Canadian Policy Research Networks | Réseaux canadiens de recherche en politiques publiques

SCHOOL OF Policy Studies

Statistics Canada | Statistique Canada

Increasing Adaptive Expertise: The Next Frontier in Human Capital Development

by

Jacqueline P. Leighton
University of Alberta
Centre for Research in Applied Measurement and Evaluation (CRAME)

Skills and Knowledge for Canada's Future: Seven Perspectives

Towards an Integrated Approach to Human Capital Development

Table of Contents

Executive Summary

Human capital is an economic term used to describe the *skills and knowledge that individuals draw upon to generate outputs of value*, such as innovation and productivity in job performance. In the present paper, the lower-order variables (i.e., neural efficiency, neural plasticity and working memory) associated with the development of human capital are examined. A large body of research suggests that variables such as neural efficiency and working memory predict measured intelligence (Kyllonen and Christal 1990; see also Engle, Tuholski, Laughlin, and Conway 1999; Hambrick, Kane, and Engle 2005). In turn, tests of intelligence have been found to aid in the prediction of school grades, occupational outcomes (especially academic, professional and management) and performance on the job (Ceci 2000; Schmidt and Hunter 2004). Simply put, then, intelligence tests reliably predict performance in knowledge-intensive domains. As such, when negative relationships are found between neural efficiency and cognitive activity (for example, Haier et al. 1988; Haier et al. 1992a, 1992b; Neubauer, Freudenthaler, and Pfurtscheller 1995; Neubauer, Sange, and Pfurtscheller 1999; Parks et al. 1988), suggesting that more intelligent people use their brains and manage information processes more efficiently, it is critical to take notice.

After an extensive review of the research literature, Garlick (2002) summarizes some significant policy implications arising out of the connections between neural efficiency, neural plasticity and measured intelligence. Garlick claims that valued forms of thinking, whether in science and math or music and art, should be introduced to students at a younger age than is currently the case in educational settings. More succinctly, Garlick states that “the educational system…presents these phenomena to people in college when they are past the critical period. It [educational system] is then surprised when these young adults cannot acquire these abilities” (127). Waiting until adulthood to create educational interventions to develop human capital may be too late.

The present paper also examines the higher-order variables (for example, knowledge, context and person-based characteristics) associated with human capital development. These higher-order variables are instrumental to understanding the development of human capital because a large body of research suggests that variables such as intensive training, knowledge acquisition and familiarity, contextual relevance and capacity to generate explanations predict expert or skilled performance (Charness and Schultetus 1999; Ericsson 1996; Ericsson and Charness 1994; Ericsson and Kintsch 1995; Ericsson and Smith 1991; Gobet 2005; Johnson 2003; Siegler 2002; Sternberg 1999; Wellman and Lagattuta 2004). Research on expertise indicates that working memory can be reasonably enhanced at any age through deliberate practice and chunking of information so as to permit experts (of varying levels) to flourish within domains throughout the lifespan.

Part of the goal in developing human capital is also to enhance the performance of those experts already in knowledge-intensive occupations so as to help them become *adaptive experts*—individuals who reuse their knowledge and transfer their skills to new domains for innovation and growth. Many researchers recognize (for example, Gentner 1999; Gobet 2005; Sternberg 1999) that transfer of skill is nominal from one domain of expertise to another. However, research has demonstrated that the reuse of knowledge and transfer of skill can take place when children and adults are taught to engage in *theoretical-based reasoning*. This is a form of thinking that seeks to uncover the underlying causal principles in physical, social and psychological domains (Brown 1989; Catrambone and Holyoak 1989; Cummins 1992; Dunbar 1995; Gick and Holyoak 1983; Hatano 1982; Holyoak 1991; Leighton and Bisanz 2003). Moreover, research suggests that the *breadth* or variety of an individual's prior experience may be the key to the development of deep, theory-based reasoning in the service of knowledge reuse and the transfer of skill (Barnett and Ceci 2002 ; Brown 1989; Hatano 1982; Wellman and Lagatutta 2004).

