatic and controlled

processing of social groups, and suggests that controlled processes may modulate automatic evaluation.

These results suggest that individual differences in measures of Controlled Cognition may predict the extent to which automatic evaluations influence behavior. Taken together, the research suggests at least two promising lines of research that can be directly informed by the DP model. Firstly, individual differences in various measures of Autonomous Cognition could be investigated in relation to individual differences in measures of implicit social cognition. Secondly, individual differences in various measures of Controlled Cognition could be assessed as a mediating variable between performance on measures of implicit social cognition, measures of explicit attitudes, and real-world behavior. Toward this goal, it would be useful to construct new implicit learning tasks that consist of stimuli relating to the learning of real-world contingencies in the social domain. Tasks that already exist that could be adapted include the task used by Lewicki, Hill and Sasaki (1989), in which participants implicitly learn to judge the intelligence of individuals from brain scans or the adaptation of that task employed by Woolhouse and Bayne (2000) where participants implicitly learn to judge the job suitability of job candidates based on their personality profile.

Creativity

According to the DP model, neither component—Controlled Cognition or Autonomous Cognition—is by itself sufficient to understand human intelligence. Instead, it's the dynamic regulation of the two components that may be seen as the

key for a successful adaptation to complex environmental constraints. This conceptualization has implications for understanding creative cognition. The highest levels of creativity require both novelty and usefulness (Kaufman, 2007a). Therefore, both Controlled Cognition and Autonomous Cognition contribute to creativity. Consistent with this idea, Bristol and Viskontas (Bristol & Viskontas, 2006) proposed that creative individuals are good at modulating inhibitory processes, so that they have both the capability for cognitive control and the capacity for disinhibition, and can fluidly switch from one mode to another. In particular, creative individuals can defocus their attention at the early stages of creative cognition, so that they grasp the whole set of potential covariations, and then, during the retrieval and elaboration stage, they can control attention so that they can inhibit prepotent responses and thereby allow remote associations to enter into consciousness without intrusions. Therefore, they argue that creative individuals are both able to overcome cognitive inhibition and are capable of suppressing undesired responses. This requires the ability to activate the Dorsolateral Prefrontal Cortex and inhibit retrieval-related processes that may interfere with accessing remote associations, as well as decactivate the Dorsolateral Prefrontal Cortex, depending on the context of the task and the goals of the individual.

Although still tentative, these ideas are consistent with the behavioral and brain research studies sugesting that creative people are characterized by a lack of inhibition (Eysenck, 1995; Martindale, 1999). Additionally, case studies repeatedly

show that creative people do describe the creative process as effortless and lacking

in deliberation (Csikzentmihalyi, 1996). At the same time, studies also show that

creative individuals defocus their attention when approaching a creative task but

are also capable of focusing their attention when it comes time to make the ideas

practical (Martindale, 1999). Along similar lines, the great French mathematician

Henri Poincaré (1921) described incidents in which an answer came to him only

after his conscious attention was directed away from the problem and he wasn't

consciously deliberating on the problem. Poincaré has argued that these moments of

sudden inspiration are the result of unconscious thinking. Based on reflections of his

creative thought process, he has argued that the creative process starts with

conscious work on a problem, followed by unconscious work, and then, if insight is

successful, another stage of conscious work to verify that the ideas makes sense, and

to work out the implications of the idea. Indeed, insight is considered an important

component of the creative process (Wallas, 1926).

An interesting research direction would to use the DP model to further

elucidate the Controlled and Autonomous Cognitive mechanisms that underlie

insight (see Sternberg & Davidson, 1995 for a review of research on insight). A

methodology that shows promise is the Accumulated Clues Task (ACT), in which

participants must discover a word, but are given clues (e.g., words that are

associated with the answer) along the way. After each clue is presented, participants

are required to provide an answer. The clues get increasingly helpful (are more

related to the answer) and the answers given by the participants get objectively

closer to the answer in an incremental fashion that occurs before their subjective ratings of feeling close to an answer, which they often report occurring to them in a sudden flash of insight (Bowers, Regehr, Balthazard, & Parker, 1990; Bowers, Farvolden, & Mermigis, 1995). Interestingly, in these studies, individual differences in how long it takes participants to arrive at the correct answer correlates with verbal intelligence. Recent research, however, suggests that different components of the task may differentially relate to Explicit Cognitive Ability. Reber, et al., 2007 first replicated earlier research on the ACT by finding that participants often underestimated their degree of closeness to the answer and these subjective reports of closeness exhibited a positive slope, suggesting that participants possessed implicit knowledge about the task and indeed felt hunches about their progress that weren't necessarily aligned with objective incremental progress. The researchers then distinguished between performance level, processing style, implicit knowledge and subjective feeling of closeness to the solution on the ACT. While performance level correlated with verbal intelligence, processing style and implicit knowledge was not correlated with verbal intelligence. Further, Faith in Intuition, Openness to Experience, and Conscientiousness were correlated with processing style, but not with implicit knowledge on the task. These results suggest that a promising research direction is to decompose problem solving tasks into their processing style and intuitive components and investigate relations between individual differences in these components and individual differences in various forms of Controlled and Autonomous Cognition.

The idea of the importance of both Controlled and Autonomous Cognition for creative cognition is also compatible with an active area of research based on the Creative Cognition Approach (Smith, Ward, & Finke, 1995; Finke, Ward, & Smith, 1992; Ward, Smith, & Finke, 1999). The Creative Cognition Approach adopted the experimental methodologies of cognitive psychology to elucidate the creative thinking process. Creative Cognition researchers have identified two main phases of creative invention that occur in a cyclical fashion in ordinary individuals. During the generative phase, the individual generates numerous candidate ideas or solutions and forms a mental representation (referred to as a preinventive structure). Then during the exploratory stage, the individual examines the candidate mental representations and ideas and works out their implications. Autonomous Cognitive processes play more of a role during the generative stage, whereas Controlled Cognitive processes play more of a role during the exploratory stage. The highest levels of creativity, however, most likely require the ability for both modes of thought and the flexibility to switch modes of thought throughout the creative process.

It would be interesting to assess an individual's ability and desire for Engagement in Controlled and Autonomous Cognition and devise tests that measure an individual's ability to switch back and forth between both modes of thought depending on the task's demands for each type of function. Then, the functioning of each mode of thought as well as the flexibility among the different modes of thought can be employed to predict various measures of creative potential. Possible

candidates for measures of creative potential include measures of divergent

thinking (Guilford, 1959; Torrance, 1974; Getzels & Jackson, 1962; Wallach & Kogan,

1965) and consensually assessed products that consist of creative products such as

paintings, stories, or captions to cartoons which are then judged by a panel of

experts within the respective domain (Amabile, 1982). It would also be interesting

to investigate individual differences in the mental processes that Creative Cognition

researchers typically study such as retrieval, association, synthesis, transformation,

analogical transfer, and categorical reduction. If meaningful individual differences in

these measures predict measures of creative potential above and beyond Explicit

Cognitive Ability, then these measures might be considered as additional

Autonomous Cognitive processes that could be added to the DP model.

Bridging Personality and Cognition

The results of this dissertation have implications for bridging research on

personality with research on intelligence. Some researchers (e.g., Eysenck, 2000)

have argued that intelligence and personality are completely separate constructs.

Prior research suggests differences, however, in the information processing ability

of introverts and extraverts. In prior studies, extraverts have been found to have

greater working memory than introverts and have been found to be better at

handling multiple social-interaction goals (Lieberman, 2000a; Lieberman &

Rosenthal, 2001; Oya, Manalo, & Greenwood, 2004). Research also shows that those

higher in anxiety, which is a trait associated with neuroticism, is linked to greater

automatic interference effects (Egloff & Hock, 2001) and reduced working memory

(Darke, 1988). Other research suggests that under conditions where participants have to perform a demanding working memory test, or must perform a discrepancy detection task, extraverts tend to activate areas of the brain relating to control, whereas neurotics tend to activate areas of the brain relating to the automatic detection of threats and conflict (Gray & Braver, 2002; Eisenberger, Lieberman, & Satpute, 2005).

The results of the current dissertation suggest that the personality traits of Intellect and Openness to Experience are two related by partially separable personality traits that are also strongly related to individual differences in controlled and automatic processes. In the current dissertation, higher Explicit Cognitive Ability was correlated with Intellectual Engagement, reduced Latent Inhibition was correlated with Affective Engagement, and better Implicit Learning was correlated with Aesthetic Engagement. Additionally, a double dissociation was found between intellect and working memory on the one hand and a latent Openness to Experience construct and implicit learning on the other hand (see Chapter 4: I*mplicit Learning*). Further, Affective and Aesthetic Engagement were positively correlated with multiple UPPS dimensions of impulsivity, whereas Intellectual Engagement was only related to one UPPS impulsivity dimension, relating negatively to Lack of Perseverance (suggesting higher perseverance in those with higher Intellectual Engagement).

A promising research direction, therefore, would be to investigate the cognitive correlates of different personality traits, under differing laboratory

conditions (e.g., emotional manipulations). A battery of tasks measuring Meta-Cognitive Ability and Autonomous Information Acquisition Ability could be administered along with a battery of personality measures, including self-report and behavioral measures of impulsivity. Such research could also integrate various traditions within the personality field. Traditionally, the study of individual differences in intuition as a cognitive style (e.g., Epstein, et al., 1996; Myers, et al., 1998) has been primarily investigated separately from the Five-Factor Model (FFM; Costa & McCrae, 1992) framework. The results of the current dissertation suggest that various intuitive thinking style measures can be mapped on to different aspects of the Openness to Experience construct. Therefore, the DP model suggests future avenues of research that can bridge research on cognition (both explicit and implicit) with research on personality (FFM and Intuition), as well as bridge sub areas of investigation within personality psychology.

Expertise

Multiple threads of research demonstrate that interest and expertise can trump IQ in predicting performance on various tests related to a particular area of interest (Ceci & Liker, 1986; Walker, 1987; Schneider, Körkel, & Weinert, 1990). Additionally, studies show that poor, uneducated children can solve problems when information is presented in a context in which they are familiar, but may fail when presented with abstract versions of the same problem (see Ceci & Roazzi, 1994). Similar results have been found for adults who can do quite complex reasoning within their area of expertise, but do poorly operating on content that is not within

their specialty or is in a configuration that does not involve learned patterns or chunks (Bennett, 1983; Charness, 1989; Chase & Simon, 1973; De Groot, 1965 De Groot, 1965; Lave, Murtaugh, & de la Rocha, 1984).

Other research supports the importance of expertise for intelligent functioning. In a series of naturalistic studies, various researchers have come to the conclusion that in many situations, such as decision making in groups, very little Controlled Cognition is required (Klein, 1999; Zsambok & Klein, 1997). Instead, they note that expertise seems to be related to recognition of a situation that had been encountered previously, and the retrieval of schemas that match the situation. They argue that while Controlled Cognition is sometimes important, the key to intelligent behavior is the automatic retrieval process.

Along similar lines, Reyna (2004) argues that experts acquire knowledge that allows them to make fast, intuitive, and effective decisions whereas novices need to rely on deliberate, effortful reasoning. Reyna notes however that automatic processes can lead to bias and error when experts are presented with novel problems. Wilson & Schooler (1991) also show the importance of automatic processing in decision making—they demonstrate that when making a decision that is complex and multi-attributed, people do better when conscious deliberation is intentionally prevented. This idea is also a major tenet of the Unconscious Thought Theory (UTT), in which is it argued that decisions about simple issues can be better tackled by conscious thought, whereas decisions about complex matter can be better approached with unconscious thought (Dijksterhuis & Nordgren, 2006).

How are these findings reconciled with g theory, and how do they fit within the DP framework? Some researchers have gone so far as to argue that g does not exist, and intelligence is just the sum of knowledge and expertise in a variety of domains acquired through deliberate practice (Ceci, 1990; Ericsson, Roring, & Nandagopal, 2007; Hirschfeld & Gelman, 1994; but see Kaufman, 2007b). Others, such as Robert Sternberg take a less extreme view and argues that "Practical Intelligence" is a component of "Successful Intelligence" alongside "Analytical" and "Creative Intelligence" (Sternberg, 1997b). According to the theory of Successful Intelligence, Analytical Intelligence is the intelligence most tied to the skills that are tapped by measures of g, but Practical Intelligence predicts successful intelligence above and beyond Analytical Intelligence (see Cianciolo, et al., 2006).

It is unclear, however, as to the precise cognitive mechanisms that underlie practical intelligence apart from the cognitive mechanisms that support g. Mackintosh (1998) raised the possibility that differences in the efficiency with which people acquire complex knowledge and skills may be partly a function of individual differences in implicit learning. According to Mackintosh (1998), "There is no reason to question that differences in IQ have a significant effect on the acquisition of skill at early stages of practice. There is even less reason to doubt that experience and practice are essential for high levels of expertise. But it is possible that variations in implicit learning account for an important part of the remaining variance in the tacit knowledge, practical competence, or expertise that contributes to the efficient performance of a complex job (p. 366)". Indeed, the highly complex

underlying probabilistic structure of the SRT task administered in the current dissertation can be discovered without the aid of Controlled Cognition. In fact, those who scored higher in premeditation did worse on the task (see *Chapter 4: Implicit Learning*), suggesting that Controlled Cognition can sometimes even impede implicit learning.

Mackintosh's (1998) hypothesis is directly in line with the DP model. Klein (1999) is certainly right that many expert decisions involve rapid, intuitive judgments. This is also true of many every day behaviors—to act intelligently for many every day behaviors require the proper functioning of Autonomous Information Acquisition Mechanisms. Further, the amount of knowledge stored in associative memory also greatly facilitates performance in daily life. The more knowledge that is stored, the more that chunking and pattern detection can bring to bear on a task and thus the decreased role for Controlled Cognition. However, for many novel situations, in which prior expertise can't be brought to bear, *g* and its associated Controlled Cognitive mechanisms will be more important. According to the DP model, both domain-general components of the DP theory (Controlled Cognition and Autonomous Cognition) will contribute to performance (although in varying degrees) on nearly any task that requires intelligence—contextualized or not.

Consider the findings of *Chapter 9: Deductive Reasoning*. At the group level, participants found the Precautionary and Social Exchange problems easier than the Descriptive items. Therefore, it is true that contextual problems are easier for most

people to solve, consistent with the literature just reviewed. However, the results from that chapter also suggest that variations in a latent contextual reasoning factor (regardless of content) are influenced by individual differences in Explicit Cognitive Ability as well as dispositions for Engagement in Autonomous Cognitive processes such as affect and fantasy (see *Chapter 9: Deductive Reasoning*). This supports the idea that individual differences in both Controlled Cognition and Autonomous Cognition independently predict variation in reasoning across different contexts.

Intelligence

In his 1957 presidential address to the American Psychological Association, Lee Cronbach pleaded his case for the uniting of the burgeoning field of cognitive psychology, with its focus on the experimental psychology of higher-order information processing, with the study of individual differences in Spearman's *g*. Cronbach's call to unite experimental psychology with individual differences in Spearman's *g* set off a great deal of research that would demonstrate that the newer theories regarding the nature of intelligence, and the burgeoning field of information processing psychology were indeed quite compatible.

One major influence of the information-processing approach to intelligence was the work by Hunt and colleagues (Hunt, Frost, & Lunneborg, 1973; Hunt, Lunneborg, & Lewis, 1975). They studied laboratory tasks that were assumed to be tapping into verbal ability. They found that individuals scoring high on standard tests of verbal ability had more rapid access to semantic codes as measured by their reaction time on the Posner and Mitchell (1967) letter matching and sentence-

verification tasks than those with lower verbal ability scores. Another major influence was the seminal and novel approach taken by Robert Sternberg (1977). Sternberg decided to break up the process by which people solve problems on tests of intelligence into "component" parts. Specifically, he specified the cognitive processes that influence analogical reasoning performance, and then he experimentally manipulated characteristics of the task to determine which elements displayed the most important sources of individual differences in overall performance.

The work by Hunt and Sternberg helped lay the foundation for the experimental study of intelligent reasoning processes that are deliberate and effortful. To be sure, subsequent research has tended to focus on both lower-level as well as higher-level correlates of general intelligence. In terms of lower-level correlates, an active research topic has been the study of the relationship between intelligence and speed of information processing (Neubauer & Fink, 2005). This has focused mainly on reaction time (Jensen, 1982; 1998) and inspection time (Nettelbeck, 1987, Deary & Stough, 1996). Nevertheless, a currently active area of intelligence research links psychometric intelligence with a "higher-level" process—working memory capacity (Kyllonen & Christal, 1990, Hambrick, Kane, & Engle, 2005), which involves the ability to hold a representation active for a brief period of time while other cognitive decisions or operations are taking place, and the ability to manipulate that information or use it to guide action (see *Chapter 3: Explicit Cognitive Ability*).

In this dissertation, I adopted dual-process theory and investigated sources of variance in cognition that go beyond explicit, deliberate, intentional cognition. I have argued in this dissertation, individual differences in ability and Engagement in cognition that is autonomous of a central pool of resources have been neglected as an important contributor to human intelligence. I believe that by adopting tasks from the experimental literature in cognitive psychology, social psychology, and related fields, and then investigating individual differences in Controlled and Autonomous processes, we will more completely fulfill Cronbach's worthy call. I commend multiple intelligence researchers for suggesting new avenues for intelligence research and new forms of intelligence that have been neglected by g-factor theorists. Multiple intelligences researchers are indeed producing tests that predict real world outcomes above and beyond g (even if they are strongly correlated with g). Robert Sternberg is actively constructing tests to measure Practical and Creative Intelligence, in addition to Analytical Intelligence (which he argues is what IQ tests measure, Sternberg and the Rainbow Project Collaborators, 2006). Emotional Intelligence researchers are showing that the MSCEIT predicts outcomes independent of g (Mayer, Salovey, et al., 2008; Mayer, Roberts, et al., 2008).

In this dissertation, I proposed additional individual differences variables that ought to be considered by intelligence researchers. According to Mackintosh (1998), "…associative learning theory has provided a powerful explanation of the way intelligent people (college students) learn a variety of tasks—including judging

contingencies between events, diagnosing the relationship between symptoms and diseases, and classifying variable instances of two or more categories into their appropriate classes (Shanks, 1995b). Outside the psychological laboratory, it seems possible that the same process underlies the acquisition of much knowledge and a variety of skills that enter into our everyday life. If this is true, IQ tests measure only *part* of the general cognitive processes determining success in the outside world (p. 367)."

With this spirit, I look forward to the future of intelligence research. By charting new terrains, we can increase our understanding of the determinants of intelligent behavior. We should welcome new constructs that are not related to Explicit Cognitive Ability but help explain intelligent behavior independent of Explicit Cognitive Ability. And then we should investigate the precise cognitive and neural mechanisms that underlie these new constructs and develop interventions to raise these skills in everyone. Hopefully by fostering collaborations across the various areas of psychology and related disciplines, and incorporating dual-process theory into our thinking, we can come to a fuller, more complete understanding of human intelligence.

References

Achter, J.A., Lubinski, D., Benbow, C.P., & Eftekhari-Sanjani, H. (1999). Assessing vocational preferences among gifted adolescents adds incremental validity to abilities: A discriminant analysis of educational outcomes over a 10-year interval. *Journal of Educational Psychology, 91*, 777-786.

Ackerman, P.L. (1988). Determinants of individual differences during skill acquisition: cognitive abilities and information processing. *Journal of experimental psychology: General, 117*, 288-318.

Ackerman, P.L. (1996). A theory of adult intellectual development: Process, personality, interests, and knowledge. *Intelligence, 22*, 227-257.

Ackerman, P.L., & Beier, M.E. (2003). Trait complexes, cognitive investment, and domain knowledge. In R. J. Sternberg & E. L. Grigorenko (Eds.), *The psychology of abilities, competencies, and expertise.* (pp. 1-30). New York, NY: Cambridge University Press.

Ackerman, P.L., Beier, M.E., & Boyle, M.O. (2005). Working memory and intelligence: The same or different constructs. *Psychological Bulletin, 131*, 30-60.

Ackerman, P.L., & Heggestad, E.D. (1997). Intelligence, personality, and interests: Evidence for overlapping traits. *Psychological Bulletin, 121*, 219-245.

Albright, L., Kenny, D.A., & Malloy, T.E. (1988). Consensus in personality judgments at zero acquaintance. *Journal of Personality and Social Psychology, 55*, 387-395.

Alexander, J.R., & Smales, S. (1997). Intelligence, learning and long-term memory. *Personality and Individual Differences, 23*, 815-825.

Amabile, T.M. (1982). Social psychology of creativity: A consensual assessment technique. *Journal of Personality and Social Psychology, 43*, 997-1013.

Amabile, T.M. (1996). *Creativity in context.* Boulder, CO: Westview Press.

Anderson, J.R. (1990). *The adaptive character of thought.* Hillsdale, NJ: Lawrence Erlbaum.

Anderson, J.R. (1991). Is human cognition adaptive? *Behavioral and Brain Sciences, 14*, 471-517.

Anderson, J.R. (1993). *Rules of the mind.* Hillsdale, NJ: Erlbaum.

Anderson, M. (1992). *Intelligence and development: A cognitive theory.* Malden, MA: Blackwell Publishing.