To conclude, the research findings presented in the current paper provide compelling evidence for the association of the following factors with human capital development: *measured intelligence* because it predicts school grades and occupational outcomes, *neural efficiency* and *neural plasticity* because they predict measured intelligence, *working memory* because it predicts knowledge management within academic and nonacademic domains, *knowledge (expertise)* and *context* because individuals who can use what they know in familiar contexts can solve problems more successfully, and *learning for meaning* through a variety of exemplars, explanations, and a focus on discriminating features. The upshot of these findings is that educational curricula and opportunities should, in some cases, be introduced to children earlier. Moreover, educational programs must be strategic in their presentation of material and encourage students to engage in deliberate practice with the aim to improve their working memory and performance. Although there is great optimism in the potential of human capital, unleashing it will require a shift in standards and the expectations made of students. Moreover, initiatives to continually understand the development of human capital must aim to bring teachers and educators together with researchers and policy-makers so that methods for examining the best way to teach thinking and adaptive expertise can be realized.

Increasing Adaptive Expertise:
The Next Frontier in Human Capital Development

Introduction

At least two books represent the fascination with experts on the one hand and the need for knowledge management on the other. In the recent *New York Times* bestseller *Blink* by Malcolm Gladwell (2005), we learn that expertise or very good decision-making involves frugality of thought. This frugality means that experts use a few good variables to generate conclusions, without being overloaded by irrelevant and excessive information. This might seem paradoxical at first. If experts have more knowledge than novices, should they not consult this accumulated knowledge every time they make a decision? Actually, not really. If there is one thing that psychologists have learned over 40 years of research it is that experts within content domains such as chess, physics, medicine, mathematics and logic are extraordinarily efficient in their thinking (de Groot 1965; Ericsson and Smith 1991; Gigerenzer, Todd, and the ABC Research Group 1999; Haverty, et al. 2000; Leighton 2006; Priest and Lindsay 1992).

In another book, *Thinking for a Living*, by Thomas H. Davenport (2005), we learn that knowledge workers are important because they are “closely aligned with the organization’s growth prospects … without [them] there would be no new products and services, and no growth” (7). Davenport goes on to describe the single most important capability for knowledge workers: *the management of personal information and the knowledge environment.* Those few, highly skilled individuals who have mastered the management of personal information and the knowledge environment have “much more sophisticated strategies, including minimizing the number of devices they use, learning one piece of organizational software very well, and devoting considerable time to organizing and managing their information flows” (139). My objective in this paper is to examine the variables that explain the efficiency and success with which highly skilled, expert performers manage their knowledge and why knowledge management is a goal in the development of human capital.

1. Human Capital and Expertise

Human capital is an economic term used in the present paper to describe *the skills and knowledge that individuals draw upon to generate outputs of value*. In other words, human capital refers to the generation of ideas, processes and products that leads to success in job performance and economic growth. An assumption in human capital development is that all individuals possess rich cognitive resources (knowledge and skills), which, if developed and managed appropriately, can be used to maximize their participation in and contribution to the creation of new and better ways of doing things.

Skilled performers in all domains possess human capital in the form of acquired knowledge and skills in the service of outstanding thinking, judgment and decision-making (Ericsson and Smith 1991). Experts draw on their human capital to quickly understand the nature of problems and to solve problems efficiently. A psychological perspective for developing human capital must focus on (a) what makes experts who they are and (b) how other individuals can be trained to acquire the intellectual prowess experts have developed. Many questions can be asked from a number of different perspectives about how to unleash human capital. One objective of this paper is to consider questions from a broad, policy-focused perspective, such as:

1. What does existing research in psychology tell us about the factors that influence human capital development?
2. Which causal connections are well established, and which are more speculative? Which influences have the greatest impact?
3. What key questions are not being answered or asked? What new ways of framing the issues might be worth exploring?
4. How can we look beyond conventional disciplinary boundaries? Where could those boundaries be breached in the most interesting, creative, and useful manner, in terms of subject matter, methodology or in any other respect?

Questions 1 and 2 will guide the discussion in the present paper, and I will address questions 3 and 4 in the discussion and conclusion to the paper. As I address these four questions, I will also address another set of four questions because they help set the theoretical and empirical stage for understanding human capital from a psychological perspective. These questions are:

5. How is human capital conceptualized within the psychological domain?
6. Assuming indicators of human capital can be identified, do individuals differ in their human capital?
7. If individuals do differ in human capital, which variables account for most of the differences?
8. How is human capital enhanced?

In the first section of the paper, I define human capital from a psychological perspective and discuss the two branches of psychology that focus on human capital development. In the second section, I review the differential[1] psychology branch and its focus on the neural basis of general intelligence. In the third section, I discuss the information-processing mechanism (working memory) that translates intelligence into effective knowledge management, including learning and productivity. In the fourth section, I discuss the cognitive psychological perspective and its focus on the person-based and contextual variables associated with knowledge management and skilled performance. In the fifth section, I discuss adaptive expertise and ways to promote the reuse of knowledge and transfer of skill. After each section, I discuss policy-relevant conclusions and implications. I summarize the paper by highlighting key questions for examining how adaptive expertise can be trained and how this research, which will most likely involve educational interventions, will rely on new partnerships between research organizations and school systems.

[1] This is the field of psychology established by Sir Francis Galton, which focuses on all the behavioural and cognitive differences between people, including individual differences in personality, intellect, and physical characteristics. Differences in intellect are often believed to be fixed and stable characteristics and, therefore, differential psychology is sometimes referred to as trait psychology.

2. Human Capital as a Psychological Construct

If human capital refers to *the skills and knowledge that individuals draw upon to generate outputs of value*, then there are two main branches of psychology that focus on the study of human capital. These two branches include differential psychology and cognitive psychology. Differential psychologists study intelligence, broadly defined as the ability to learn from experience and adapt to the surrounding environment (Sternberg and Ben-Zeev 2001, 368) and narrowly defined as what intelligence tests measure[2] (Hunt 2005; see Sternberg and Grigorenko 2002 for a review of the debate). Tests of general intelligence in particular have been found to aid in the prediction of school grades, occupational outcomes (especially academic, professional and management) and performance on the job (Ceci 2000; Schmidt and Hunter 2004). It is for this reason that it is important to consider intelligence in any discussion of human capital; simply put, intelligence tests predict performance in knowledge-intensive domains.

Cognitive psychologists study complex cognition, broadly defined as the causal mechanisms or processes that people use to manage knowledge (Sternberg and Ben-Zeev 2001, 360). For example, adults and children who provide *explanations* for events within the physical, biological, mathematical and psychological domains have been shown to learn and perform better in knowledge-intensive or academic domains than individuals who do not provide such explanations (Wellman and Lagattuta 2004). This occurs because in the process of providing an explanation, individuals teach themselves about the underlying principles of the domain. Studies in cognitive psychology aim to identify why some variables are correlated; for example, why performance on intelligence tests predicts performance in knowledge-intensive domains. Both of these disciplines are therefore equally important to understanding how to develop human capital.

2.1 Differential Psychology

Psychologists who study intelligence operationalize intelligence as the kind of behaviour that can be measured by intelligence tests, such as the Wechsler Adult Intelligence Scale (WAIS) or the Raven's Advanced Progressive Matrices. Intelligence tests are thought to be measures of knowledge or past academic achievement (Barnett and Ceci 2005). Investigations of intelligence have led to the identification of two dimensions of intelligent behavior—crystallized and fluid (Carroll 1993; Cattell 1971; Horn and Noll 1994; Hunt 2005). Crystallized intelligence consists of context-dependent knowledge, defined as the ability to apply previously learned methods to solve current problems. Fluid intelligence is a context-independent skill, and is defined as the ability to develop solutions to relatively novel problems. Individuals who score high on measures of crystallized intelligence also tend to score high on measures of fluid intelligence (Jensen 2005). In other words, the two forms of intelligence are positively correlated. One possible explanation for this relationship is that persons use their fluid intelligence to acquire crystallized