Anderson, M. (2005). Marrying intelligence and cognition: A developmental review. In R. J. Sternberg & J. E. Pretz (Eds.), *Cognition & intelligence: Identifying the mechanisms of the mind* (pp. 268-288). Cambridge, UK: Cambridge University Press.

Antrobus, J.S., Singer, J.L., & Greenberg, S. (1966). Studies in the stream of consciousness: Experimental enhancement and suppression of spontaneous cognitive processes. *Perceptual and Motor Skills, 23*, 399-417.

Arbuckle, JL (2006). *Amos 7.0 (Build 1140)*: Amos Development Corporation.

Aslin, R.N., Saffran, J.R., & Newport, E.L. (1998). Computation of conditional probability statistics by 8-month-old infants. *Psychological Science, 9*, 321-324.

Baddeley, A.D. (1986). *Working memory*. New York, NY: Oxford University Press.

Bakan, P. (1976). The right brain is the dreamer. *Psychology Today, 10*, 66-68.

Bakan, P. (1978). Two streams of consciousness. In K. S. Pope & J. L. Singer (Eds.), *The streams of consciousness*. New York, NY: Plenum Press.

Baker, C.I., Olson, C.R., & Behrmann, M. (2004). Role of attention and perceptual grouping in visual statistical learning. *Psychological Science, 15*, 460-466.

Bar-On, R. (1997). *BarOn Emotional Quotient Inventory: Technical Manual*. Toronto, Ontario, Canada: Multi-Health Systems.

Barch, D. M. (2005). The cognitive neuroscience of schizophrenia. *Annual Review of Clinical Psychology, 1*, 321-353.

Barchard, K.A., & Hakstian, A.R. (2004). The nature and measurement of emotional intelligence abilities: Basic dimensions and their relationships with other cognitive abilities and personality variables. *Educational and Psychological Measurement, 64*, 437-462.

Bargh, J.A. (1994). The four horsemen of automaticity: Awareness, intention, efficiency, and control in social cognition. In J. R.S. Wyer & T. K. Srull (Eds.), *Handbook of social cognition, Vol. 1: Basic processes Vol. 2: Applications* (2nd ed., pp. 1-40). Hillsdale, NJ, England: Lawrence Erlbaum Associates Inc.

Bargh, J.A. (1997). The automaticity of everyday life. In R. S. Wyer, Jr. (Ed.), *The automaticity of everyday life: Advances in social cognition, Vol. 10.* (pp. 1-61). Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Bargh, J.A., Chaiken, S., Raymond, P., & Hymes, C. (1996). The automatic evaluation effect: Unconditional automatic attitude activation with a pronunciation task. *Journal of Experimental Social Psychology, 32*, 104-128.

Bargh, J.A., & Chartrand, T.L. (1999). The unbearable automaticity of being. *American Psychologist, 54*, 462-479.

Bargh, J.A., & Williams, E.L. (2006). The Automaticity of Social Life. *Current Directions in Psychological Science, 15*(1), 1-4.

Barkow, J.H., Cosmides, L., & Tooby, J. (1992). *The adapted mind: Evolutionary psychology and the generation of culture.* New York, NY: Oxford University Press.

Baron, J. (1985). *Rationality and intelligence.* Cambridge, UK: Cambridge University Press.

Baron, J. (1988). *Thinking and deciding.* Cambridge, UK: Cambridge University Press.

Baron, J. (1994). Nonconsequentialist decisions. *Behavioral and Brain Sciences, 17*, 1-42.

Baron, Jonathan (1993). Why teach thinking? An essay. *Applied Psychology: An International Review, 42*, 191-214.

Barratt, E.S. (1993). Impulsivity: Integrating cognitive, behavioral, biological and environmental data. In W. McCowa, J. Johnson & M. Shure (Eds.), *The*

impulsive client: Theory, research, and treatment. Washington, DC: American Psychological Association.

Barrett, L.F., Tugade, M.M., & Engle, R.W. (2004). Individual differences in working memory capacity and dual-process theories of the mind. *Psychological Bulletin, 130*, 553-573.

Barron, F. (1969). *Creative person and creative process.* New York, NY: Holt, Rinehart, and Winston.

Baruch, I., Hemsley, D.R., & Gray, J.A. (1988a). Latent inhibition and "psychotic proneness" in normal subjects. *Personality and Individual Differences, 9*, 777-783.

Baruch, I., Hemsley, DR, & Gray, J.A. (1988b). Differential performance of acute and chronic schizophrenics in a latent inhibition task. *The Journal of Nervous and Mental Disease, 176*, 598-606.

Baumeister, R.F. (2005). *The cultural animal: Human nature, meaning, and social life.* New York, NY: Oxford University Press.

Benbow, C.P. (1992). Academic achievement in mathematics and science of students between ages 13 and 23: Are there differences among students in the top one percent of mathematical ability? *Journal of Educational Psychology, 84*, 51-61.

Bennett, H.L. (1983). Remembering drink orders: The memory skills of cocktail waitresses. *Human Learning: Journal of Practical Research and Applications, 2*, 157-169.

Berns, G.S., Cohen, J.D., & Mintun, M.A. (1997). Brain regions responsive to novelty in the absence of awareness. *Science, 276*, 1272-1275.

Berridge, K.C., & Robinson, T.E. (1998). What is the role of dopamine in reward: Hedonic impact, reward learning, or incentive salience? *Brain Research Reviews, 28*, 309-369.

Berry, D.C., & Broadbent, D.E. (1984). On the relationship between task performance and associated verbalizable knowledge. *The Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 36A*, 209-231.

Binet, A., & Simon, T. (1916). *The development of intelligence in children* (E. S. Kite, Trans.). Balitmore, MD: Williams & Wilkens.

Bogen, J.E., & Bogen, G.M. (1969). The other side of the brain: III. The corpus callosum and creativity. *Bulletin of the Los Angeles Neurological Society, 34*, 191-220.

Bosson, J.K., Swann, W.B., Jr., & Pennebaker, J.W. (2000). Stalking the perfect measure of implicit self-esteem: The blind men and the elephant revisited? *Journal of Personality and Social Psychology, 79*, 631-643.

Bowers, K.S., Farvolden, P., & Mermigis, L. (1995). Intuitive antecedents of insight. In S. M. Smith, T. B. Ward & R. A. Finke (Eds.), *The creative cognition approach.* (pp. 27-51). Cambridge, MA: MIT Press.

Bowers, K.S., Regehr, G., Balthazard, C., & Parker, K. (1990). Intuition in the context of discovery. *Cognitive Psychology, 22*, 72-110.

Brackett, M.A., & Mayer, J.D. (2003). Convergent, discriminant, and incremental validity of competing measures of emotional intelligence. *Personality and Social Psychology Bulletin, 29*, 1147-1158.

Brackett, M.A., Mayer, J.D., & Warner, R.M. (2004). Emotional intelligence and its relation to everyday behaviour. *Personality and Individual Differences, 36*, 1387-1402.

Brackett, M.A., Rivers, S.E., Shiffman, S., Lerner, N., & Salovey, P. (2006). Relating emotional abilities to social functioning: A comparison of self-report and performance measures of emotional intelligence. *Journal of Personality and Social Psychology, 91*, 780-795.

Brackett, Marc A., Warner, R.M., & Bosco, J.S. (2005). Emotional intelligence and relationship quality among couples. *Personal Relationships, 12*, 197-212.

Bristol, A.S., & Viskontas, I.V. (2006). Dynamic processes within associative memory stores: Piecing together the neural basis of creative cognition. In J. C. Kaufman & J. Baer (Eds.), *Creativity and reason in cognitive development.* (pp. 60-80). New York, NY: Cambridge University Press.

Brody, N. (2004). What cognitive intelligence is and what emotional intelligence is not. *Psychological Inquiry, 15*, 234-238.

Bruner, J. (1986). *Actual minds, possible worlds.* Cambridge, MA: Harvard University Press.

Buckner, R.L., Andrews-Hanna, J.R., & Schacter, D.L. (2008). Anatomy, function, and relevance to disease. *Annals of the New York Academy of Sciences, 1124*, 1-38.

Buss, A.H., & Plomin, R. (1975). *A temperament theory of personality development.* New York, NY: John Wiley & Sons.

Cacioppo, J.T., & Petty, R.E. (1982). The need for cognition. *Journal of Personality and Social Psychology, 42*, 116-131.

Cacioppo, J.T., Petty, R.E., Feinstein, J., & Jarvis, W. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin, 119*, 197-253.

Campbell, D.T. (1987). Rationality and utility from the standpoint of evolutionary biology. In R. M. Hogarth & M. W. Reder (Eds.), *Rational choice: The contrast between economics and psychology.* (pp. 171-180). Chicago, IL: University of Chicago Press.

Carey, S., & Spelke, E. (1994). Domain-specific knowledge and conceptual change. In L. A. Hirschfeld & S. A. Gelman (Eds.), *Mapping the mind: Domain specificity in cognition and culture.* (pp. 169-200). New York, NY: Cambridge University Press.

Carne, G. C., & Kirton, M. J. (1982). Styles of creativity: Test-score correlations between Kirton Adaption-Innovation Inventory and Myers-Briggs Type Indicator. *Psychological Reports, 50*, 31-36.

Carpenter, P.A., Just, M.A., & Shell, P. (1990). What one intelligence test measures: A theoretical account of the processing in the raven progressive matrices test. *Psychological Review, 97*, 404-431.

Carroll, J.B. (1993). *Human cognitive abilities: A survey of factor-analytic studies.* Cambridge, UK: Cambridge University Press.

Carson, S.H., Peterson, J.B., & Higgins, D.M. (2003). Decreased latent inhibition Is associated with increased creative achievement in high-functioning individuals. *Journal of Personality and Social Psychology, 85*, 499-506.

Carson, S.H., Peterson, J.B., & Higgins, D.M. (2005). Reliability, validity, and factor structure of the creative achievement questionnaire. *Creativity Research Journal, 17*, 37-50.

Ceci, S.J. (1990). *On Intelligence...More or less: A biological treatise on intellectual development.* Englewood Cliffs, NJ: Prentice Hall.

Ceci, S.J. (1996). *On intelligence: A bioecological treatise on intellectual development.* Boston, MA: Harvard University Press.

Ceci, S.J., & Liker, J.K. (1986). A day at the races: A study of IQ, expertise, and cognitive complexity. *Journal of Experimental Psychology: General, 115*, 255-266.

Ceci, S.J., & Roazzi, A. (1994). The effects of context on cognition: Postcards from Brazil. In R. J. Sternberg & R. K. Wagner (Eds.), *Mind in context: Interactionist perspectives on human intelligence.* (pp. 74-101). New York, NY: Cambridge University Press.

Cermak, L.S., Lewis, R., Butters, N., & Goodglass, H. (1973). Role of verbal mediation in performance of motor tasks by Korsakoff patients. *Perceptual and Motor Skills, 37*, 259-262.

Chabris, C.F. (2006). Cognitive and neurobiological mechanisms of the law of

general intelligence. In M. J. Roberts (Ed.), *Integrating the mind: Domain*

general versus domain-specific processes in higher cognition (pp. 449-492).

Hove, UK: Psychology Press.

Chaiken, S. (1980). Heuristic versus systematic information processing and the use

of source versus message cues in persuasion. *Journal of Personality and Social*

Psychology, 39, 752-766.

Chaiken, S. (1987). The heuristic model of persuasion. In M. P. Zanna, J. M. Olson & C.

P. Herman (Eds.), *Social influence: The Ontario symposium, Vol. 5.* (pp. 3-39).

Hillsdale, NJ: Lawrence Erlbaum Associates Inc.

Chaiken, S., & Trope, Y. (1999). *Dual-process theories in social psychology*. New York,

NY: Guilford Press.

Chang, F. (2008). Implicit learning as a mechanism of language change. *Theoretical*

Linguistics, 34, 115.

Charness, N. (1989). Expertise in chess and bridge. In D. Klahr & K. Kotovsky (Eds.),

Complex information processing: The impact of Herbert A. Simon (pp. 183-

208). Hillsdale, NJ: Lawrence Erlbaum

Chase, W.G., & Simon, H.A. (1973). Perception in chess. *Cognitive Psychology, 4*, 55-

81.

Chee, M.W.L., Sriram, N., Soon, C.S., & Lee, K.M. (2000). Dorsolateral prefrontal

cortex and the implicit association of concepts and attributes. *Neuroreport:*

For Rapid Communication of Neuroscience Research, 11, 135-140.

Chun, M.M. (2005). Drug-induced amnesia impairs implicit relational memory. *Trends in Cognitive Sciences, 9*, 355-357.

Cianciolo, A.T., Grigorenko, E.L., Jarvin, L., Guillermo, G., Drebot, M.E., & Sternberg, R.J. (2006). Practical intelligence and tacit knowledge: Advancements in the measurement of developing expertise. *Learning and Individual Differences, 16*, 235-253.

Cleeremans, A. (1993). *Mechanisms of implicit learning: Connectionist models of sequence processing*. Cambridge, MA: MIT Press.

Cleeremans, A., & Dienes, Z. (2008). Computational models of implicit learning. In R. Sun (Ed.), *The Cambridge Handbook of Computational Psychology* (pp. 396-421). London, UK: Cambridge University Press.

Cloninger, C.R., Svrakic, D.M., & Przybeck, T.R. (1993). A psychobiological model of temperament and character. *Archives of General Psychiatry, 50*, 975-990.

Cohen, L.J. (1981). Can human irrationality be experimentally demonstrated? *Behavioral and Brain Sciences, 4*, 317-370.

Colangelo, N., Kerr, B., Hallowell, K., Huesman, R., & Gaeth, J. (1992). The Iowa Inventiveness Inventory: Toward a measure of mechanical inventiveness. *Creativity Research Journal, 5*, 157-163.

Colom, R., Franciso, J.A., Quiroga, M.Á., Shih, P.C., & Flores-Mendoza, C. (2008). Working memory and intelligence are highly related constructs, but why? *Intelligence, 36*, 584-606.

Conway, A.R.A., Cowan, N., & Bunting, M.F. (2001). The cocktail party phenomenon revisited: The importance of working memory capacity. *Psychonomic Bulletin & Review, 8*, 331-335.

Conway, A.R.A., Cowan, N., Bunting, M.F., Therriault, D.J., & Minkoff, S.R.B. (2002). A latent variable analysis of working memory capacity, short-term memory capacity, processing speed, and general fluid intelligence. *Intelligence, 30*, 163-183.

Conway, A.R.A., Jarrold, C., Kane, M.J., Miyake, A., & Towse, J.N. (2007). *Variation in working memory*. New York, NY: Oxford University Press.

Conway, C.M., & Pisoni, D.B. (2008). Neurocognitive basis of implicit learning of sequential structure and its relation to language processing. *Annals of the New York Academy of Sciences, 1145*, 113-131.

Cooper, W.S. (1989). How evolutionary biology challenges the classical theory of rational choice. *Biology and Philosophy, 4*, 457-481.

Corkin, S. (1965). Tactually-guided maze learning in man: Effects of unilateral cortical excisions and bilateral hippocampal lesions. *Neuropsychologia, 3*, 339-351.

Cosmides, L. (1989). The logic of social exchange: Has natural selection shaped how humans reason? Studies with the Wason selection task. *Cognition, 31*, 187-276.

Cosmides, L., & Tooby, J. (1994). Beyond intuition and instinct blindness: Toward an evolutionarily rigorous cognitive science. *Cognition, 50*, 41-77.

Cosmides, L., & Tooby, J. (1996). Are humans good intuitive statisticians after all? Rethinking some conclusions from the literature on judgment under uncertainty. *Cognition, 58*, 1-73.

Cosmides, L., & Tooby, J. (2004). Social exchange: The evolutionary design of a neurocognitive system. In M. S. Gazzaniga (Ed.), *The cognitive neurosciences* (3rd ed., pp. 1295-1308). Cambridge, MA: MIT Press.

Costa, P.T., Jr., & McCrae, R.R. (1992). Four ways five factors are basic. *Personality and Individual Differences, 13*, 653-665.

Côté, S., & Miners, C.T. H. (2006). Emotional intelligence, cognitive intelligence, and job performance. *Administrative Science Quarterly, 51*, 1-28.

Cowan, N. (1988). Evolving conceptions of memory storage, selective attention, and their mutual constraints within the human information-processing system. *Psychological Bulletin, 104*, 163-191.

Cowan, N. (1995). *Attention and memory: An integrated framework*. Oxford, UK: Oxford University Press, USA.

Cronbach, L.J. (1957). The two disciplines of scientific psychology. *American Psychologist, 12*, 671-684.

Csikzentmihalyi, M. (1988). Society, culture, and person: A systems view of creativity. In R. J. Sternberg (Ed.), *The nature of creativity*. Cambridge, UK: Cambridge University Press.

Csikzentmihalyi, M. (1996). *Creativity: Flow and the psychology of discovery and invention*. New York, NY: Harper Collins.

Cunningham, W.A., Johnson, M.K., Raye, C.L., Gatenby, J.C., Gore, J.C., & Banaji, M.R. (2004). Separable neural components in the processing of black and white faces. *Psychological Science, 15*, 806-813.

Cunningham, W.A., Preacher, K.J., & Banaji, M.R. (2001). Implicit attitude measures: Consistency, stability, and convergent validity. *Psychological Science, 12*, 163-170.

Cyders, M.A., & Smith, G.T. (2008). Emotion-based dispositions to rash action: Positive and negative urgency. *Psychological Bulletin, 134*, 807-828.

Darke, S. (1988). Effects of anxiety on inferential reasoning task performance. *Journal of Personality and Social Psychology, 55*, 499-505.

David, S.A. (2005). Emotional intelligence: Conceptual and methodological issues, and its role in coping and well-being. Unpublished doctoral dissertation, University of Melbourne, Melbourne, Victoria, Australia.

Davies, M., Stankov, L., & Roberts, R.D. (1998). Emotional intelligence: In search of an elusive construct. *Journal of Personality and Social Psychology, 75*, 989-1015.

Dawis, R.V. , & Lofquist, L.H. (1984). *Psychological theory of work adjustment: An individual-differences model and its applications.* Minneapolis, MN: University of Minnesota Press.

De Groot, A.D. (1965). *Thought and choice in chess.* The Hague, Netherlands: Mouton.

Deane, D.H., Hammond, K.R., & Summers, D.A. (1972). Acquisition and application of knowledge in complex inference tasks. *Journal of Experimental Psychology, 92*, 20-26.

Deary, I. (2000). *Looking down on human intelligence: From psychometrics to the brain.* Oxford, UK: Oxford University Press.

Deary, I. (2001). Human intelligence differences: a recent history. *Trends in Cognitive Sciences, 5*, 127-130.

Deary, I., Der, G., & Ford, G. (2001). Reaction times and intelligence differences: A population-based cohort study. *Intelligence, 29*, 389-399.

Deary, I., & Stough, C. (1996). Intelligence and inspection time: Achievements, prospects, and problems. *American Psychologist, 51*, 599-608.

Dennett, D.C. (1992). *Consciousness explained*. New York, NY: Back Bay Books.

Dennett, D.C. (1996). *Darwin's dangerous idea: Evolution and the meanings of life*. London, UK: Simon & Schuster.

Dennett, D.C. (1997). *Kinds of minds: Toward an understanding of consciousness*. New York, NY: Basic Books.

Depue, R.A., & Collins, P.F. (1999). Neurobiology of the structure of personality: Dopamine, facilitation of incentive motivation, and extraversion. *Behavioral and Brain Sciences, 22*, 491-569.

Destrebecqz, A., & Cleeremans, A. (2008). *How do we find words in implicit artificial language learning?* Paper presented at the Association for the Scientific Study of Consciousness.

Devine, Patricia G. (1989). Automatic and controlled processes in prejudice: The role of stereotypes and personal beliefs. In A. R. Pratkanis, S. J. Breckler & A. G. Greenwald (Eds.), *Attitude structure and function.* (pp. 181-212). Hillsdale, NJ, England: Lawrence Erlbaum Associates Inc.

DeYoung, C.G., Peterson, J.B., & Higgins, D.M. (2002). Higher-order factors of the Big Five predict conformity: Are there neuroses of health? *Personality and Individual Differences, 33*, 533-552.

DeYoung, C.G., Peterson, J.B., & Higgins, D.M. (2005). Sources of Openness/Intellect: Cognitive and neuropsychological correlates of the fifth factor of personality. *Journal of Personality, 73*, 825-858.

DeYoung, C.G., Peterson, J.B., Seguin, J.R., Mejia, J.M., Pihl, R.O., Beitchman, J.H., et al. (2006). The dopamine D4 receptor gene and moderation of the association between externalizing behavior and IQ. *Archives of General Psychiatry, 63*, 1410-1416.

DeYoung, C.G., Quilty, L.C., & Peterson, J.B. (2007). Between facets and domains: 10 aspects of the Big Five. *Journal of Personality and Social Psychology, 93*, 880-896.

DeYoung, C.G., Shamosh, N.A., Green, A.E., Braver, T. S., & Gray, J. R. (in press). Intellect as distinct from openness: Differences revealed by fMRI of working memory. *Journal of Personality and Social Psychology*.

DeYoung, Colin G. (2006). Higher-order factors of the Big Five in a multi-informant sample. *Journal of Personality and Social Psychology, 91*, 1138-1151.

Dickman, S.J. (1990). Functional and dysfunctional impulsivity: Personality and cognitive correlates. *Journal of Personality and Social Psychology, 58*, 95-102.

Dienes, Z. (2008). Subjective measures of unconscious knowledge. *Progress in Brain Research, 168*, 49-64.

Digman, John M. (1997). Higher-order factors of the Big Five. *Journal of Personality and Social Psychology, 73*, 1246-1256.

Dijksterhuis, A., & Nordgren, L.F. (2006). A theory of unconscious thought. *Perspectives on Psychological Science, 1*, 95-109.

Dollinger, S.J. (2003). Need for uniqueness, need for cognition and creativity. *Journal of Creative Behavior, 37*, 99-116.

Dollinger, S.J., Palaskonis, D.G., & Pearson, J.L. (2004). Creativity and intuition revisited. *Journal of Creative Behavior, 38*, 244-259.

Dominowski, R.L., & Dallob, P. (1991). *Reasoning abilities, individual differences, and the four card problem.* Paper presented at the the Eighth Annual Conference, Cognitive Psychology Section, British Psychological Association, Oxford.

Dweck, C.S. (2006). *Mindset: The new psychology of success*. New York, NY: Random House.

Egloff, Boris, & Hock, Michael (2001). Interactive effects of state anxiety and trait anxiety on emotional Stroop interference. *Personality and Individual Differences, 31*, 875-882.

Eisenberger, N.I., Lieberman, M.D., & Satpute, A.B. (2005). Personality from a controlled processing perspective: An fMRI study of neuroticism,

extraversion, and self-consciousness. *Cognitive, Affective & Behavioral Neuroscience, 5*, 169-181.

Elliot, C.D. (1996). British Ability Scales II. *Windsor, Berkshire, UK: NFER-Nelson*.

Ellis, H. (1926). *A study of British genius*. New York, NY: Houghton-Mifflin.

Ellis, N.C. (Ed.). (1994). *Implicit and explicit learning of languages*. New York, NY: Academic Press.

Engle, R.W., & Kane, M.J. (2004). Executive attention, working memory capacity, and a two-factor theory of cognitive control. In B. Ross (Ed.), *The psychology of learning and motivation: Advances in research and theory* (Vol. 44, pp. 145–199). New York, NY: Elsevier.

Engle, R.W., Tuholski, S.W., Laughlin, J.E., & Conway, A.R.A. (1999). Working memory, short-term memory, and general fluid intelligence: A latent-variable approach. *Journal of Experimental Psycholology: General, 128*, 309-331.

Ennis, R.H. (1987). A taxonomy of critical thinking dispositions and abilities. In J. Baron & R. Sternberg (Eds.), *Teaching and thinking skills: Theory and practice* (pp. 9-26). New York, NY: Freeman.

Epstein, S. (1994). Integration of the cognitive and the psychodynamic unconscious. *American Psychologist, 49*, 709-724.

Epstein, S., Pacini, R., Denes-Raj, V., & Heier, H. (1996). Individual differences in intuitive-experiential and analytical-rational thinking styles. *Journal of Personality and Social Psychology, 71*, 390-405.

Epstein, S., Pacini, R., & Norris, P. (1998). *The Rational-Experiential Inventory: Long form*. University of Massachsetts at Amherst: Unpublished inventory.

Ericsson, K.A. (1996). *The road to excellence: The acquisition of expert performance in the arts and sciences, sports, and games*. Hillsdale, NJ: Lawrence Erlbaum.

Ericsson, K.A., Roring, R.W., & Nandagopal, K. (2007). Giftedness and evidence for reproducibly superior performance: An account based on the expert performance framework. *High Ability Studies, 18*, 3-56.

Ermer, E., Guerin, S.A., Cosmides, L., Tooby, J., & Miller, M.B. (2006). Theory of mind broad and narrow: Reasoning about social exchange engages ToM areas, precautionary reasoning does not. *Social Neuroscience, 1*, 196-219.

Estes, W.K. (1970). *Learning theory and mental development*. New York, NY: Academic Press.

Evans, J. St. B. T. (1998). Matching bias in conditional reasoning: Do we understand it after 25 years? *Thinking & Reasoning, 4*, 45-82.

Evans, J. St. B. T., & Over, D.E. (1996). *Rationality and reasoning*. Oxford, UK: Psychology Press.

Evans, J.St.B.T. (1984). Heuristic and analytic processes in reasoning. *British Journal of Psychology, 75*, 451-468.

Evans, J.St.B.T. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology, 59*, 255-278.

Evans, J.St.B.T., & Frankish, K. (2009). *In two minds: Dual processes and beyond.* New York, NY: Oxford University Press.

Evans, Jonathan St B. T. (2002). Logic and human reasoning: An assessment of the deduction paradigm. *Psychological Bulletin, 128*, 978-996.

Evans, Jonathan St B. T. (2003). In two minds: Dual-process accounts of reasoning. *Trends in Cognitive Sciences, 7*, 454-459.

Evans, Jonathan St. B. T. (1989). *Bias in human reasoning: Causes and consequences*. Hillsdale, NJ: Lawrence Erlbaum.

Eysenck, H. J. (1995). Creativity as a product of intelligence and personality. In D. Saklofske & M. Zeidner (Eds.), *International handbook of personality and intelligence: Perspectives on individual differences* (pp. 231-247). New York, NY: Plenum Press.

Eysenck, H. J., & Eysenck, S.B.G. (1975). *Manual of the Eysenck Personality Questionnaire*. London, UK: Hodder and Stoughton.

Eysenck, H.J. (1997). Personality and experimental psychology: The unification of psychology and the possibility of a paradigm. *Journal of Personality and Social Psychology, 73*, 1224-1237.

Eysenck, H.J. (2000). *Intelligence: A new look*. Edison, NJ: Transaction Publishers.

Fazio, R.H., Sanbonmatsu, D.M., Powell, M.C., & Kardes, F.R. (1986). On the automatic activation of attitudes. *Journal of Personality and Social Psychology, 50*, 229-238.

Fehr, E., & Gachter, S. (2002). Altruistic punishment in humans. *Nature, 415*, 137-140.

Feist, G.J. (2001). Natural and sexual selection in the evolution of creativity. *Bulletin of Psychology and the Arts, 2*, 11-16.

Feist, G.J. (2006). *The psychology of science and the origins of the scientific mind*. New Haven, CT: Yale University Press.

Feldman, J., Kerr, B., & Streissguth, A.P. (1995). Correlational analyses of procedural and declarative learning performance. *Intelligence, 20*, 87-114.

Ferraro, F.R., Balota, D.A., & Connor, L.T. (1993). Implicit memory and the formation of new associations in nondemented Parkinson's disease individuals and individuals with senile dementia of the Alzheimer type: A serial reaction time (SRT) investigation. *Brain and Cognition, 21*, 163-180.

Fiddick, L. (2004). Domains of deontic reasoning: Resolving the discrepancy between the cognitive and moral reasoning literatures. *The Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 57A*, 447-474.

Fiddick, L., Cosmides, L., & Tooby, J. (2000). No interpretation without representation: The role of domain-specific representations and inferences in the Wason selection task. *Cognition, 77*, 1-79.

Finke, R.A., Ward, T.B., & Smith, S.M. (1992). *Creative cognition: Theory, research, and applications*. Cambridge, MA: MIT Press.

Fleenor, J.W. (1997). The relationship between the MBTI and measures of personality and performance in management groups. In C. R. Fitzgerald & L. K. Kirby (Eds.), *Developing leaders: Research and applications in psychological*

type and leadership development: Integrating reality and vision, mind and heart. (pp. 115-138). Palo Alto, CA: Davies-Black

Fleenor, J.W., & Taylor, S. (1994). Construct validity of three self-report measures of creativity. *Educational and Psychological Measurement, 54*, 464-470.

Fletcher, J., Maybery, M.T., & Bennett, S. (2000). Implicit learning differences: a question of developmental level? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26*, 246-252.

Fodor, J. (1983). *The modularity of mind*. Boston, MA: The MIT Press.

Fodor, J. (2001). *The mind doesn't work that way*. Boston, MA: MIT Press.

Franks, I.M. (1982). Rehearsal and learning of embedded movement sequences during a tracking task. *Perceptual and Motor Skills, 55*, 615-622.

Frensch, P.A., & Miner, C.S. (1995). Zur Rolle des Arbeitsgedächtnisses beim impliziten Sequenzlernen [The role of working memory in implicit sequence learning]. *Zeitschrift für Experimentelle Psychologie, 42*, 545-575.

Freud, S. (1900/1976). *The interpretation of dreams.* (Vol. 4). London, UK: Penguin Books.

Freud, S. (1976). *The interpretation of dreams. (1900)* (Vol. 4). London, UK: Penguin Books.

Fried, L.S., & Holyoak, K.J. (1984). Induction of category distributions: A framework for classification learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 10*, 234-257.

Friedman, N.P., & Miyake, A. (2004). The relations among inhibition and interference control functions: A latent-variable analysis. *Journal of Experimental Psychology: General, 133*, 101-135.

Friedman, N.P., Miyake, A., Corley, R.P., Young, S.E., DeFries, J.C., & Hewitt, J.K. (2006). Not all executive functions are related to intelligence. *Psychological Science, 17*, 172-179.

Friedman, Naomi P., Miyake, Akira, Young, Susan E., DeFries, John C., Corley, Robin P., & Hewitt, John K. (2008). Individual differences in executive functions are almost entirely genetic in origin. *Journal of Experimental Psychology: General, 137*, 201-225.

Frisch, D. (2000). The tao of thinking. *Behavioral and Brain Sciences, 23*, 672-673.

Fry, A.F., & Hale, S. (1996). Processing speed, working memory, and fluid intelligence: Evidence for a developmental cascade. *Psychological Science, 7*, 237-241.

Fuchs-Beauchamp, K.D., Karnes, M.B., & Johnson, L.J. (1993). Creativity and intelligence in preschoolers. *Gifted Child Quarterly, 37*, 113-117.

Gabora, L. (2003). Contextual focus: A tentative cognitive explanation for the cultural transition of the middle/upper Paleolithic. In R. Alterman & D. Hirsch (Eds.), *Proceedings of the 25th Annual Meeting of the Cognitive Science Society*. Boston, MA: Lawrence Erlbaum Associates.

Gabora, L. (in press). Revenge of the 'neurds': Characterizing creative thought in

    terms of the structure and dynamics of human memory. *Creativity Research*

    Journal.

Gabora, L., & Kaufman, S.B. (2009). Evolutionary approaches to creativity. In J. C.

    Kaufman & R. J. Sternberg (Eds.), *Cambridge Handbook of Creativity*.

    Cambridge, UK: Cambridge University Press. Manuscript in preparation.

Gardner, H. (1983). *Frames of mind: The theory of multiple intelligences*. New York,

    NY: Basic Books.

Gardner, H. (1993a). *Creating minds: An anatomy of creativity seen through the lives*

    of Freud, Einstein, Picasso, Stravinsky, Eliot, Graham, and Gandhi. New York,

    NY: Basic Books.

Gardner, H. (1993b). *Frames of mind: The theory of multiple intelligences (2nd ed.)*.

    New York, NY: Basic Books.

Gardner, H. (1999). *Intelligence reframed: Multiple intelligences for the 21st century*.

    New York, NY: Basic Books.

Garrity, A. G., Pearlson, G.D., McKiernan, K., Lloyd, D., Kiehl, K.A., & Calhoun, V.D.

    (2007). Aberrant "default mode" functional connectivity in schizophrenia.

    American Journal of Psychiatry, 164, 450-457.

Geary, D.C., & Huffman, K.J. (2002). Brain and cognitive evolution: Forms of

    modularity and functions of mind. *Psychological Bulletin, 128*, 667-698.

Gebauer, G. F., & Mackintosh, N.J. (2007). Psychometric intelligence dissociates

implicit and explicit learning. *Journal of Experimental Psychology: Learning,*

Memory, and Cognition, 33, 34-54.

Gebauer, G. F., & Mackintosh, N.J. (2009). Implicit learning and intelligence: A

principal component analysis. Manuscript submitted for publication.

Gelman, R., & Brenneman, K. (1994). First principles can support both universal and

culture-specific learning about number and music. In L. A. Hirschfeld & S. A.

Gelman (Eds.), *Mapping the mind: Domain specificity in cognition and culture.*

(pp. 369-390). New York, NY: Cambridge University Press.

Gendler, T. (2006). Imaginative Contagion. *Metaphilosophy, 37*, 1-21.

Getzels, J.W., & Jackson, P.W. (1962). *Creativity and intelligence: Explorations with*

gifted students. Hoboken, NJ: Wiley.

Gigerenzer, G (1991). How to make cognitive illusions disappear: Beyond "heuristics

and biases". *European Review of Social Psychology, 2*, 83-115.

Gigerenzer, G. (1993). The bounded rationality of probabilistic mental models. In K.

I. Manktelow & D. E. Over (Eds.), *Rationality: Psychological and philosophical*

perspectives. (pp. 284-313). Florence, KY: Taylor & Frances/Routledge.

Gigerenzer, G. (1996). On narrow norms and vague heuristics: A reply to Kahneman

and Tversky. *Psychological Review, 103*, 592-596.

Gigerenzer, G., & Hug, K. (1992). Domain-specific reasoning: Social contracts,

cheating, and perspective change. *Cognition, 43*, 127-171.

Goff, M., & Ackerman, P.L. (1992). Personality-intelligence relations: Assessment of typical intellectual engagement. *Journal of Educational Psychology, 84*, 537-552.

Goldberg, L.R. (1990). An alternative "description of personality": the big-five factor structure. *Journal of Personality and Social Psycholology, 59*, 1216-1229.

Goldberg, L.R. (1992). The development of markers for the big-five factor structure. *Psychological Assessment, 4*, 26-42.

Goldberg, L.R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. In I. Mervielde, I. Deary, F. D. Fruyt & F. Ostendorf (Eds.), *Personality psychology in Europe* (Vol. 7, pp. 7–28). Tilburg, the Netherlands: Tilburg University Press.

Goldberg, L.R. (2006). Doing it all Bass-Ackwards: The development of hierarchical factor structures from the top down. *Journal of Research in Personality, 40*, 347-358.

Goldman-Rakic, P.S. (1987). Circuitry of primate prefrontal cortex and regulation of behavior by representational memory. In F. Plum & V. Mountcastle (Eds.), *Handbook of physiology--The nervous ystem* (Vol. V, pp. 373-417). Bethesda, MD: Waverly Press.

Goleman, D. (1998). *Working with emotional intelligence.* New York, NY: Bantam.

Gómez, R.L., & Gerken, L.A. (2000). Infant artificial language learning and language acquisition. *Trends in Cognitive Sciences, 4*, 178-186.

Gopnik, A., Meltzoff, A.N., & Kuhl, P.K. (1999). *The scientist in the crib: Minds, brains, and how children learn.* New York, NY: William Morrow & Co.

Gottfredson, L.S. (2002). g: Highly general and highly practical. In R. J. Sternberg & E. L. Grigorenko (Eds.), *The general factor of intelligence: How general is it?* (pp. 331-380). Mahwah, NJ: Lawrence Erlbaum.

Gottfredson, L.S. (2003). Dissecting practical intelligence theory: Its claims and evidence. *Intelligence, 31*, 343-397.

Grafton, S.T., Hazeltine, E., & Ivry, R. (1995). Functional mapping of sequence learning in normal humans. *Journal of Cognitive Neuroscience, 7*, 497-510.

Gray, J.A., & McNaughton, N. (2000). *The neuropsychology of anxiety: An enquiry into the functions of the septo-hippocampal system.* Oxford, UK: Oxford University Press.

Gray, J.R., & Braver, T.S. (2002). Personality predicts working-memory-related activation in the caudal anterior cingulate cortex. *Cognitive, Affective & Behavioral Neuroscience, 2*, 64-75.

Gray, J.R., Chabris, C.F., & Braver, T.S. (2003). Neural mechanisms of general fluid intelligence. *Nature Neuroscience, 6*, 316-322.

Gray, J.R., & Thompson, P.M. (2004). Neurobiology of intelligence: science and ethics. *Nature Reviews Neuroscience, 5*, 471-482.

Greenwald, A.G., & Banaji, M.R. (1995). Implicit social cognition: Attitudes, self-esteem, and stereotypes. *Psychological Review, 102*, 4-27.

Greenwald, A.G., McGhee, D.E., & Schwartz, J.L.K. (1998). Measuring individual

differences in implicit cognition: The Implicit Association Test. *Journal of*

Personality and Social Psychology, 74, 1464-1480.

Greenwald, A.G., Poehlman, T.A., Uhlmann, E., & Banaji, M.R. (in press).

Understanding and using the Implicit Association Test: III. Meta-analysis of

predictive validity. *Journal of Personality and Social Psychology*.

Grudnik, J.L., & Kranzler, J.H. (2001). Meta-analysis of the relationship between

intelligence and inspection time. *Intelligence, 29*, 523-535.

Gryskiewicz, N.D., & Tullar, W.L. (1995). The relationship between personality type

and creativity style among managers. *Journal of Psychological Type, 32*, 30-35.

Guilford, J. P. (1959). Three faces of intellect. *American Psychologist, 14*, 469-479.

Gustafsson, J.-E. (1988). Hierarchical models of individual differences in cognitive

abilities. In R. J. Sternberg (Ed.), *Advances in the psychology of human*

intelligence (Vol. 4, pp. 35-71). Hillsdale, NJ: Lawrence Erlbaum Associates

Inc.

Guttman, L. (1954). A new approach to factor analysis: The radex. In P. F. Lazarsfeld

(Ed.), *Mathematical thinking in the social sciences.* (pp. 258-348). New York,

NY: Free Press.

Haidt, J. (2001). The emotional dog and its rational tail: A social intuitionist

approach to moral judgment. *Psychological Review, 108*, 814-834.

Hall, W.B., & MacKinnon, D.W. (1969). Personality inventory correlates of creativity

among architects. *Journal of Applied Psychology, 53*, 322-326.

Hambrick, D.Z., Kane, M.J., & Engle, R.W. (2005). The role of working memory in high-level cognition: Domain-specific versus domain-general perspectives. In R. J. Sternberg & J. E. Pretz (Eds.), *Cognition & Intelligence: Identifying the Mechanisms of the Mind* (pp. 104-122). Cambridge, UK: Cambridge University Press.

Hammond, K.R. (1996). *Human judgement and social policy: Irreducible uncertainty, inevitable error, unavoidable injustice.* New York, NY: Oxford University Press.

Hampson, M., Driesen, N.R., Skudlarski, P., Gore, J.C., & Constable, R.T. (2006). Brain connectivity related to working memory performance. *The Journal of Neuroscience, 26*, 13338-13343.

Harris, S.E., Wright, A.F., Haywood, C., Starr, J.M., Whalley, L.J, & Deary, I.J. (2005). The functional COMT polymorphism, Val158Met, is associated with logical memory and the personality trait intellect/imagination in a cohort of healthy 79 year olds. *Neuroscience Letters, 385*, 1-6.

Hassabis, D., & Maguire, E.A. (2007). Deconstructing episodic memory with construction. *Trends in Cognitive Sciences, 11*, 299-306.

Hassin, R.R, Uleman, J.S., & Bargh, J.A. (2005). *The new unconscious*. New York, NY: Oxford University Press.

Hawkins, J. (2005). *On intelligence*. New York, NY: Holt.

Hazeltine, E., Grafton, S.T., & Ivry, R. (1997). Attention and stimulus characteristics determine the locus of motor-sequence encoding: A PET study. *Brain, 120*, 123-140.

Hebb, D.O. (1961). Distinctive features of learning in the higher animal. In J. F.

    Delafresnaye (Ed.), *Brain mechanisms and learning* (pp. 37-51). London, UK:

    Oxford University Press.

Heitz, R.P., Unsworth, N., & Engle, R.W. (2004). Working memory capacity, attention

    control, and fluid intelligence. In I. O. Wilhelm & R. Engle (Eds.), *Handbook of*

    understanding and measuring intelligence (pp. 61-77). New York, NY: Sage.

Hines, D., & Martindale, C. (1974). Induced lateral eye-movements and creative and

    intellectual performance. *Perceptual and Motor Skills, 39*, 153-154.

Hirsch, J., DeYoung, C.G., & Peterson, J.B. (2009). Metatraits of the Big Five

    differentially predict engagement and retraint of behavior. Manuscript

    submitted for publication.

Hirschfeld, L.A., & Gelman, S.A. (1994). *Mapping the mind: Domain specificity in*

    cognition and culture. New York, NY: Cambridge University Press.

Hocevar, D. (1979). *The developent of the Creative Behavior Inventory*. Paper

    presented at the annual meeting of the Rocky Mountain Psychological

    Association.

Hocevar, D., & Bachelor, P. (1989). A taxonomy and critique of measurements used

    in the study of creativity. In J. A. Glover, R. R. Ronning & C. R. Reynolds (Eds.),

    Handbook of creativity. (pp. 53-75). New York, NY: Plenum Press.

Holland, J.L., & Nichols, R.C. (1964). Prediction of academic and extra-curricular

    achievement in college. *Journal of Educational Psychology, 55*, 55-65.

Horn, J.L. (1986). Intellectual ability concepts. In R. J. Sternberg (Ed.), *Advances in the psychology of human intelligence* (Vol. 3, pp. 35-77). Hillsdale, NJ: Erlbaum.

Horn, J.L., & Cattell, R.B. (1966). Refinement and test of the theory of fluid and crystallized general intelligences. *Journal of Educational Psychology, 57*, 253-270.

Howard-Jones, P. A., & Murray, S. (2003). Ideational productivity, focus of attention, and context. *Creativity Research Journal, 15*, 153-166.

Humphreys, L.G., Lubinski, D., & Yao, G. (1993). Utility of predicting group membership and the role of spatial visualization in becoming an engineer, physical scientist, or artist. *Journal of Applied Psychology, 78*, 250-261.

Hunt, E. (2000). Situational constraints on normative reasoning. *Behavioral and Brain Sciences, 23*, 680-680.

Hunt, E., Frost, N., & Lunneborg, C. (1973). Individual differences in cognition: A new approach to intelligence. In G. H. Bower (Ed.), *The psychology of learning and motivation: Advances in research and theory.* Oxford, UK: Academic Press.

Hunt, E., Lunneborg, C., & Lewis, J. (1975). What does it mean to be high verbal? *Cognitive Psychology, 7*, 194-227.

Jackson, D.N. (1984). *Personality research from manual.* Goshen, NY: Research Psychologists Press.

Jackson, G.M., Jackson, S.R., Harrison, J., Henderson, L., & Kennard, C. (1995). Serial reaction time learning and Parkinson's disease: Evidence for a procedural learning deficit. *Neuropsychologia, 33*, 577-593.

Jackson, J.H. (1958). *Selected writings of . . . Vol. 1. On epilepsy and epileptiform convulsions. Vol. 2. Evolution and dissolution of the nervous system; speech; various papers, addresses and lectures.* Oxford, UK: Basic Books.

Jacobson, C.M. (1993). Cognitive styles of creativity: Relations of scores on the Kirton Adaption-Innovation Inventory and the Myers-Briggs Type Indicator among managers in USA. *Psychological Reports, 72*, 1131-1138.

Jacoby, L.L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Journal of Memory and Language, 30*, 513-541.

Jaeger, A. O. (1984). Intelligenzstructurforschung: Konkurriende Modelle, neue Entwicklungen, Perspectiven [Research in the structure of intelligence: competing models, new developments, perspectives]. *Psychologische Rundschau, 35*, 21-35.

Jaeger, A.O. (1982). Mehrmodale Klassification von Intelligenzleistungen: experimentell kontrollierte Weiterentwicklungeines deskriptiven Intelligenzstructurmodells. [Multimodal classification of cognitive abilities: an experimentally controlled development of a descriptive model of intelligence structure]. *Diagnostica, 28*, 195-225.

Jaeggi, S.M., Buschkuehl, M., Jonides, J., & Perrig, W.J. (2008). Improving fluid intelligence with training on working memory *Proceedings of the National Academy of Sciences of the United States of America, 105*, 6829-6833.

James, W. (1890). *The Principles of Psychology*. New, York, NY: Dover Publications, Inc.

Jang, K.L., Livesley, W.J., Angleitner, A., Riemann, R., & Vernon, P.A. (2002). Genetic and environmental influences on the covariance of facets defining the domains of the five-factor model of personality. *Personality and Individual Differences, 33*, 83-101.

Janowsky, Jeri S., Shimamura, Arthur P., & Squire, Larry R. (1989). Memory and metamemory: Comparisons between patients with frontal lobe lesions and amnesic patients. *Psychobiology, 17*, 3-11.

Jensen, A. R. (1998). *The g factor: The science of mental ability*. Westport, CT: Praeger.

Jensen, A.R. (1982). Reaction time and psychometric g. In H. J. Eysenck (Ed.), *A model for intelligence* (pp. 93-132). Heidelberg, Germany: Springer.

Jensen, A.R. (2006). *Clocking the mind: Mental chronometry and individual differences*. St. Louis, MO: Elsevier Science.

Jiang, Y., & Chun, M.M. (2001). Selective attention modulates implicit learning. *The Quarterly Journal of Experimental Psychology, 54A*, 1105-1124.

Jiménez, L. (2003). *Attention and implicit learning*. Amsterdam, Netherlands: John Benjamins Publishing Company.

Jiménez, L., & Mendez, C. (1999). Which attention is needed for implicit sequence learning? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25*, 236-259.

Jiménez, L., & Vázquez, G. (2005). Sequence learning under dual-task conditions: Alternatives to a resource-based account. *Psychological Research, 69*, 352-368.

Johnson-Laird, P.N. (1983). *Mental Models*. Cambridge, UK: Cambridge University Press.

Johnson, J.A. (1994). Clarification of factor five with the help of the AB5C model. *European Journal of Personality, 8*, 311-334.

Johnson, M.K., & Hirst, W. (1993). MEM: Memory subsystems as processes. In A. F. Collins, S. E. Gathercole, M. A. Conway & P. E. Morris (Eds.), *Theories of memory* (pp. 241–286). Hillsdale, NJ: Lawrence Erlbaum.

Johnson, W., & Bouchard Jr., T.J. (2005). The structure of human intelligence: It is verbal, perceptual, and image rotation (VPR), not fluid and crystallized. *Intelligence, 33*, 393-416.

Johnson, W., Bouchard Jr., T.J., Krueger, R.F., McGue, M., & Gottesman, I.I. (2004). Just one g: consistent results from three test batteries. *Intelligence, 32*, 95-107.

Jung, C.G. (1921/1971). *Psychological types* (H. G. Baynes, Trans., revised by R.F.C. Hull). Princeton, NJ: Princeton University Press.

Kahneman, D. (2003). A perspective on judgment and choice: Mapping bounded rationality. *American Psychologist, 58*, 697-720.

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In T. Gilovich, D. Griffin & D. Kahneman

(Eds.), *Heuristics and biases: The psychology of intuitive judgment.* (pp. 49-81).

New York, NY: Cambridge University Press.

Kahneman, D., & Tversky, A. (1996). On the reality of cognitive illusions.

Psychological Review, 103, 582-591.

Kail, R., & Salthouse, T.A. (1994). Processing speed as a mental capacity. *Acta*

Psychologica, 86, 199-225.

Kane, M.J., Bleckley, M.K., Conway, A.R.A., & Engle, R.W. (2001). A controlled-

attention view of working-memory capacity. *Journal of Experimental*

Psychology: General, 130, 169-183.

Kane, M.J., Brown, L.H., McVay, J.C., Silvia, P.J., Myin-Germeys, I., & Kwapil, T.R.

(2007). For whom the mind wanders, and when: An experience-sampling

study of working memory and executive control in daily life. *Psychological*

Science, 18, 614-621.

Kane, M.J., & Engle, R.W. (2002). The role of prefrontal cortex in working-memory

capacity, executive attention, and general fluid intelligence: An individual-

differences perspective. *Psychonomic Bulletin & Review, 9*(4), 637-671.

Kane, M.J., Hambrick, D.Z., & Conway, A.R.A. (2005). Working memory capacity and

fluid intelligence are strongly related constructs: Comment on Ackerman,

Beier, and Boyle (2005). *Psychological Bulletin, 131*, 66-71.

Kane, M.J., Hambrick, D.Z., Tuholski, S.W., Wilhelm, O., Payne, T.W., & Engle, R.W.

(2004). The generality of working memory capacity: A latent-variable

approach to verbal and visuospatial memory span and reasoning. *Journal of Experimental Psychology: General, 133*, 189-217.

Kardash, C.M., & Scholes, R.J. (1996). Effects of pre-existing beliefs, epistemological beliefs, and need for cognition on interpretation of controversial issues. *Journal of Educational Psychology, 88*, 260-271.

Karmiloff-Smith, A. (1992). *Beyond Modularity: A Developmental Perspective on Cognitive Science*. Boston, MA: MIT Press.

Kaufman, J.C., Kaufman, S.B., Beghetto, R.A., Burgess, S.A., & Persson, R.S. (2009). Creative giftedness: Beginnings, developments, and future promises. To appear in. In L. Shavinina (Ed.), *International handbook on giftedness*. New York, NY: Springer Science.

Kaufman, S.B. (2007a). Creativity. In C. R. Reynolds & E. Fletcher-Janzen (Eds.), *Encyclopedia of Special Education* (3rd ed.). New York, NY: Wiley.

Kaufman, S.B. (2007b). Investigating the role of domain general mechanisms in the acquisition of domain specific expertise. *High Ability Studies, 18*, 71-73.

Kaufman, S.B. (2007c). Sex differences in mental rotation and spatial visualization ability: Can they be accounted for by differences in working memory capacity? *Intelligence, 35*, 211-223.

Kaufman, S.B. (2009). Faith in intuition is associated with decreased latent inhibition in a sample of high-achieving adolescents. *Psychology of Aesthetics, Creativity, and the Arts, 3*, 28-34.

Kaufman, S.B., DeYoung, C.G., Gray, J.R., Brown, J., & Mackintosh, N (2009). Associative learning predicts intelligence above and beyond working memory and processing speed. Manuscript under revision.

Kaufman, S.B., & Kaufman, J.C. (2007). Ten years to expertise, many more to greatness: An investigation of modern writers. *Journal of Creative Behavior, 41*, 114-124.

Keller, J., Bohner, G., & Erb, H.P. (2000). Intuitive und heuristische Urteilsbildung–verschiedene Prozesse? Präsentation einer deutschen Fassung des' Rational-Experiential Inventory'sowie neuer Selbstberichtskalen zur Heuristiknutzung. *Zeitschrift für Sozialpsychologie, 31*, 87-101.

Kerr, R., Garvin, J., Heaton, N., & Boyle, E. (2006). Emotional intelligence and leadership effectiveness. *Leadership & Organization Development Journal, 27*, 265-279.

Kihlstrom, John F. (1987). The cognitive unconscious. *Science, 237*(4821), 1445-1452.

Kim, K.H. (2005). Can only intelligent people be creative? A meta-analysis. *Journal of Secondary Gifted Education, 16*, 57-66.

King, L.A., Walker, L., & Broyles, S. (1996). Creativity and the five-factor model. *Journal of Research in Personality, 30*, 189-203.

Klaczynski, P.A. (2001). Analytic and heuristic processing influences on adolescent reasoning and decision-making. *Child Development, 72*, 844-861.

Klaczynski, P.A., Gordon, D.H., & Fauth, J. (1997). Goal-oriented critical reasoning and individual differences in critical reasoning biases. *Journal of Educational Psychology, 89*, 470-485.

Klaczynski, Paul A., & Cottrell, Jennifer M. (2004). A dual-process approach to cognitive development: The case of children's understanding of sunk cost decisions. *Thinking & Reasoning, 10*, 147-174.

Klein, G. (1999). *Sources of power: How people make decisions*. Cambridge, UK: Cambridge University Press.

Kline, R.B. (2005). *Principles and practice of structural equation modeling*. New York, NY: The Guilford Press.

Klingberg, T. (2008). *The overflowing brain: Information overload and the limits of working memory*. New York, NY: Oxford.

Klingberg, T., Fernell, E., Olesen, P.J., Johnson, M.H., Gustafsson, P., Dahlstrom, K., et al. (2005). Computerized Training of Working Memory in Children With ADHD--A Randomized, Controlled Trial. *Journal of the American Academy of Child & Adolescent Psychiatry, 44*, 177-186.

Klingberg, T., Forssberg, H., & Westerberg, H. (2002). Training of working memory in children with ADHD. *Journal of Clinical and Experimental Neuropsychology, 24*, 781-791.

Klinger, E. (1971). *Structure and functions of fantasy*. New York, NY: Wiley.

Knopman, D., & Nissen, M.J. (1991). Procedural learning is impaired in Huntington's disease: Evidence from the serial reaction time task. *Neuropsychologia, 29*, 245-254.

Koehler, J.J. (1996). The base rate fallacy reconsidered: Descriptive, normative, and methodological challenges. *Behavioral and Brain Sciences, 19*, 1-53.

Kokis, J.V., Macpherson, R., Toplak, M.E., West, R.F., & Stanovich, K.E. (2002). Heuristic and analytic processing: Age trends and associations with cognitive ability and cognitive styles. *Journal of Experimental Child Psychology, 83*, 26-52.

Krashen, S. (1992). Formal grammar instruction: Another educator comments. *TESOL Quarterly, 26*, 409-411.

Kuntsi, J., Eley, T.C., Taylor, A., Hughes, C., Asherson, P., Caspi, A., et al. (2004). Co-occurrence of ADHD and low IQ has genetic origins. *American Journal of Medical Genetics, 124*, 41-47.

Kushner, M., Cleeremans, A., & Reber, A. (1991). Implicit detection of event interdependencies and a PDP model of the process *Proceedings of the 13th annual meeting of the Cognitive Science Society* (pp. 215-220): Hillsdale, NJ: Lawrence Erlbaum.

Kyllonen, P.C. (1996). Is working memory capacity Spearman's g? In I. Dennis & P. Tapsfield (Eds.), *Human abilities: Their nature and measurement* (pp. 49-75). Mahwah, NJ: Erlbaum.

Kyllonen, P.C., & Christal, R.E. (1990). Reasoning ability is (little more than) working-memory capacity?! *Intelligence, 14*, 389-433.

Lave, J., Murtaugh, M., & de la Rocha, O. (1984). The dialectic of arithmetic in grocery shopping. In B. Rogoff & J. Lave (Eds.), *Everyday cognition: Its development in social context.* (pp. 67-94). Cambridge, MA: Harvard University Press.

Leonesio, R.J., & Nelson, T.O. (1990). Do different metamemory judgments tap the same underlying aspects of memory? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*, 464-470.

Leslie, A.M. (1987). Pretense and representation: The origins of "theory of mind.". *Psychological Review, 94*, 412-426.

Levinson, S.C. (1995). Interactional biases in human thinking. In E. Goody (Ed.), *Social intelligence and interaction* (pp. 221-260). Cambridge, UK: Cambridge University Press.

Lewicki, P. (1986). Processing information about covariations that cannot be articulated. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 12*, 135-146.

Lewicki, P., Czyzewska, M., & Hoffman, H. (1987). Unconscious acquisition of complex procedural knowledge. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 13*, 523-530.

Lewicki, P., & Hill, T. (1987). Unconscious processes as explanations of behavior in cognitive, personality, and social psychology. *Personality and Social Psychology Bulletin, 13*, 355-362.

Lewicki, P., Hill, T., & Czyzewska, M. (1992). Nonconscious acquisition of information. *American Psychologist, 47*, 796-801.

Lewicki, P., Hill, T., & Sasaki, I. (1989). Self-perpetuating development of encoding biases. [Empirical Study]. *Journal of Experimental Psychology: General, 118*, 323-337.

Lieberman, M.D. (2000a). Introversion and working memory: Central executive differences. *Personality and Individual Differences, 28*, 479-486.

Lieberman, M.D. (2000b). Intuition: A social cognitive neuroscience approach. *Psychological Bulletin, 126*, 109-137.

Lieberman, M.D. (2007). The X-and C-systems: The neural basis of automatic and controlled social cognition. *Social Neuroscience: Integrating biological and psychological explanations of social behavior*, 290-315.

Lieberman, M.D., Chang, G.Y., Chiao, J., Bookheimer, S.Y., & Knowlton, B.J. (2004). An event-related fMRI study of artificial grammar learning in a balanced chunk strength design. *Journal of Cognitive Neuroscience, 16*, 427-438.

Lieberman, M.D., & Rosenthal, R. (2001). Why introverts can't always tell who likes them: Multitasking and nonverbal decoding. *Journal of Personality and Social Psychology, 80*, 294-310.

Locke, E.A. (2005). Why emotional intelligence is an invalid concept. *Journal of Organizational Behavior, 26*, 425-431.

Loftus, E.F., & Klinger, M.R. (1992). Is the unconscious smart or dumb? *American Psychologist, 47*, 761-765.

Lohman, D.F. (2001). Fluid intelligence, inductive reasoning, and working memory: Where the theory of multiple intelligences falls short. In N. Colangelo & S. G. Assouline (Eds.), *Talent development IV: Proceedings from the 1998 Henry B. and Jocelyn Wallace National Research Symposium on Talent Development.* (pp. 219-227). Scottsdale, AZ: Gifted Psychology Press.

Lopes, P.N., Brackett, M.A., Nezlek, J.B., Schütz, A., Sellin, I., & Salovey, P. (2004). Emotional intelligence and social interaction. *Personality and Social Psychology Bulletin, 30*, 1018-1034.

Lopes, P.N., Grewal, D., Kadis, J., Gall, M., & Salovey, P. (2006). Evidence that emotional intelligence is related to job performance and affect and attitudes at work. *Psicothema, 18*, 132-138.

Lopes, P.N., Salovey, P., Côté, S., Beers, M., & Petty, R.E. (2005). Emotion regulation abilities and the quality of social interaction. *Emotion, 5*, 113-118.

Lopes, P.N., Salovey, P., & Straus, R. (2003). Emotional intelligence, personality, and the perceived quality of social relationships. *Personality and Individual Differences, 35*, 641-658.

Lubow, R.E. (1989). *Latent inhibition and conditioned attention theory*. Cambridge, UK: Cambridge University Press.

Lubow, R.E., & Gewirtz, J.C. (1995). Latent inhibition in humans: Data, theory, and implications for schizophrenia. *Psychological Bulletin, 117*, 87-103.

Lubow, R.E., Ingberg-Sachs, Y., Zalstein-Orda, N., & Gewirtz, J.C. (1992). Latent inhibition in low and high "psychotic-prone" normal subjects. *Personality and Individual Differences, 13*, 563-572.

Ludwig, A.M. (1995). *The price of greatness: Resolving the creativity and madness controversy*. New York, NY: Guilford Press.

Ludwig, Arnold M. (1992). The Creative Achievement Scale. *Creativity Research Journal, 5*, 109-124.

Mackinnon, D. W. (1978). *In search of human effectiveness*. Buffalo, NY: Creative Education Foundation.

Mackinnon, D.W. (1962). The nature and nurture of creative talent. *American Psychologist, 17*, 484-495.

Mackintosh, N.J. (1998). *IQ and human intelligence*. Oxford, UK: Oxford University Press.

Malmi, R.A., Underwood, B.J., & Carroll, J.B. (1979). The interrelationships among some associative learning tasks. *Bulletin of the Psychonomic Society, 13*, 121-123.

Mar, R.A., & Oatley, K. (2008). The function of fiction is the abstraction and simulation of social experience. *Perspectives on Psychological Science, 3*, 173-192.

Mar, R.A., Oatley, K., Hirsh, J., dela Paz, J., & Peterson, J.B. (2006). Bookworms versus nerds: Exposure to fiction versus non-fiction, divergent associations with

social ability, and the simulation of fictional social worlds. *Journal of Research in Personality, 40*, 694-712.

Margolis, H. (1987). *Patterns, thinking, and cognition: A theory of judgment.* Chicago, IL: University of Chicago Press.

Markon, K.E., Krueger, R.F., & Watson, D. (2005). Delineating the structure of normal and abnormal personality: An integrative hierarchical approach. *Journal of Personality and Social Psychology, 88*, 139-157.

Marshalek, B., Lohman, D.F., & Snow, R. E. (1983). The complexity continuum in the radex and hierarchical models of intelligence. *Intelligence, 7*, 107-127.

Martindale, C. (1999). Biological bases of creativity. In R. J. Sternberg (Ed.), *Handbook of Creativity* (pp. 137-152). Cambridge, UK: Cambridge University Press.

Martindale, Colin (1995). Creativity and connectionism. In S. M. Smith, T. B. Ward & R. A. Finke (Eds.), *The creative cognition approach.* (pp. 249-268). Cambridge, MA: The MIT Press.

Mason, M.F., Norton, M.I., Van Horn, J.D., Wegner, D.M., Grafton, S.T., & Macrae, C.N. (2007). Wandering minds: The default network and stimulus-independent thought. *Science, 315*, 393-395.

Mayer, J. D., Salovey, P., & Caruso, D.R. (2008). Emotional intelligence: New ability or eclectic traits? *American Psychologist, 63*, 503-517.

Mayer, J.D., Caruso, D.R., & Salovey, P. (2000). Emotional intelligence meets traditional standards for an intelligence. *Intelligence, 27*, 267-298.

Mayer, J.D., Perkins, D.M., Caruso, D.R., & Salovey, P. (2001). Emotional intelligence
and giftedness. *Roeper Review, 23*, 131-137.

Mayer, J.D., Roberts, R.D., & Barsade, S.G. (2008). Human abilities: Emotional
intelligence. *Annual Review of Psychology, 59*, 507-536.

Mayer, J.D., & Salovey, P. (1993). The intelligence of emotional intelligence.
Intelligence, 17, 433-442.

Mayer, J.D., Salovey, P., & Caruso, D.R. (2000). Models of emotional intelligence. In R.
J. Sternberg (Ed.), *Handbook of intelligence* (pp. 396-420). Cambridge, UK:
Cambridge University Press.

Mayer, J.D., Salovey, P., & Caruso, D.R. (2002). *Mayer-Salovey-Caruso Emotional
Intelligence Test (MSCEIT) user's manual*. Toronto, Ontario, Canada: Multi-
Health Systems.

Mayer, J.D., Salovey, P., Caruso, D.R., & Sitarenios, G. (2003). Measuring emotional
intelligence with the MSCEIT V2. 0. *Emotion, 3*, 97-105.

McCrae, R.R. (1987). Creativity, divergent thinking, and openness to experience.
Journal of Personality and Social Psychology, 52, 1258-1263.

McCrae, R.R. (1994). Openness to experience: Expanding the boundaries of Factor V.
European Journal of Personalily, 8, 251-272.

McCrae, R.R., & Costa, P.T. Jr. (1990). *Personality in adulthood*. New York, NY:
Guilford.

McGeorge, P., Crawford, J.R., & Kelly, S.W. (1997). The relationships between
psychometric intelligence and learning in an explicit and an implicit task.

Journal of Experimental Psychology: Learning, Memory, and Cognition, 23,

239-245.

McLaren, I.P.L., Green, R.E.A., & Mackintosh, N.J. (1994). Animal learning and the

implicit/explicit distinction. In N. C. Ellis (Ed.), *Implicit and explicit learning of

languages* (pp. 313–332). New York, NY: Academic Press.

McVay, J.C., & Kane, M.J. (2009). Conducting the train of thought: Working memory

capacity, goal neglect, and mind wandering in an executive-control task.

Journal of Experimental Psychology: Learning, Memory, and Cognition, 35,

196-204.

Mednick, S. (1962). The associative basis of the creative process. *Psychological

Review, 69*, 220-232.

Meskin, Bonnie B., & Singer, Jerome L. (1974). Daydreaming, reflective thought, and

laterality of eye movements. *Journal of Personality and Social Psychology,

30*(1), 64-71.

Metcalfe, J., & Mischel, W. (1999). A hot/cool-system analysis of delay of

gratification: Dynamics of willpower. *Psychological Review, 106*, 3-19.

Miller, G.A. (2003). The cognitive revolution: A historical perspective. *Trends in

Cognitive Sciences, 7*, 141-144.

Milner, B., Petrides, M., & Smith, M.L. (1985). Frontal lobes and the temporal

organization of memory. *Human Neurobiology, 4*, 137-142.

Mishkin, M., Malamut, B.L., & Bachevalier, J. (1984). Memories and habits: Two

neural systems. In G. Lynch, J. L. McGaugh & N. M. Weinberger (Eds.),

Neurobiology of learning and memory (pp. 65-77). New York, NY: Guilford Press.

Mithen, S. (1996). *The prehistory of the mind: The cognitive origins of art and science.* London: Thames and Hudson.

Mithen, S. (2007). *The singing Neanderthals: The origins of music, language, mind, and body.* Boston, MA: Harvard University Press.

Miyake, A., Friedman, N.P., Emerson, M.J., Witzki, A.H., Howerter, A., & Wager, T.D. (2000). The unity and diversity of executive functions and their contributions to complex '"frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology, 41*, 49-100.

Miyake, A., & Shah, P. (1999). *Models of working memory: Mechanisms of active maintenance and executive control.* New York, NY: Cambridge University Press.

Murray, E.A., & Richmond, B.J. (2001). Role of perirhinal cortex in object perception, memory, and associations. *Current Opinion in Neurobiology, 11*, 188-193.

Myers, I., McCaulley, M.H., Quenk, N.L., & Hammer, A.L. (1998). *Manual: A guide to the development and use of the Myers-Briggs Type Indicator (2nd ed.).* Palo Alto, CA: Consulting Psychologists Press.

Nettelbeck, T. (1987). Inspection time and intelligence. In P. A. Vernon (Ed.), *Speed of information-processing and intelligence.* (pp. 295-346). Westport, CT: Ablex Publishing.

Neubauer, A.C., & Fink, A. (2005). Basic information processing and the psychophysiology of intelligence. In R. J. Sternberg & J. E. Pretz (Eds.), *Cognition and intelligence: Identifying the mechanisms of the mind* (pp. 68-87). New York, NY: Cambride University Press.

Newman, J.P., & Wallace, J.F. (1993). Divergent pathways to deficient self-regulation: Implications for disinhibitory psychopathalogy in children. *Clinical Psychology Review, 13*, 699-720.

Newstead, S.E., Handley, S.J., Harley, C., Wright, H., & Farelly, D. (2004). Individual differences in deductive reasoning. *The Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 57A*, 33-60.

Nichols, S., & Stich, S.P. (2003). *Mindreading: An integrated account of pretence, self-awareness, and understanding other minds*. New York, NY: Oxford University Press.

Nisbett, R., Peng, K., Choi, I., & Norenzayan, A. (2001). Culture and systems of thought: Holistic vs. analytic cognition. *Psychological Review, 108*, 291-310.

Nissen, M.J., & Bullemer, P. (1987). Attentional requirements of learning: Evidence from performance measures. *Cognitive Psychology, 19*, 1-32.

Nissen, M.J., Willingham, D.B., & Hartman, M. (1989). Explicit and implicit remembering: When is learning preserved in amnesia? *Neuropsychologia, 27*, 341-352.

Norman, E., Price, M.C., & Duff, S.C. (2006). Fringe consciousness in sequence

learning: The influence of individual differences. *Consciousness and Cognition,*

15, 723-760.

Norman, E., Price, M.C., Duff, S.C., & Mentzoni, R.A. (2007). Gradations of awareness

in a modified sequence learning task. *Consciousness and Cognition, 16*, 809-

837.

Norris, S.P. (1992). Testing for the disposition to think critically. *Informal Logic, 14*,

157-164.

Nosek, B.A., Greenwald, A.G., & Banaji, M.R. (2007). The Implicit Association Test at

age 7: A methodological and conceptual review. In J. A. Bargh (Ed.), *Social*

psychology and the unconscious: The automaticity of higher mental processes.

(pp. 265-292). New York, NY: Psychology Press.

Oaksford, M. , & Chater, N. (1994). A rational analysis of the selection task as optimal

data selection. *Psychological Review, 101*, 608-631.

Oaksford, M., & Chater, N. (1993). Reasoning theories and bounded rationality. In K.

I. Manktelow & D. E. Over (Eds.), *Rationality: Psychological and philosophical*

perspectives. (pp. 31-60). Florence, KY: Taylor & Frances/Routledge.

Oaksford, M., & Chater, N. (1995). Theories of reasoning and the computational

explanation of everyday inference. *Thinking & Reasoning, 1*, 121-152.

Oatley, K. (2004). Emotional intelligence and the intelligence of emotions.

Psychological Inquiry, 15, 216-221.

Oberauer, K., Schulze, R., Wilhelm, O., & Süß, H.M. (2005). Working memory and intelligence—their correlation and their relation: Comment on Ackerman, Beier, and Boyle (2005). *Psychological Bulletin, 131*, 61-65.

Ohnmacht, F.W. (1970). Personality and cognitive referents of creativity: A second look. *Psychological Reports, 26*, 336-338.

Olesen, P.J., Westerberg, H., & Klingberg, T. (2004). Increased prefrontal and parietal activity after training of working memory. *Nature Neuroscience, 7*, 75-79.

Olson, K.R. (2005). Engagement and Self-Control: Superordinate dimensions of Big Five traits. *Personality and Individual Differences, 38*, 1689-1700.

Oya, Taeko, Manalo, Emmanuel, & Greenwood, Jackie (2004). The influence of personality and anxiety on the oral performance of japanese speakers of english. *Applied Cognitive Psychology, 18*, 841-855.

Pacini, R., & Epstein, S. (1999). The relation of rational and experiential information processing styles to personality, basic beliefs, and the ratio-bias phenomenon. *Journal of Personality and Social Psychology, 76*, 972-987.

Packard, M.G., Hirsh, R., & White, N.M. (1989). Differential effects of fornix and caudate nucleus lesions on two radial maze tasks: evidence for multiple memory systems. *Journal of Neuroscience, 9*, 1465-1472.

Pacton, S., Fayol, M., & Perruchet, P. (2005). Children's implicit learning of graphotactic and morphological regularities. *Child Development, 76*, 324-339.

Paivio, A. (2007). *Mind and its evolution: A dual coding theoretical approach.* Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Panksepp, J. (1998). *Affective neuroscience: The foundations of human and animal emotions*. Oxford, UK: Oxford University Press.

Park, G., Lubinski, D., & Benbow, C.P. (2007). Contrasting intellectual patterns predict creativity in the arts and sciences: Tracking intellectually precocious youth over 25 years. *Psychological Science, 18*, 948-952.

Park, H., Quinlan, J., Thornton, E., & Reder, L.M. (2004). The effect of midazolam on visual search: Implications for understanding amnesia. *Proceedings of the National Academy of Sciences, 101*, 17879-17883.

Parker, S.T., & McKinney, M.L. (1999). *Origins of intelligence: The evolution of cognitive development in monkeys, apes, and humans*. Baltimore, MD: Johns Hopkins University Press.

Payne, B.K., & Stewart, B.D. (2007). Automatic and Controlled Components of Social Cognition: A Process Dissociation Approach. In J. A. Bargh (Ed.), *Social psychology and the unconscious: The automaticity of higher mental processes.* (pp. 293-315). New York, NY: Psychology Press.

Payne, J.W., Bettman, J.R., Coupey, E., & Johnson, E.J. (1992). A constructive process view of decision making: Multiple strategies in judgment and choice. *Acta Psychologica, 80*, 107-141.

Perruchet, P. (2005). Statistical approaches to language acquisition and the self-organizing consciousness: A reversal of perspective. *Psychological Research, 69*, 316-329.

Perruchet, P. (2008). Implicit Learning. In H. L. Roediger (Ed.), *Cognitive psychology of memory* (Vol. 2). Oxford, UK: Elsevier.

Peterson, J.B., & Carson, S. (2000). Latent inhibition and openness to experience in a high-achieving student population. *Personality and Individual Differences, 28*, 323-332.

Peterson, J.B., Smith, K.W., & Carson, S. (2002). Openness and extraversion are associated with reduced latent inhibition: Replication and commentary. *Personality and Individual Differences, 33*, 1137-1147.

Petrides, K. V., & Furnham, A. (2001). Trait emotional intelligence: Psychometric investigation with reference to established trait taxonomies. *European Journal of Personality, 15*, 425-448.

Petrides, K.V., & Furnham, A. (2003). Trait emotional intelligence: Behavioural validation in two studies of emotion recognition and reactivity to mood induction. *European Journal of Personality, 17*, 39-57.

Petrides, M. (1995). Impairments on non-spatial self-ordered and externally ordered working memory tasks after lesions of the mid-dorsal part of the lateral frontal cortex in the monkey. *Journal of Neuroscience, 15*, 359-375.

Petrides, M. (2000). Dissociable roles of mid-dorsolateral prefrontal and anterior inferotemporal cortex in visual working memory. *The Journal of Neuroscience, 20*, 7496-7503.

Petrides, M., Alivisatos, B., Evans, A.C., & Meyer, E. (1993). Dissociation of human mid-dorsolateral from posterior dorsolateral frontal cortex in memory

processing. *Proceedings of the National Academy of Sciences of the U.S.A., 90*, 873-877.

Phelps, E.A., O'Connor, K.J., Cunningham, W.A., Funayama, E.S., Gatenby, J. C., Gore, J.C., et al. (2000). Performance on indirect measures of race evaluation predicts amygdala activation. *Journal of Cognitive Neuroscience, 12*, 729-738.

Piaget, J. (1952). *The Origins of Intelligence in Children*. Madison, CT: International Universities Press.

Piattelli-Palmarini, M. (1994). *Inevitable illusions: How mistakes of reason rule our minds*. New York, NY: Wiley.

Piedmont, R.L. (1998). *The revised NEO personality inventory: Clinical and research applications*. New York, NY: Springer.

Pinker, S. (1999). *How the mind works*. New York, NY: W.W. Norton & Company.

Pinker, S. (2002). *The blank slate: The modern denial of human nature*. New York, NY: Viking.

Plucker, J.A., Callahan, C.M., & Tomchin, E.M. (1996). Wherefore art thou, multiple intelligences? Alternative asessments for identifying talent in ethnically diverse and low income families. *Gifted Child Quarterly, 40*, 81-92.

Poincaré, H. (1921). *The foundations of science* (G. B. Halstead, Trans.). New York, NY: Science Press.

Poldrack, R.A., & Packard, M.G. (2003). Competition among multiple memory systems: Converging evidence from animal and human brain studies. *Neuropsychologia, 41*, 245-251.

Pollock, J.L. (1991). OSCAR: A general theory of rationality. In R. Cummins & J. L.

Pollock (Eds.), *Philosophy and AI: Essays at the interface.* (pp. 189-213).

Cambridge, MA: The MIT Press.

Posner, M.I., & Keele, S.W. (1968). On the genesis of abstract ideas. *Journal of*

Experimental Psychology, 77, 353-363.

Posner, M.I., & Mitchell, R.F. (1967). Chronometric analysis of classification.

Psychological Review, 74, 392-409.

Posner, M.I., & Snyder, C.R.R. (1975). Attention and cognitive control. In R. L. Solso

(Ed.), *Information processing and cognition: The Loyola Symposium*. Hoboken,

NJ: Wiley.

Posner, M.I., & Snyder, C.R.R. (2004). Attention and Cognitive Control. In D. A. Balota

& E. J. Marsh (Eds.), *Cognitive psychology: Key readings* (pp. 205-223). New

York, NY: Psychology Press.

Preckel, F., Holling, H., & Wiese, M. (2006). Relationship of intelligence and creativity

in gifted and non-gifted students: An investigation of threshold theory.

Personality and Individual Differences, 40, 159-170.

Pretz, J.E., & Totz, K.S. (2007). Measuring individual differences in affective,

heuristic, and holistic intuition. *Personality and Individual Differences, 43*,

1247-1257.

Pretz, J.E., Totz, K.S., & Kaufman, S.B. (2009). The effects of mood, cognitive style,

and cognitive ability on implicit learning. Manuscript submitted for

publication.

Ramos-Ford, V., & Gardner, H. (1997). Giftedness from a multiple intelligences perspective. In N. Colangelo & G. A. David (Eds.), *Handbook of gifted education* (2 ed., pp. 439-459). Boston, MA: Allyn & Bacon.

Rausch, S.L., Savage, C.R., Brown, H.D., Curran, T., Alpert, N.M., Kendrick, A., et al. (1995). A PET investigation of implicit and explicit sequence learning. *Human Brain Mapping, 5*, 124-132.

Rausch, S.L., Whalen, P.J., Savage, C.R., Curran, T., Kendrick, A., Brown, H.D., et al. (1997). Striatal recruitment during an implicit sequence learning task as measured by functional magnetic resonance imaging. *Human Brain Mapping, 5*, 124-132.

Raven, J., Raven, J.C., & Court, J.H. (1998). *Manual for raven's progressive matrices and vocabularly scales.* Oxford, UK: Oxford Psychologists Press.

Reber, A.S. (1967). Implicit learning of artificial grammars. *Journal of Verbal Learning and Verbal Behavior, 6*, 855-863.

Reber, A.S. (1989). Implicit learning and tacit knowledge. *Journal of Experimental Psychology: General, 118*, 219-235.

Reber, A.S. (1993). *Implicit learning and tacit knowledge: An essay on the cognitive unconscious.* New York, NY: Oxford University Press.

Reber, A.S., & Allen, R. (2000). Individual differences in implicit learning: Implications for the evolution of consciousness. In R. G. Kunzendorf & B. Wallace (Eds.), *Individual differences in conscious experience* (pp. 227-247). Amsterdam, Netherlands: John Benjamins Publishing Company.

Reber, A.S., Walkenfeld, F.F., & Hernstadt, R. (1991). Implicit and explicit learning: Individual differences and IQ. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 17*, 888-896.

Reber, P.J., & Kotovsky, K. (1997). Implicit learning in problem solving: The role of working memory capacity. *Journal of Experimental Psychology: General, 126*, 178-203.

Reber, R., Ruch-Monachon, M-A., & Perrig, W.J. (2007). Decomposing intuitive components in a conceptual problem solving task. *Consciousness and Cognition: An International Journal, 16*, 294-309.

Reed, J., & Johnson, P. (1994). Assessing implicit learning with indirect tests: Determining what is learned about sequence structure. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 20*, 585-594.

Reis, D.L., Brackett, M.A., Shamosh, N.A., Kiehl, K.A., Salovey, P., & Gray, J.R. (2007). Emotional Intelligence predicts individual differences in social exchange reasoning. *Neuroimage, 35*, 1385-1391.

Reyna, V.F. (2004). How people make decisions that involve risk: A dual-processes approach. *Current Directions in Psychological Science, 13*, 60-66.

Richards, R., Kinney, D.K., Benet, M., & Merzel, A.P. (1988). Assessing everyday creativity: Characteristics of the Lifetime Creativity Scales and validation with three large samples. *Journal of Personality and Social Psychology, 54*, 476-485.

Richter, R.H., & Winter, W.D. (1966). Holtzman inkblot correlates of creative
potential. *Journal of Projective Techniques and Personality Assessment, 30*, 62-
67.

Roberts, R.D., Zeidner, M., & Matthews, G. (2001). Does emotional intelligence meet
traditional standards for an intelligence? Some new data and conclusions.
Emotion, 1, 196-231.

Robinson, P. (2001). Individual differences, cognitive abilities, aptitude complexes
and learning conditions in second language acquisition. *Second Language
Research, 17*, 368-392.

Roe, A. (1952). *The making of a scientist*. New York, NY: Dodd Mead.

Rohrmeier, M., & Fu, Q. (2008). *Implicit learning of phrase-structure grammar in
language and music.* Paper presented at the Association for the Scientific
Study of Consciousness, Taiwan.

Rosete, D. (2007). Does emotional intelligence play an important role in leadership
effectiveness? Unpublished doctoral dissertation. University of Wollongong,
Wollongong, New South Wales, Australia.

Rosete, D., & Ciarrochi, J. (2005). Emotional intelligence and its relationship to
workplace performance outcomes of leadership effectiveness. *Leadership &
Organization Development Journal, 26*, 388-399.

Rubin, M.M. (1999). *Emotional intelligence and its role in mitigating aggression: A
correlational study of the relationship between emotional intelligence and*

aggression in urban adolescents: Unpublished doctoral dissertation, Immaculata College, Immaculata, Pennsylvania.

Rudman, L.A., & Ashmore, R.D. (2007). Discrimination and the Implicit Association Test. *Group Processes & Intergroup Relations, 10*, 359-372.

Saffran, J.R., Aslin, R.N., & Newport, E.L. (1996). Statistical learning by 8-month-old infants. *Science, 274*, 1926-1928.

Sagar, H.J., Gabrielli, J.D.E., Sullivan, E.V., & Corkin, S. (1990). Recency and frequency discrimination in the amnesic patient H.M. *Brain, 113*, 581-602.

Sagar, H.J., Sullivan, E.V., Gabrieli, J.D.E., Corkin, S., & Growdon, J.H. (1988). Temporal ordering and short-term memory deficits in Parkinson's disease. *Brain, 111*, 525-539.

Salovey, P., & Mayer, J.D. (1990). Emotional intelligence. *Imagination, Cognition and Personality, 9*, 185-211.

Salthouse, T.A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review, 103*, 403-428.

Salthouse, T.A., McGuthry, K.E., & Hambrick, D.Z. (1999). A framework for analyzing and interpreting differential aging patterns: Application to three measures of implicit learning. *Aging, Neuropsychology, and Cognition, 6*, 1-18.

Saucier, G. (1992). Openness versus intellect: Much ado about nothing? *European Journal of Personality, 6*, 381-386.

Schacter, D.L. (1987). Implicit memory: History and current status. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 13*, 501-518.

Schmidt, D.B., Lubinski, D., & Benbow, C.P. (1998). Validity of assessing educational-vocational preference dimensions among intellectually talented 13-year-olds. *Journal of Counseling Psychology, 45*, 436-453.

Schneider, W., Körkel, J., & Weinert, F.E. (1990). Expert knowledge, general abilities, and text processing. In W. Schneider & F. E. Weinert (Eds.), *Interactions among aptitudes, strategies, and knowledge in cognitive performance* (pp. 235-251). New York, NY: Springer-Verlag.

Schneider, W., & Shiffrin, R.M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review, 84*, 1-66.

Schoemaker, P.J. (1991). The quest for optimality: A positive heuristic of science? *Behavioral and Brain Sciences, 14*, 205-245.

Schommer, M. (1990). Effects of beliefs about the nature of knowledge on comprehension. *Journal of Educational Psychology, 82*, 498-504.

Schulte, M.J., Ree, M.J., & Carretta, T.R. (2004). Emotional intelligence: not much more than g and personality. *Personality and Individual Differences, 37*, 1059-1068.

Schvaneveldt, R.W., & Gómez, R.L. (1998). Attention and probabilistic sequence learning. *Psychological Research, 61*, 175-190.

Seger, C.A. (1994). Implicit learning. *Psychological Bulletin, 115*, 163-196.

Shallice, T. (1988). *From neuropsychology to mental structure*. New York, NY: Cambridge University Press.

Shamosh, N.A., DeYoung, C.G., Green, A.E., Reis, D.L., Johnson, M.R., Conway, A.R.A., et al. (2008). Individual differences in delay discounting: Relation to intelligence, working memory, and anterior prefrontal cortex. *Psychological Science, 19*, 904-911.

Shamosh, N.A., & Gray, J.R. (2007). Delay discounting and intelligence: A meta-analysis. *Intelligence, 36*, 289-305.

Shanks, D.R. (1995a). Is human learning rational? *The Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 48A*, 257-279.

Shanks, D.R. (1995b). *The psychology of associative learning*. New York, NY: Cambridge University Press.

Shanks, D.R. (2003). Attention and awareness in ''implicit''sequence learning. In L. Jiménez (Ed.), *Attention and implicit learning* (pp. 11-42). Amsterdam, Netherlands: John Benjamins.

Shimamura, A.P., & Squire, L.R. (1986). Memory and metamemory: A study of the feeling-of-knowing phenomenon in amnesic patients. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 12*, 452-460.

Simon, H.A. (1979). *Models of thought*. New Haven, CT: Yale University Press.

Simonton, D.K. (1975). Sociocultural context of individual creativity: A transhistorical time-series analysis. *Journal of Personality and Social Psychology, 32*, 1119-1133.

Simonton, D.K. (1980). Thematic fame, melodic originality, and musical zeitgeist: A

    biographical and transhistorical content analysis. *Journal of Personality and*

    Social Psychology, 38, 972-983.

Simonton, D.K. (1988). *Scientific genius: A psychology of science.* New York, NY:

    Cambridge University Press.

Simonton, D.K. (1994). *Greatness: Who makes history and why.* New York, NY:

    Guilford Press.

Simonton, D.K. (1999). Talent and its development: An emergenic and epigenetic

    model. *Psychological Review, 106*, 435-457.

Simonton, D.K. (2005). Giftedness and genetics: The emergenic-epigenetic model

    and its implications. *Journal for the Education of the Gifted, 28*, 270-286.

Singer, J.L. (1966). *Daydreaming: An introduction to the experimental study of inner*

    experience. New York, NY: Random House.

Singer, J.L. (1974). Daydreaming and the stream of thought. *American Scientist, 62*,

    417-425.

Singer, J.L. (1988). Sampling ongoing consciousness and emotional experience:

    Implications for health. In M. J. Horowitz (Ed.), *Psychodynamics and cognition*

    (pp. 297-346). Chicago, IL: University of Chicago Press.

Sligh, A.C., Conners, F.A., & Roskos-Ewoldsen, B. (2005). Relation of creativity to

    fluid and crystallized intelligence *Journal of Creative Behavior, 39*, 123-136.

Sloman, S.A. (1996). The empirical case for two systems of reasoning. *Psychological*

    Bulletin, 119, 3-22.

Smallwood, J., & Schooler, J.W. (2006). The restless mind. *Psychological Bulletin, 132*, 946-958.

Smith, E.R., & DeCoster, J. (2000). Dual-process models in social and cognitive psychology: Conceptual integration and links to underlying memory systems. *Personality and Social Psychological Review, 4*, 108-131.

Smith, S. M., Ward, T.B., & Finke, R.A. (1995). *The creative cognition approach*. Cambridge, MA: The MIT Press.

Snow, C.P. (1967). *The two cultures*. Cambridge, UK: Cambridge University Press.

Snow, R.E. (1991). The concept of aptitude. In R. E. Snow & D. E. Wiley (Eds.), *Improving inquiry in social science: A volume in honor of Lee J. Cronbach.* (pp. 249-284). Hillsdale, NJ: Lawrence Erlbaum.

Snow, R.E., Corno, L., & Jackson, D., III. (1996). Individual differences in affective and conative functions. In D. C. Berliner & R. C. Calfee (Eds.), *Handbook of educational psychology.* (pp. 243-310). New York, NY: Macmillan.

Snyder, C.R., & Fromkin, H.L. (1977). Abnormality as a positive characteristic: The development and validation of a scale measuring need for uniqueness. *Journal of Abnormal Psychology, 86*, 518-527.

Snyder, C.R., & Fromkin, H.L. (1980). *Uniqueness: The human pursuit of difference*. New York, NY: Springer.

Spearman, C. (1904). "General intelligence," objectively determined and measured. *American Journal of Psychology, 15*, 201-293.

Spearman, C. (1927). *The abilities of man*. London, UK: Macmillan.

Sperry, R. W. (1968). Hemisphere deconnection and unity in conscious awareness. *American Psychologist, 23*, 723-733.

Spoont, M.R. (1992). Modulatory role of serotonin in neural information processing: Implications for human psychopathology. *Psychological Bulletin, 112*, 330-350.

Spreng, R.N., Mar, R.A., & Kim, A.S.N. (in press). The common neural basis of autobiographical memory, prospection, navigation, theory of mind and the default mode: A quantitative meta-anaysis. *Journal of Cognitive Neuroscience*.

Stadler, M.A., & Frensch, P.A. (1997). *Handbook of implicit learning*. Thousand Oaks, CA: Sage Publications.

Stanovich, K. (2009a). *What intelligence tests miss: The psychology of rational thought*. New Haven, CT: Yale University Press.

Stanovich, K.E. (2004). *The robot's rebellion: Finding meaning in the age of Darwin*. Chicago, IL: University of Chicago Press.

Stanovich, K.E. (2009b). Distinguishing the reflective, algorithmic, and autonomous minds: Is it time for a tri-process theory. In J. S. B. T. Evans & K. Frankish (Eds.), *In two minds: Dual processes and beyond*. Oxford, UK: Oxford University Press.

Stanovich, K.E., & West, R.F. (1998a). Cognitive ability and variation in selection task performance. *Thinking & Reasoning, 4*, 193-230.

Stanovich, K.E., & West, R.F. (1998b). Individual differences in rational thought. *Journal of Experimental Psychology: General, 127*, 161-188.

Stanovich, K.E., & West, R.F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences, 23*, 645-726.

Stanovich, K.E., & West, R.F. (2003). Evolutionary versus instrumental goals: How evolutionary psychology misconceives human rationality. In D. E. Over (Ed.), *Evolution and the psychology of thinking* (pp. 171-230). Hove, UK: Psychology Press.

Stanovich, KE (1999). *Who is rational?: Studies of individual differences in reasoning*. Mahwah, NJ: Lawrence Erlbaum

Stanovich, Keith E., & West, Richard F. (1997). Reasoning independently of prior belief and individual differences in actively open-minded thinking. *Journal of Educational Psychology, 89*, 342-357.

Steiger, J.H. (1980). Tests for comparing elements of a correlation matrix. *Psychological Bulletin, 87*, 245-251.

Stein, E. (1996). *Without good reason: The rationality debate in philosophy and cognitive science*. New York, NY: Oxford University Press.

Sternberg, R.J. (1977). Component processes in analogical reasoning. *Psychological Review, 84*, 353-378.

Sternberg, R.J. (1988). *The triarchic mind: A new theory of human intelligence*. New York, NY: Viking Penguin.

Sternberg, R.J. (1997a). *Successful intelligence: How practical and creative intelligence determine success in life* New York, NY: Plume.

Sternberg, R.J. (1997b). *Thinking styles*. Cambridge, UK: Cambridge University Press.

Sternberg, R.J. & The Rainbow Project Collaborators (2006). The Rainbow Project: Enhancing the SAT through assessments of analytical, practical and creative skills. *Intelligence, 34*, 321–350.

Sternberg, R.J., & Davidson, J.E. (1995). *The nature of insight*. Cambridge, MA: MIT Press.

Sternberg, R.J., Forsythe, G.B., Hedlund, J., Horvath, J.A., Wagner, R.K., Williams, W.M., et al. (2000). *Practical intelligence in everyday life*. New York, NY: Cambridge University Press.

Sternberg, R.J., Grigorenko, E.L., Ferrari, M., & Clinkenbeard, P. (1999). A triarchic analysis of an aptitude-treatment interaction. *European Journal of Psychological Assessment, 15*, 3-13.

Sternberg, R.J., & O'Hara, L.A. (2000). Intelligence and creativity. In R. J. Sternberg (Ed.), *Handbook of intelligence.* (pp. 611-630). New York, NY: Cambridge University Press.

Sternberg, R.J., & Pretz, J.E. (2005). *Cognition & intelligence: Identifying the mechanisms of the mind*. New York, NY: Cambridge University Press

Stone, V.E., Cosmides, L., Tooby, J., Kroll, N., & Knight, R.T. (2002). Selective impairment of reasoning about social exchange in a patient with bilateral limbic system damage. *Proceedings of the National Academy of Sciences, 99*, 11531-11536.

Strack, F., & Deutsch, R. (2004). Reflective and impulsive determinants of social

behavior. *Personality and Social Psychology Review, 8*, 220-247.

Strauss, M.E., Weingartner, H., & Thompson, K. (1985). Remembering words and

how often they occurred in memory-impaired patients. *Memory & Cognition,*

13, 507-510.

Sullivan, E. V., Sagar, H. J., Gabrieli, J. D., & Corkin, S. (1989). Different cognitive

profiles on standard behavioral tests in Parkinson's disease and Alzheimer's

disease. *Journal of Clinical and Experimental Neuropsychology, 11*, 799-820.

Sundstrom, E., Koenigs, R.G., & Huet-Cox, D. (1994). Personality and expressed

values in management teams: MBTI and co-worker ratings on SYMLOG

values. In C. R. Fitzgerald (Ed.), *The Myers-Briggs Type Indicator and*

leadership: Proceedings from an international research conference (pp. 49-59).

College Park, MD: National Leadership Institute.

Tamez, E., Myerson, J., & Hale, S. (2008). Learning, working memory, and

intelligence revisited. *Behavioural Processes, 78*, 240-245.

Taylor, C.W., & Ellison, R.L. (1967). Biographical predictors of scientific

performance. *Science, 155*, 1075-1080.

Tellegen, A. (1985). Structure of mood and personality and their relevance to

assessing anxiety, with an emphasis on self-report. In A. H. Tuma & J. D.

Maser (Eds.), *Anxiety and the anxiety disorders* (pp. 681-706). Minneapolis,

MN: University of Minnesota Press.

The Psychological Corporation. (1995). *DAT for selection-verbal reasoning (European adaptation)*. Orlando, FL: Harcourt Brace and Company.

Thorell, L.B., Lindqvist, S., Nutley, S.B., Bohlin, G., & Klingberg, T. (2009). Training and transfer effects of executive functions in preschool children. *Developmental Science, 12*, 106-113.

Thurstone, L. L. (1938). *Primary Mental Abilities*. Chicago, IL: University of Chicago Press.

Thurstone, L.L. (1924). *The nature of intelligence*. London, UK: Kegan Paul, Trench, Trubner & Co.

Toates, F. (2006). A model of the hierarchy of behaviour, cognition, and consciousness. *Consciousness and Cognition: An International Journal, 15*, 75-118.

Torrance, E.P. (1972). Career patterns and peak creative achievements of creative high school students twelve years later. *Gifted Child Quarterly, 16*, 75-88.

Torrance, E.P. (1974). *Torrance tests of creative thinking*. Bensonville, IL: Scholastic.

Trinidad, D.R., & Johnson, C.A. (2002). The association between emotional intelligence and early adolescent tobacco and alcohol use. *Personality and Individual Differences, 32*, 95-105.

Turke-Browne, N.B., Junge, J.A., & Scholl, B.J. (2005). The automaticity of visual statistical learning. *Journal of Experimental Psychology: General, 134*, 552-564.

Turner, M.L., & Engle, R.W. (1989). Is working memory capacity task dependent? *Journal of Memory and Language, 28*, 127-154.

Underwood, B.J., Boruch, R.F., & Malmi, R.A. (1978). Composition of episodic memory. *Journal of Experimental Psychology: General, 107*, 393-419.

Unsworth, N., & Engle, R.W. (2005a). Individual differences in working memory capacity and learning: Evidence from the serial reaction time task. *Memory & Cognition, 33*, 213-220.

Unsworth, N., & Engle, R.W. (2005b). Working memory capacity and fluid abilities: Examining the correlation between operation span and raven. *Intelligence, 33*, 67-81.

Unsworth, N., & Engle, R.W. (2007). The nature of individual differences in working memory capacity: Active maintenance in primary memory and controlled search from secondary memory. *Psychological Review, 114*, 104-132.

Unsworth, N., Heitz, R., Schrock, J.C., & Engle, R.W. (2005). An automated version of the operation span task. *Behavior Research Methods, 37*, 498-505.

Unsworth, N., Schrock, J.C., & Engle, R.W. (2004). Working memory capacity and the antisaccade task: Individual differences in voluntary saccade control. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 30*, 1302-1321.

Valentine, Elizabeth R. (1975). Performance on two reasoning tasks in relation to intelligence, divergence and interference proneness. *British Journal of Educational Psychology, 45*, 198-205.

van der Zee, K, Thijs, M, & Schakel, L (2002). The relationship of emotional intelligence with academic intelligence and the Big Five. *European Journal of Personality, 16*, 103-125.

Van Rooyen, J. (1994). Creativity: An important managerial requirement: A South African perspective. . In C. Fitzgerald (Ed.), *The Myers-Briggs Type Indicator and leadership: Proceedings from an international research conference* (pp. 49-59). College Park, MD: National Leadership Institute.

Vandenberg, S.G., & Kruse, A.R. (1978). Mental rotations: Group tests of three-dimensional spatial visualization. *Perceptual and Motor Skills, 47*, 599-604.

Vernon, P.E. (1971). *The structure of human abilities*. New York, NY: Methuen.

Visser, B.A., Ashton, M.C., & Vernon, P.A. (2006). Beyond g: Putting multiple intelligences theory to the test. *Intelligence, 34*, 487-502.

Wagner, R.K., & Sternberg, R.J. (1986). Tacit knowledge and intelligence in the everyday world. In R. J. Sternberg & R. K. Wagner (Eds.), *Practical intelligence: Nature and origins of competence in the everyday world* (pp. 51-83). New York, NY: Cambridge University Press.

Walker, C.H. (1987). Relative importance of domain knowledge and overall aptitude on acquisition of domain-related information. *Cognition and Instruction, 4*, 25-42.

Wallach, M. A., & Kogan, N. (1965). *Modes of thinking in young children*: New York, NY: Holt, Rinehart, and Winston.

Wallas (1926). *The art of thought*. New York, NY: Harcout Brace.

Ward, T.B., Smith, S.M., & Finke, R.A. (1999). Creative cognition. In R. J. Sternberg (Ed.), *Handbook of creativity.* (pp. 189-212). New York, NY: Cambridge University Press.

Wason, P. C. (1968). Reasoning about a rule. *The Quarterly Journal of Experimental Psychology, 20*, 273-281.

Wason, P. C., & Evans, J.St.B.T. (1975). Dual processes in reasoning? *Cognition, 3*, 141-154.

Wason, P. C., & Johnson-Laird, P. N. (1972). *Psychology of reasoning: Structure and content.* Oxford, England: Harvard University Press.

Wechsler, D. (1943). Non-intellective factors in general intelligence. *Journal of Abnormal and Social Psychology, 38*, 101-103.

Wechsler, D. (1958). *The Measurement and Appraisal of Adult Intelligence* (4 ed.). Baltimore, MA: The Williams and Wilkins Company.

Wegner, D.M. (1994). Ironic processes of mental control. *Psychological Review, 101*, 34-52.

Westerberg, H., Jacobaeus, H., Hirvikoski, T., Clevberger, P., Ostensson, M. L., Bartfai, A., et al. (2007). Computerized working memory training after stroke -- A pilot study. *Brain Injury, 21*, 21-29.

Westerberg, H., & Klingberg, T. (2007). Changes in cortical activity after training of working memory--a single-subject analysis. *Physiology & Behavior, 92*, 186-192.

Wetherick, N. E. (1995). Reasoning and rationality: A critique of some experimental paradigms. *Theory & Psychology, 5*, 429-448.

Whiteside, S.P., & Lynam, D.R. (2001). The Five Factor Model and impulsivity: Using a structural model of personality to understand impulsivity. *Personality and Individual Differences, 30*, 669-689.

Whiteside, S.P., Lynam, D.R., Miller, J.D., & Reynolds, S.K. (2005). Validation of the UPPS impulsive behaviour scale: A four-factor model of impulsivity. *European Journal of Personality, 19*, 559-574.

Whittemore, R.G., & Heimann, R.A. (1965). Originality responses in academically talented male university freshmen. *Psychological Reports, 16*, 439-442.

Wigan, A.L. (1844). *The duality of mind*. London, UK: Longman, Brown, Green, and Longmans.

Williams, B.A., Myerson, J., & Hale, S. (2008). Individual differences, intelligence, and behavior analysis. *Journal of the Experimental Analysis of Behavior, 90*, 219-231.

Williams, B.A., & Pearlberg, S.L. (2006). Learning of three-term contingencies correlates with Raven scores, but not with measures of cognitive processing. *Intelligence, 34*, 177-191.

Willingham, D.B., & Koroshetz, W.J. (1993). Evidence for dissociable motor skills in Huntington's disease patients. *Psychobiology, 21*, 173-182.

Wilson, T.D. (2002). *Strangers to ourselves*. Cambridge, MA: Belknap Press.

Wilson, T.D., Lindsey, S., & Schooler, T.Y. (2000). A model of dual attitudes. *Psychological Review, 107*, 101-126.

Wilson, T.D., & Schooler, J.W. (1991). Thinking too much: Introspection can reduce the quality of preferences and decisions. *Journal of Personality and Social Psychology, 60*, 181-192.

Winter, B., & Reber, A.S. (1994). Implicit learning and the acquisition of natural languages. In N. Ellis (Ed.), *Implicit and explicit learning of languages* (pp. 115–147). London, UK: Academic Press.

Wirth, S., Yanike, M., Frank, L.M., Smith, A.C., Brown, E.N., & Suzuki, W.A. (2003). Single neurons in the monkey hippocampus and learning of new associations. *Science, 300*, 1578-1581.

Woodrow, H. (1938). The relation between abilities and improvement with practice. *Journal of Educational Psychology, 29*, 215-230.

Woodrow, H. (1946). The ability to learn. *Psychological Review, 53*, 147-158.

Woolhouse, L.S., & Bayne, R. (2000). Personality and the use of intuition: Individual differences in strategy and performance on an implicit learning task. *European Journal of Personality, 14*, 157-169.

Wyer, R.S., Jr. (1997). *The automaticity of everyday life: Advances in social cognition* (Vol. 10). Mahwah, NJ: Lawrence Erlbaum.

Zajonc, R. B. (1980). Feeling and thinking: Preferences need no inferences. *American Psychologist, 35*, 151-175.

Zeidner, M., Matthews, G., & Roberts, R.D. (2001). Slow down, you move too fast: Emotional intelligence remains an 'elusive' intelligence. *Emotion, 1*, 265-275.

Zeidner, M., Roberts, R.D., & Matthews, G. (2004). The emotional intelligence bandwagon: Too fast to live, too young to die? *Psychological Inquiry, 15*, 239-248.

Zhiyan, T., & Singer, J.L. (1997). Daydreaming styles, emotionality and the Big Five personality dimensions. *Imagination, Cognition and Personality, 16*, 399-414.

Zhou, Y., Liang, M., Tian, L., Wang, K., Hao, Y., Liu, H., et al. (2007). Functional disintegration in paranoid schizophrenia using resting-state fMRI. *Schizophrenia Research, 97*, 194-205.

Zsambok, C.E., & Klein, G. (1997). *Naturalistic decision making*. Hillsdale, NJ: Lawrence Erlbaum

Zuckerman, H. (1977). *Scientific elite: Nobel laureates in the United States*. New York, NY: Free Press.

Zuckerman, M. (1994). *Behavioral expressions and biosocial bases of sensation seeking*. New York, NY: Cambridge University Press.

Myers-Briggs Type Indicator (MBTI) (Myers, McCaulley, Quenk, & Hammer, 1998) Thinking/Feeling and Intuition/Sensation Subscales

KEY
I=Intuition
T=Thinking

Part I Which answer comes closest to describing how you usually feel or act?

1.   If you were a teacher, would you rather teach **(I1)**
      (a) fact courses, or
      (b) courses involving theory?

2.   Do you usually get along better with **(I2)**
      (a) imaginative people, or
      (b) realistic people?

3.   Do you more often let **(T1)**
      (a) your heart rule your head, or
      (b) your head rule your heart?

4.   Would you rather be considered **(I3)**
      (a) a practical person, or
      (b) an ingenious person?

5.   Are you more attracted to **(I4)**
      (a) a person with a quick and brilliant mind, or
      (b) a practical person with a lot of common sense?

6.   Is it a higher compliment to be called **(T2)**
      (a) a person of real feeling, or
      (b) a consistently reasonable person?

7.   Would you rather have as a friend someone who **(I5)**
      (a) is always coming up with new ideas, or
      (b) has both feet on the ground?

8.   Are you inclined to **(T3)**
      (a) value sentiment more than logic, or
      (b) value logic more than sentiment?

9.   In reading for pleasure, do you **(I6)**
      (a) enjoy odd or original ways of saying things, or

(b) like the writers to say exactly what they mean?

10.   In doing something that many other people do, does it appeal to you more to
(I7)
(a) do it in the accepted way, or
(b) invent a way of your own?

Part II Which word in each pair appeals to you more? Think about what the words mean, not about how they look or how they sound.

11. (a) abstract   (b) solid **(I8)**

12. (a) gentle   (b) firm **(T4)**

13. (a) facts   (b) ideas **(I9)**

14. (a) thinking   (b) feeling **(T5)**

15. (a) convincing   (b) touching **(T6)**

16. (a) statement   (b) concept **(I10)**

17. (a) analyze   (b) sympathize **(T7)**

18. (a) sensitive   (b) just **(T8)**

19. (a) no-nonsense   (b) theoretical **(I11)**

20. (a) compassion   (b) foresight **(T9)**

21. (a) benefits   (b) blessings **(T10)**

22. (a) theory   (b) certainty **(I12)**

23. (a) determined   (b) devoted **(T11)**

24. (a) idea   (b) actuality **(I13)**

25. (a) strong-willed   (b) tenderhearted **(T12)**

26. (a) imaginative   (b) matter-of-fact **(I14)**

27. (a) objective   (b) passionate **(T13)**

28. (a) make   (b) create **(I15)**

29. (a) warm   (b) objective **(T14)**

30. (a) sensible   (b) fascinating **(I16)**

31. (a) compassionate   (b) logical **(T15)**

32.   (a) production   (b) design **(I17)**

33.   (a) fair-minded   (b) caring **(T16)**

34.   (a) analytical   (b) sentimental **(T17)**

35.   (a) concrete   (b) abstract **(I18)**

36.   (a) practical   (b) sentimental **(T18)**

37.   (a) build   (b) invent **(I19)**

38.   (a) imaginative   (b) realistic **(I20)**

39.   (a) competent   (b) kindhearted **(T19)**

40.   (a) theory   (b) fact **(I21)**

41.   (a) possibilities   (b) certainties **(I22)**

42.   (a) bighearted   (b) firm-minded **(T20)**

43.   (a) novel   (b) already known **(I23)**

44.   (a) tenderness   (b) strength **(T21)**

45.   (a) practical   (b) innovative **(I24)**

Part III   Which answer comes closest to describing how you usually feel or act?

46.   When making a decision, is it more important to you to **(T22)**
       (a) weigh the facts, or
       (b) consider people's feelings and opinions?

47.   Do you generally prefer courses that teach **(I25)**
       (a) concepts and principles, or
       (b) facts and figures?

48.   Which is a higher compliment, to be called **(T23)**
       (a) competent, or

(b) compassionate?

49.   Would you rather work under a boss (or teacher) who is **(T24)**
        (a) good-natured but often inconsistent, or
        (b) sharp-tongued but always logical?

50.   Would you rather **(I26)**
        (a) support the established methods of doing good, or
        (b) analyze what is still wrong and attack unsolved problems?

The Big Five Aspect Scales (BFAS)
(DeYoung, Quilty, & Peterson, 2007)
<u>**KEY**</u>
NW=Neuroticism Withdrawal; NV=Neuroticism Volatility; EA=Extraversion Assertative; EE=Extraversion Enthusiasm; CI=Consientiousness Industriousness; CO=Conscientiousnesss Orderliness; AC=Agreeableness Compassion; AP=Agreeableness Politencess; OI=Intellect/Oppeness Intellect; OO=Intellect/Openess Openness
*Reverse Coded

NW Am easily discouraged.
 AP Avoid imposing my will on others.
*EA Do not have an assertive personality.
 EE Laugh a lot.
 *CI Find it difficult to get down to work.
 *EA Lack the talent for influencing people.
 CO Follow a schedule.
 *EE Rarely get caught up in the excitement.
OI Like to solve complex problems.
 CO Keep things tidy.
 AC Take an interest in other people's lives.
 *AC Am not interested in other people's problems.
 CI Get things done quickly.
NV Get easily agitated.
 AC Sympathize with others' feelings.
 *AP Take advantage of others.
OI Am quick to understand things.
OO See beauty in things that others might not notice.
 AC Inquire about others' well-being.
 *AP Love a good fight.
 *CI Mess things up.
 AP Rarely put people under pressure.
OI Formulate ideas clearly.
 AP Respect authority.
 OO Enjoy the beauty of nature.
 *AP Am out for my own personal gain.
OI Have a rich vocabulary.
*AP   Seek conflict.
OO Need a creative outlet.
*OO Seldom daydream.
 *CO Leave my belongings around.
*OI Avoid philosophical discussions.
*CI Don't put my mind on the task at hand.

*NW Am not embarrassed easily.
 CO See that rules are observed.
*OO Seldom notice the emotional aspects of paintings and pictures.
 NV Can be stirred up easily.
*OI Avoid difficult reading material.
 *CO Dislike routine.
 *EE Am not a very enthusiastic person.
EA See myself as a good leader.
 NW Am afraid of many things.
 *NV Rarely get irritated.
EA Am the first to act.
CO Want everything to be 'just right'.
 *CI Waste my time.
 AC Like to do things for others.
 *NV Keep my emotions under control.
 *CI Am easily distracted.
 *NV Rarely lose my composure.
*OI Have difficulty understanding abstract ideas.
 AC Feel others' emotions.
 *CO Am not bothered by messy people.
 EA Have a strong personality.
 *AC Don't have a soft side.
 *NW Seldom feel blue.
*OO Do not like poetry.
 OO Believe in the importance of art.
OO Love to reflect on things.
 *AP Insult people.
 NW Am filled with doubts about things.
*EA Wait for others to lead the way.
OI Think quickly.
 CI Finish what I start.
 CO Want every detail taken care of.
 *AC Can't be bothered with other's needs.
 *CI Postpone decisions.
 CI Always know what I am doing.
 *AC Am indifferent to the feelings of others.
*EA Hold back my opinions.
 EE Make friends easily.
 *NW Feel comfortable with myself.
 *EE Reveal little about myself.
 *EE Am hard to get to know.
 AP Hate to seem pushy.
 NV Get angry easily
 NW Become overwhelmed by events.

*CO Am not bothered by disorder.
 EA Take charge.
OI Can handle a lot of information.
 EE Warm up quickly to others.
 NV Get upset easily.
 *AP Believe that I am better than others.
 CO Like order.
EA Can talk others into doing things.
 *NV Am not easily annoyed.
 *EE Keep others at a distance.
 EE Have a lot of fun.
 EE Show my feelings when I'm happy.
 CI Carry out my plans.
 NV Change my mood a lot.
*OI Learn things slowly.
 EA Know how to captivate people.
 *AC Take no time for others.
 *NW Rarely feel depressed.
*OO Seldom get lost in thought.
 NV Am a person whose moods go up and down easily.
 NW Feel threatened easily.
 NW Worry about things.
OO Get deeply immersed in music.

NEO-PI-R (Costa & McCrae, 1992) Openness to Experience Facets
<u>KEY</u>
I=Ideas; FE=Feelings; AC=Actions; A=Aesthetics; V=Values; F=Fantasy

I I sometimes lose interest when people talk about very abstract, theoretical matters.
*FE I seldom notice the mood or feelings that difference environments produce.
*AC Once I find the right way to do something, I stick to it.
*AC I prefer to spend my time in familiar surroundings.
A I am sometimes completely absorbed in music I am listening to.
I I have a lot of intellectual curiosity.
*I I find philosophy arguments boring.
*FE I rarely experience strong emotions.
FE I experience a wide range of emotions and feelings.
*A Watching ballet or modern dance bores me.
*AC I'm pretty set in my ways.
A I enjoy reading poetry that emphasizes feelings and images more than story lines.
AC I think it's interesting to learn and develop new hobbies.
*V I believe that loyalty to one's ideals and principles is more important than 'open-mindedness.'
*V I believe we should look to our religious authorities for decisions on moral issues.
I I enjoy working on 'mind-twister'-type puzzles.
AC Sometimes I make changes around the house just to try something different.
A Certain kinds of music have an endless fascination for me.
V I believe that the different ideas of right and wrong that people in other societies have may be valid for them.
V I believe that laws and social policies should change to reflect the needs of a changing world.
FE I find it easy to empathize-to feel myself what others are feeling.
*AC On a vacation, I prefer going back to a tried and true spot.
I I enjoy solving problems or puzzles.
A Sometimes when I am reading poetry or looking at a work of art, I feel a chill or wave of excitement.
AC I often try new and foreign foods.
I I often enjoy playing with theories or abstract ideas.
FE Without strong emotion, life would be uninteresting to me.
*I I have little interest in speculating on the nature of the universe or the human condition.
V I consider myself broad-minded and tolerant of other people's lifestyles.
*AC I follow the same route when I go someplace.
F I have a very active imagination.
A I am intrigued by the patterns I find in art and nature.

I I have a wide range of intellectual interests.

*F I try to keep all my thoughts directed along realistic lines and avoid flights of fancy.

FE How I feel about things is important to me.

*F I would have difficulty just letting my mind wander without control of guidance.

*V I believe letting students hear controversial speakers can only confuse and mislead them.

F I enjoy concentrating on a fantasy or daydream and exploring all its possibilities, letting it grow and develop.

FE Odd things-like certain scents or the names of distant places-can evoke strong mood in me.

*V I believe that the 'new morality' of permissiveness is no morality at all.

*FE I seldom pay much attention to my feelings of the moment.

*F As a child I rarely enjoyed games of make believe.

*F I don't like to waste my time daydreaming.

*A Poetry has little or no effect on me.

*A Aesthetic and artistic concerns aren't very important to me.

*V I think that if people don't know what they believe in by the time they're 25, there's something wrong with them.

F I have an active fantasy life.

*F If I feel my mind starting to drift off into daydreams, I usually get busy and start concentrating on some work or activity instead.

Rational-Experiential Inventory (REI)
(Epstein, Pacini, & Norris, 1998)

Key

RA=Rational Ability; RF=Rational Favorability; EA=Experiential Ability;
EF=Experiential Favorability

*RA I'm not that good at figuring out complicated problems.

*EA If I were to rely on my gut feelings, I would often make mistakes.

RF I prefer complex to simple problems.

*EF I generally don't depend on my feelings to help me make decisions.

RA I have no problem in thinking things through clearly.

EA When it comes to trusting people, I can usually rely on my gut feelings.

*RF Thinking is not my idea of an enjoyable activity.

EF I like to rely on my intuitive impressions.

*RA I am not a very analytical thinker.

EA I believe in trusting my hunches.

RF I enjoy solving problems that require hard thinking.

*EF I think it is foolish to make important decisions based on feelings.

*EA I suspect my hunches are inaccurate as often as they are accurate.

RA I usually have clear, explainable reasons for my decisions.

*RF Knowing the answer without having to understand the reasoning behind it is good enough for me.

*EF I would not want to depend on anyone who described himself or herself as intuitive.

RA Using logic usually works well for me in figuring out problems in my life.

RF I enjoy intellectual challenges.

EA I can usually feel when a person is right or wrong, even if I can't explain how I know.

EF I often go by my instincts when deciding on a course of action.

*EA My snap judgments are probably not as good as most people's.

*RA Reasoning things out carefully is not one of my strong points.

*EF I don't like situations in which I have to rely on intuition.

*RF I try to avoid situations that require thinking in depth about something.

EA I trust my initial feelings about people.

RA I have a logical mind.

*EF I don't think it is a good idea to rely on one's intuition for important decisions.

*RF I don't like to have to do a lot of thinking.

*EA I don't have a very good sense of intuition.

*RA I am not very good in solving problems that require careful logical analysis.

EF I think there are times when one should rely on one's intuition.

RF I enjoy thinking in abstract terms.

EA Using my 'gut feelings' usually works well for me in figuring out problems in my life.

*RA I don't reason well under pressure.

EF I tend to use my heart as a guide for my actions.

*RF Thinking hard and for a long time about something gives me little satisfaction.

EA I hardly ever go wrong when I listen to my deepest 'gut feelings' to find an answer.

RA I am much better at figuring things out logically than most people.

EF Intuition can be a very useful way to solve problems.

RF Learning new ways to think would be very appealing to me.

The UPPS Impulsivity Scale
(Whiteside & Lynam, 2001)

Key
U=Urgency; P=Perseverance; PR=Premeditation; S=Sensation Seeking
*Reverse Coded

U It is hard for me to resist acting on my feelings.
 P Once I start a project, I almost always finish it.
 S I would like to learn to fly an airplane.
 PR Before I get into a new situation I like to find out what to expect from it.
 P Once I get going on something I hate to stop.
 P I concentrate easily.
 S I welcome new and exciting experiences and sensations, even if they are a little frightening and unconventional.
 P I'm pretty good about pacing myself so as to get things done on time.
 S I would enjoy parachute jumping.
 P I am a productive person who always gets the job done.
 S I would like to go scuba diving.
 PR I don't like to start a project until I know exactly how to proceed.
 *P There are so many little jobs that need to be done that I sometimes just ignore them all.
 PR I like to stop and think things over before I do them.
 *P I tend to give up easily.
 PR I have a reserved and cautious attitude toward life.
 U Sometimes I do things on impulse that I later regret
 PR Before making up my mind, I consider all the advantages and disadvantageS
 U In the heat of an argument, I will often say things that I later regret.
 U I have trouble resisting my cravings (for food, cigarettes, etc.)
 S I quite enjoy taking risks.
 U I often get involved in things I later wish I could get out of.
 PR I usually think carefully before doing anything.
 U When I feel rejected, I will often say things that I later regret.
 U I often make matters worse because I act without thinking when I am upset.
 U When I feel bad, I will often do things I later regret in order to make myself feel better now.
 S I like sports and games in which you have to choose your next move very quickly.
 PR I tend to value and follow a rational, ``sensible'' approach to things.
 PR My thinking is usually careful and purposeful.
 *U I am always able to keep my feelings under control.
 P Unfinished tasks really bother me.
 S I would enjoy the sensation of skiing very fast down a high mountain slope.
 U Sometimes when I feel bad, I can't seem to stop what I am doing even though it is making me feel worse.

S I generally seek new and exciting experiences and sensations.
U I have trouble controlling my impulses.
P I finish what I start.
PR I am a cautious person.
U When I am upset I often act without thinking.
S I'll try anything once.
P I generally like to see things through to the end.
S I would enjoy fast driving.
S I sometimes like doing things that are a bit frightening.
S I would enjoy water skiing.
PR I usually make up my mind through careful reasoning.
PR I am not one of those people who blurt out things without thinking.

Need for Uniqueness Scale
(Snyder & Fromkin, 1977)

Key
LC=; D=; R=
*Reverse-Coded

*LC I do not like to say unusual things to people.
D People have sometimes called me 'stuck-up'.
*LC I am unable to express my feelings if they result in undesirable consequences.
R Whenever I take part in group activities, I am somewhat of a nonconformist.
*LC In most things in life, I believe in playing it safe rather than taking a gamble.
*LC I sometimes hesitate to use my own ideas for fear they might be impractical.
*R I always try to follow rules.
R I would rather be known for always trying new ideas than for employing well trusted methods.
*LC I do not like to go my own way.
*LC When I am with a group of people, I agree with their ideas so that no arguments will arise.
D I tend to express my opinions publicly, regardless of what others say.
*LC I would rather be just like everyone else than be called a 'freak'.
R I do not always need to live by the rules and standards of society.
*LC It bothers me if people think I am being too unconventional.
D As a rule, I strongly defend my own opinions.
R I find it sometimes amusing to upset the dignity of teachers, judges, and cultured people.
D When I am in a group of strangers, I am not reluctant to express my opinion publicly.
*LC Others' disagreements make me uncomfortable.
*LC I find that criticism affects my self-esteem.
R I think society should let reason lead it to new customs and throw aside old habits or mere traditions.
LC Being a success in one's career means making a contribution that no one else has made.
*R I like wearing a uniform because it makes me proud to be a member of the organization it represents.
*LC Feeling 'different' in a crowd of people makes me feel uncomfortable.
R It is better to break rules than always to conform with an impersonal society.
R I must admit I find it hard to work under strict rules and regulations.
*LC I tend to keep quiet in the presence of persons of higher rank, experience, etc.
*LC It is better always to agree with the opinions of others than to be considered a disagreeable person.
D If I disagree with a superior on his or her views, I usually do not keep it to myself.
R If I must die, let it be an unusal death rather than an ordinary death in bed.

R I have been quite independent and free from family rule.
*LC People frequently succeed in changing my mind.
D I speak up in meetings in order to oppose those whom I feel are wrong.

Table B-1
Full covariance matrix used to fit SEM model in Chapter 3: Explicit Cognitive Ability (N = 169)

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. RAPM	–																		
2. DAT-V	.53	–																	
3. MRT-A	.59	.43	–																
4. SPEEDV	.17	.24	.14	–															
5. SPEEDF	.24	.15	.17	.24	–														
6. SPEEDN	.25	.10	.21	.14	.51	–													
7. Ospan2	.12	.25	.11	.20	.11	.08	–												
8. Ospan3	.24	.21	.18	.19	.09	.03	.33	–											
9. Ospan4	.23	.41	.23	.19	.12	.13	.35	.38	–										
10. Ospan5	.27	.34	.21	.22	.16	.11	.27	.37	.56	–									
11. Ospan6	.21	.30	.16	.10	.08	.03	.25	.26	.55	.60	–								
12.ThreeTerm1	.17	.18	.12	.86	.23	.05	.07	.10	.08	.16	.17	–							
13.ThreeTerm2	.32	.30	.21	.84	.15	-.01	.07	.11	.04	.16	.15	.72	–						
14.ThreeTerm3	.30	.35	.20	.10	.14	.01	.12	.10	.07	.16	.20	.57	.84	–					
15.ThreeTerm4	.30	.34	.17	.07	.16	.05	.15	.14	.11	.20	.20	.46	.74	.90	–				
16. PA1	.20	.20	.07	.14	.18	-.04	.05	.08	.05	.09	.19	.48	.58	.67	.59	–			

17. PA2	.30	.25	.12	.16	.19	-.02	.05	.09	.03	.12	.17	.33	.52	.65	.65	.84	–	
18. PA3	.28	.20	.14	.16	.15	-.05	.03	.10	.01	.15	.12	.24	.45	.58	.64	.69	.89	–
19. PA4	.30	.22	.15	.16	.14	-.08	.04	.11	.02	.18	.10	.21	.44	.55	.61	.60	.82	.94	–

Table B-2

Full covariance matrix used to extract four-factor model in Chapter 6: Four-Factor Model

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. RAPM	–															
2. DAT-V	.51	–														
3. MRT-A	.58	.42	–													
4. WM	.29	.42	.24	–												
5. E-AL	.33	.32	.18	.19	–											
6. REI Rat. Fav.	.40	.32	.26	.24	.19	–										
7. NEO Ideas	.43	.37	.30	.25	.25	.79	–									
8. BFAS-I	.30	.40	.25	.25	.18	.69	.70	–								
9. NEO Feel.	.04	.13	.03	.18	.18	.28	.31	.22	–							
10. MBTI Feel.	-.12	-.06	-.23	.02	.07	-.28	-.14	-.31	.37	–						
11. REI Exp.	-.17	-.13	-.14	-.02	.00	-.06	.05	-.12	.31	.38	–					
12. BFAS-O	.14	.29	.03	.14	.12	.22	.34	.20	.50	.25	.20	–				
13.NEO Aes.	.08	.20	-.05	.14	.09	.27	.45	.29	.51	.24	.21	.73	–			
14. MBTI Int.	.16	.20	.05	.10	.03	.26	.34	.14	.17	.17	.10	.46	.37	–		
15. NEO Fant.	.16	.21	.11	.22	.12	.21	.29	.19	.37	.18	.16	.46	.36	.39	–	
16. NEO Ac.	.04	.11	.01	.15	.01	.21	.24	.22	.39	.10	.24	.36	.36	.24	.19	–

N	177	177	177	177	170	164	148	166	148	164	164	166	148	164	148	148
Mean	21.7	24.5	13.1	44.6	49.6	3.6	3.5	3.6	3.9	15.0	3.3	3.8	3.4	18.6	3.9	3.1
S.D.	5.4	5.8	5.4	8.6	18.6	.64	.70	.58	.63	5.8	.51	.60	.84	5.4	.65	.54
Reliability (α)	.81	.78	.85	.73	.92	.82	.80	.77	.78	.88	.88	.72	.81	.86	.78	.61

Notes: Correlations > .16 in absolute value are significant at p < .05. RAPM's *N* = 160; missing values were imputed using data from the other two markers of *g* (DAT-V and MRT-A). MRT-A's *N* = 176; missing values were imputed using data from the other two markers of *g* (RAPM and DAT-V). Reliability for AL was calculated by averaging the alpha reliability of PA (.94) and the alpha reliability of Three-Term (.89).

Table B-3

Factor Analysis of BFAS and UPPS scales (N = 160)

Measure	1	2	3
UPPS Perseverance	**.86**	-.05	-.32
BFAS Industriousness (C)	**.81**	.09	**-.40**
BFAS Orderliness (C)	**.72**	-.19	-.01
UPPS Premeditation	**.58**	**-.52**	-.10
BFAS Assertiveness (E)	.13	**.80**	-.13
BFAS Enthusiasm (E)	-.05	**.63**	-.10
UPPS Sensation Seeking	-.17	**.48**	-.12
BFAS Volatility (N)	-.12	.02	**.82**
BFAS Withdrawal (N)	-.17	**-.44**	**.73**
UPPS Urgency	**-.48**	.20	**.66**
BFAS Politeness (A)	.11	-.35	-.19
BFAS Compassion (A)	-.17	.20	.09

Notes: Factor analysis technique is Principal Axis Factoring with a Direct Oblimin Rotation. Factor loadings above .40 (in absolute terms) have been bolded. $\lambda 1 = 3.24$ (27.03% Variance), $\lambda 2 = 2.59$ (21.54% Variance), $\lambda 3 = 1.54$ (12.79% Variance). Total Variance Accounted for: 61.36%.

Table B-4

Factor Analysis of BFAS and UPPS Scales (N=160)

Measure	1	2	3
BFAS Conscientiousness	**.91**	-.06	-.25
UPPS Perseverance	**.87**	.00	-.30
UPPS Premeditation	**.54**	**-.53**	-.25
UPPS Urgency	**-.45**	.15	**.79**
Neuroticism	-.19	-.36	**.70**
Extraversion	.10	**.73**	.02
UPPS Sensation Seeking	-.12	**.53**	.01
Agreeableness	.01	-.03	-.04

Notes: Factor analysis technique is Principal Axis Factoring with a Direct Oblimin Rotation. Factor loadings above .40 (in absolute terms) have been bolded. $\lambda 1 = 2.61$ (32.67% Variance), $\lambda 2 = 1.77$ (22.16% Variance), $\lambda 3 = 1.04$ (12.97% Variance). Total Variance Accounted for: 67.80%.

Four implicit learning tasks were administered in the current dissertation: Probabilistic Serial Reaction Time Learning, Artificial Grammar Learning, Invariance Learning, and Contextual Cueing. While all four implicit learning tasks showed significant learning at the group level (i..e, implicit learning was demonstrated), only the Probabilistic Serial Reaction Time (P-SRT) task proved to be the most informative at the individual differences level. Therefore, the results of the P-SRT task are presented in *Chapter 4: Implicit Learning*. This appendix presents results from the other three implicit learning tasks.

Artificial Grammar Learning

Methodology

During the learning phase, participants were instructed to memorize 20 exemplary letter strings generated by a finite-state grammar (see Figure C-1). The letter strings appeared on a computer screen, one at a time for 3s, after which the participant was prompted to reproduce the string by typing it on the keyboard. If the letter string was reproduced correctly, the subject was so informed and a new letter string was presented. If an error was made, the subject was asked to try again and the letter reappeared. All 20 exemplars were presented twice for a total of 40 learning trials. Participants were not told anything at this point about the rule-governed nature of the letter strings. The instructions described a simple memory experiment.

Figure C-1

The finite-state grammar used in the current dissertation. The grammar generates letter strings by following the arrows from the input state (s1) to the terminal state (s6).
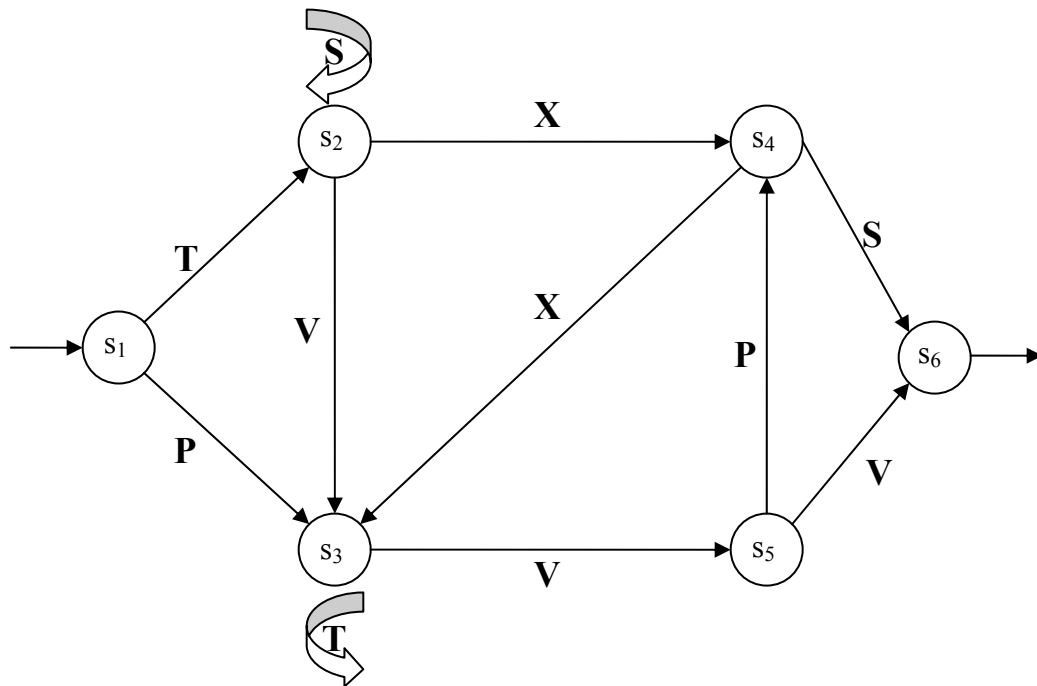
At the beginning of the testing phase, participants were informed that the letter strings they had just memorized were actually formed according to a complex set of rules, and that they would now be tested on their knowledge of those rules. During the testing phase, participants were presented with 50 letter strings, one at a time and were instructed to respond "yes" (by pressing the Y key) or "no" (by pressing the N key) depending on whether or not their immediate gut reaction told them that the string conformed to the rules of the grammar. The testing stimuli consisted of 26 grammatical letter strings (7 of which came from the original set) and 24 nongrammatical letter strings, which were formed by introducing one or more violations into otherwise grammatical letter strings. The entire set was

presented twice. Therefore, 100 well-formedness judgments were made by each participant. Participants received no feedback during this phase of the experiment, and were not told that the same test strings would be presented twice. During post-experiment interviews, participants revealed that they felt that some of the bigrams and trigrams were familiar, but said that they did not detect any underlying rule during the learning phase.

Results

The mean score for Artificial Grammar Learning was 61.6 (N=174, $S.D.$=6.7, Min=41, Max=80), which was significantly above a chance score of 50 [t(173)=22.93, p < .01]. The correlation between Block 1 and Block 2 was significant [r(174)=.57, p < .01].   The alpha reliability of the total task was .54. The alpha reliability of Block 1 was .37. The alpha reliability of Block 2 was .14. Both blocks demonstrated accuracy levels significantly above chance. Block 1 t(173)=18.08, p < .01 and Block 2 t(173)=20.30, p < .01.

Errors made during the learning phase were significantly correlated with Explicit Cognition Ability [r(143)=-.46, p < .01], Intellectual Engagement [r(143)=-.19, p < .01], and Aesthetic Engagement [r(143)=-.25, p < .01]. There was no significant correlation with Affective Engagement.

Accuracy during the test phase (out of 100) was not related to either of the four factors, but was significantly correlated with RAPM [r(174)=.15, p < .05], and NEO Ideas [r(174)=.20, p < .05]. These effects seem to be a result of Block 2, since accuracy during Block 2 was significantly correlated with Intellectual Engagement

[r(143)=.22, p < .01], REI Rational [r(161)=.22, p < .01], NEO Ideas [r(145)=.25, p < .01], and BFAS Intellect [r(163)=.19, p < .05], and self-reported Achievement in Scientific Discovery [Spearman's rho(174)=.16, p < .05], whereas accuracy during Block 1 was not correlated with any of these variables. Instead, accuracy during Block 1 was only significantly correlated (all negative correlations) with BFAS Volatility [r(163)=-.16, p < .05], and self-reported Achievement in Music [Spearman's rho(174)=-.21, p < .01], Humor [Spearman's rho(174)=-.16, p < .05], CAQ Arts factor [Spearman's rho(174)=0.16, p < .05], and CAQ total score [Spearman's rho(174)=-.16, p < .05]. In terms of GCSE scores, total AG learning was positively correlated with GCSE Math [r(165)=.17, p < .05] and negatively correlated with GCSE English Literature [r(153)=-.19, p < .05]. Again, this result seems to be a result of performance on Block 2, as accuracy on Block 1 was not related to these variables. Further, controlling for Explicit Cognitive Ability, GCSE Math was no longer correlated with total AG learning or Block 2 of learning.

Taken together, and considering that the items on block 2 are the same items as Block 1, and presented in the same order as Block 1, the results suggest that Block 2's correlation with the aforementioned variables reflect explicit memory for responses on the prior block (Block 1) than genuine implicit learning.

Invariance Learning

This task has been used to demonstrate the incidental and automatic nature of the process by which learners extract invariant information maintained across a set of stimuli, both in artificial settings (McGeorge & Burton, 1990) and in real-word situations (Kelly, Burton, Kato & Akamatsu, 2001). In contrast with the memorization task usually arranged in the artificial grammar learning paradigm, participants in this task are provided with an orienting task that does not require them to try to commit the items to memory. However, although the task does not require them either to detect regularities or to memorize individual items, the measures of learning indicate that participants acquire some sensitivity to the hidden regularity, as they tend to falsely recognize as old the new items that fulfill the observed regularity.

During the learning phase, participants are presented with a series of 40 (20 unique, each one presented twice) four digit numbers on the computer screen. Participants are instructed to compare the sum of the two left-hand digits with the sum of the two right-hand digits, and to indicate which sum is larger by pressing "Z" for right or "M" for "left". Unknown to the participants, all the letter strings in this phase have the same "invariant" feature; they all have the number 3 in them.

In the test phase, participants encountered 60 (30 unique, each one presented twice) two four digit number strings and were told to indicate which string they just encountered during the learning phase. Unknown to the participant, none of the strings in the testing phase came from the original set. Some of the

strings had a number 3 in them, and some did not. Learning was measured by how many strings the participant chose that consisted of the number 3. During post-experiment interviews, some participants reported that certain strings "felt" more familiar than others. No participant, however, discovered the invariant feature of the task (that all the learning stimuli had a number 3 in them).

Results

The mean score for invariance learning (out of 60) was 32.2 (*N*=176. *S.D.*=5.1, Min=19, Max=46), which was significantly above a chance score of 30 [t(175)=2.22, p < .01]. Learning on each Block was also significant [Block 1: t(175)=7, p < .01; Block2: t(175)=2.3, p < .05]. Cronbach's alpha for all learning was .46 (*N*= 176). Alpha for Block 1 was .27 and was .39 for Block 2.

Errors made during the learning phase were significantly correlated with Explicit Cognitive Ability [r(146)=.20, p < .05], but none of the other factors. Accuracy on the test phase, however, did not correlate with any variables of interest.

Contextual Cueing[i]

A continuous version of the Contextual Cueing task was used, in which successive trials followed each other with minimal delay and were not preceded by a fixation point. Jiménez and Vázquez (2008) have shown that this procedure results in levels of learning similar to the usual discrete version developed by Chun and Jiang (1998). In addition, Jiménez and Vázquez's (2008) procedure was followed by using four different responses instead of the usual two-alternative task. This procedure was chosen to make the motor requirements of this task more

[i] Thanks to Jamie Brown for the description of this task.

comparable to those required by the SRT task (see *Chapter 2: Methodology*). Therefore, should specific deficits emerge, they can be more confidently attributed to differences in learning rather than motor capabilities. The participants were required to detect and identify as fast and accurately as possible an even number presented among distractors, which were odd numbers. The target numbers (2, 4, 6 or 8) were presented among seven distractor stimuli of the same numerical identity (either 1's, 3's, 5's or 7's). Participants responded by pressing buttons corresponding to the target's numerical identity (2, 4, 6 or 8).

As depicted in Figure C-2, on each trial there were two stimuli of each color, the stimuli were evenly distributed over the four quadrants of the display, and within a trial, the numerical identity of the distracters was fixed. However, the precise combination of location and color of distracters created a context for the location of a target on each trial. 40 such combinations were generated. 8 of these combinations were repeated frequently (24 times within each session) and will be referred to hereon as high-frequency contexts. The remaining 32 combinations were repeated infrequently (6 times per session) and will hereon be referred to as low-frequency contexts. Of the 8 high-frequency contexts, two contexts contained 1's, two contained 3's, two contained 5's and two contained 7's. Of the 32 low-frequency contexts, there were equal numbers of each of the distracter numerical identities. Thus, the high frequency contexts allowed greater opportunity in comparison to the low frequency contexts for participants to be cued by the combination of location, identity and color to the location of the target in order for the participant to

determine its numerical identity. Different trials types (high frequency and low

frequency contexts) were randomly intermixed across all experimental blocks (1-8).

Each experimental block consisted of 48 trials. Half of all trials within a block

contained high-frequency contexts and the remaining half low frequency contexts.

Figure C-2[j]
The difference between cued (C) and random (R) trials

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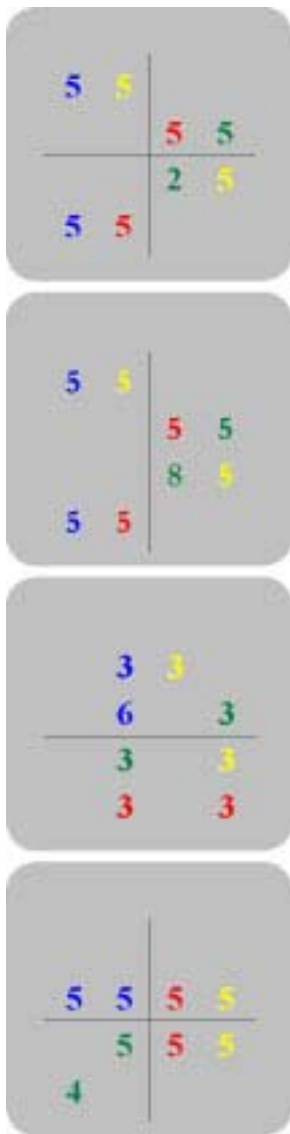
[j] Thanks to Jamie Brown for the graphic depicted in Figure C-2.

The session began with a practice block, consisting of 8 trials. The first 3 trials repeated the same context and the remaining 5 trials contained unique contexts. None of these contexts appeared in the experimental blocks. Between each block, the experimenter provided the participant with feedback about their accuracy and reaction times. Feedback was provided following any trial on which a participant made an error, by presenting the word error at the top of the screen before the next trial was presented. At the start of each session, the quadrant was presented and remained on the screen for the entire block. After 200ms, the first trial began with the presentation of the distracters and target. Each trial was terminated following a response and trials were separated by a 200 ms interval. Learning on this task is normally assessed by comparing each participant's reaction time (RT) in response to either the cued trials or the random trials.

Results

Contextual Cueing data was collected for all participants except one (#174). Further, one participant (#151) was removed from the analysis because their average RT was less than 100ms and their percentage of hits was minimal, suggesting they were not performing the task properly. Error responses were discarded (7.2%) as well as outliers beyond three standard deviations from the mean, computed individually for each block and participant. On average, 1.5% of the trials qualified as outliers according to these criteria.

A repeated-measures analysis of variance (ANOVA) with block (8) and type of trial (2, fixed vs. variable context) was conducted on the measures of RT. The

results showed a significant effect of block, $F(7,1218) = 16.46$; $p < .0001$ partial h^2 = .09, and type of trial, $F(1,174) = 364.44$ $p < .0001$, partial h^2 =0.68, as well as a significant interaction block x type of trial, $F(7,1064) = 19.99$ $p < .0001$, partial h^2 =0.10, indicating the acquisition of learning about the fixed contexts. As is evident from an inspection of Figure C-3, a change in the response trends seems to occur from block 3 onwards, in which the differences between responding to fixed vs. variable contexts increased. A comparison of the effect of learning between the first two and the last six blocks of training showed that the difference between responding to training and control trials was significantly larger over the latter blocks $F(1, 174)= 364.10$, $p <.0001$.

Figure C-3
Contextual Cueing Performance for fixed and variable trials (N = 175)
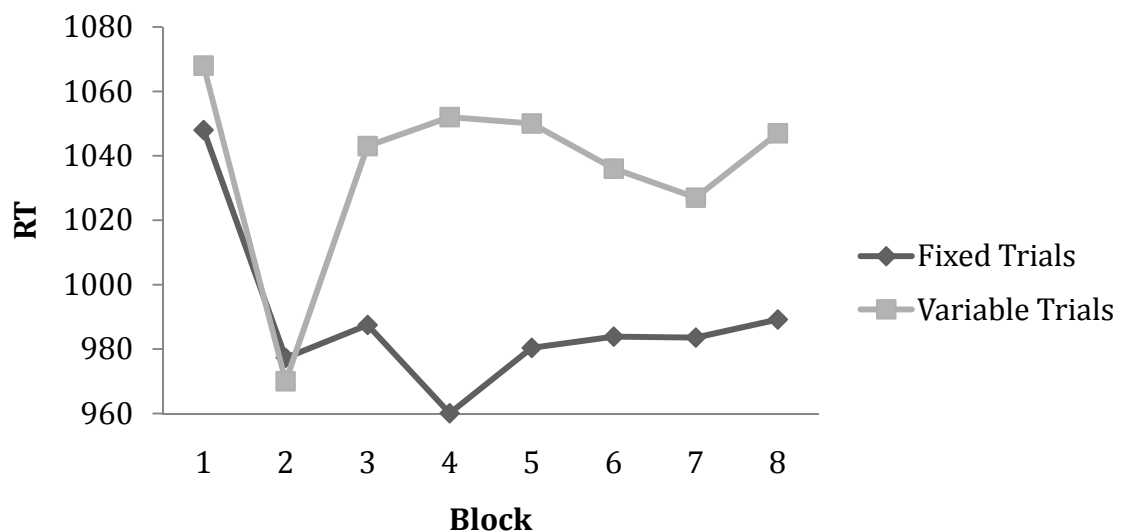
When investigating individual differences, it has been assumed that such a learning score can be used to provide a rank ordering of ability to learn on the Contextual Cueing Task. However, this assumption may be flawed because the exact

difference in RT may not be stable enough to provide a reliable rank order. More important than the exact RT difference between probable and improbable trials may be simply whether or not individuals show any reliable difference between RTs to probable and improbable trials.

I therefore employed the same dichotomous scoring method that I employed with the Probabilistic Serial Reaction Time task (see *Chapter 2: Methodology*) to the Contextual Cueing Task to assess whether each participant learned in each block. Rather than calculate an exact RT difference, I simply assessed whether participants showed a learning effect at least as large as the significant learning effect evident in the sample as a whole across blocks three through eight.

The average Cohen's *d* across these blocks was .20. Because the average difference between the conditions across these blocks was .20 standard deviations, I assessed for each participant in each block of learning whether their mean RT for probable trials was less than the difference between their mean RT for improbable trials and .20 times the standard deviation for RT on improbable trials. If it was less, they received a score of 1. If it was not, they received a score of 0. To calculate a total score for each participant, I summed their score across the last six blocks, yielding a minimum score of 0 and a maximum score of 6.

The new scoring method demonstrated an alpha reliability of .33 (split-half reliability using Spearman-Brown correction of .27) and the distribution was normal. The old scoring method relying on RT differences demonstrated an alpha

reliability of .05 (split-half reliability using Spearman-Brown correction of .03). The correlation between the old scoring method and the new scoring method was .67.

Even though the dichotomous scoring method increased the reliability of the task, Contextual Cueing did not correlate with any variables of interest. Interestingly, when a dichotomous learning score was calculated over just the last *four* blocks (instead of the last six blocks), the total contextual cueing score was negatively correlated with the Affective Engagement factor [r(144)=-.18, p < .05], and NEO Feeling [r(-162)=-.16, p < .05] and positively correlated with a summed processing speed (Gs) score [r(169)=.22, p < .01], BFAS Intellect [r(164)=.18, p < .05], BFAS Orderliness [r(164)=.16, p < .05], BFAS Conscientiousness [r(164)=.16, p < .05], and REI Rational [r(162)=.17, p < .05].

This suggests that while implicit learning on this task is robust at the group level, individual differences in performance may have to do more with concentration, as evidenced by the correlation in the later blocks with variables such as processing speed, conscientiousness, and intellect.

Correlations among the implicit learning tasks

Table C-1 shows the correlations among the four implicit learning tasks administered in the current dissertation.

Table C-1

Correlations among the four implicit learning tasks administered in the current dissertation

Measure	1	2	3	4
1. P-SRT	–	*153*	*153*	*150*
2. CC	.00	–	*176*	*174*
3. INVAR	.03	.04	–	*173*
4. AGL	-.06	.01	-.02	–

Note: *N* above diagonal. P-SRT=Probabilistic Serial Reaction Time Learning, CC=Contextual Cueing, INVAR=Invariance Learning (Total Score), AGL=Artificial Grammar Learning (Total Score).

All of the correlations hover around zero, suggesting that individual differences among these four implicit learning tasks are almost entirely uncorrelated with each other. This could be due to various reasons, such as the unreliability of the tasks, differing ratio of explicit and implicit processes required for successful completion, differing neural substrates, etc. Another reason may be that some implicit learning functions may be so optimized in humans that there are no meaningful individual differences. In the current dissertation, only the Probabilistic Serial Reaction Time Task significantly correlated with cognition and personality above and beyond the effects of g and the ECTs contributing to g (see *Chapter 4: Implicit Learning*).

Recent research (Gebauer & Mackintosh, 2009) suggests that when a larger battery of implicit learning tasks is administered, a second-order factor emerges that is distinct from a first-order general intelligence factor. Therefore, with a larger

implicit learning battery, common sources of variance amongst the various implicit

functions may be more evident. At any rate, this is an exciting line of research that

certainly deserves more attention.