---

[2] Unless otherwise stated, the term "intelligence" in this paper refers to general intelligence or *g* measured by psychometric tests, which happen to be associated with the bulk of factor analytic research (Sternberg and Pretz 2005). Terms such as *traditional*, *psychometric*, *general*, and *measured* intelligence are used interchangeably to denote intelligence measured by tests of intelligence. The term *intelligence quotient* (IQ) is used to denote a score on an intelligence test. Crystallized and fluid intelligence are dimensions of general intelligence.

intelligence. For example, a person who reasons rapidly in novel domains is able to use this skill to learn concepts quickly (Cattell 1971). The other possible explanation is that persons use their crystallized intelligence to gain fluid intelligence. For example, persons who know a lot of things are able to reason effectively in new domains because their vast background knowledge matches aspects of the novel tasks they are solving.

2.2 Cognitive Psychology

Cognitive psychologists study the information processes implicated in the management of knowledge. Knowledge management is necessary for all types of reasoning and problem-solving tasks that require the person to read, interpret, plan, compute, estimate, decide, infer, evaluate and execute. Cognitive psychologists have made unique contributions to what is known about the mental representations individuals create, and the processes individuals use as they apply strategies to reason about and solve tasks, together with the factors that facilitate or hinder problem-solving. In comparison to differential psychologists, who focus on the performance differences among individuals, cognitive psychologists tend to focus more on the process similarities among individuals. In particular, they seek to uncover what is common to the processes people use to interpret information and execute solutions. This focus on what is common has led to the creation of theories about how individuals make sense of their environments, and how tasks may be better created, presented and articulated for maximum comprehensibility (Girotto 2004). The limitation of the cognitive psychological approach is that group differences, such as gender differences, are generally downplayed in favour of what is common to all. An exception is the study of experts (Charness and Schultetus 1999), in which the focus of study is entirely on what is different about the information-processing of individuals who are considered highly knowledgeable and skilled in a domain from those individuals who are not. In the next section, I discuss the neural basis of intelligent performance.

3. Neural Efficiency and Plasticity

One avenue to understanding how individuals use their human capital to generate outputs of value begins by considering the neural basis of intelligent performance. Why do some people score better on tests of intelligence than others?
In terms of an actual location of the brain associated with intellectual performance, there is general consensus among cognitive neuroscientists that the frontal lobes are the areas underlying this form of behaviour (Duncan et al. 2000; Prabhakaran et al. 1997). Using a range of methods from positron emission tomography (PET) to functional magnetic resonant imaging (fMRI), studies of individuals with frontal lobe lesions show impairments in higher-level cognitive processes such as planning, decision-making and goal-evaluation (Duncan, Burgess, and Emslie 1995; Fiez 2001; Kessels et al. 2000).

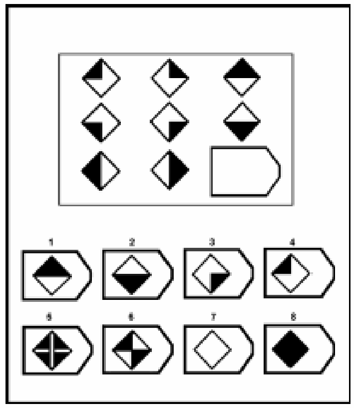
3.1 Intelligence and Neural Efficiency

Outside of identifying the frontal lobes as the specific location of the brain associated with higher-level cognitive processes, researchers have focused on identifying the specific neural processes associated with measured intelligence. This bottom-up approach to understanding intelligence has largely involved examining *neural efficiency* (Neubauer and Fink 2005; Vernon 1987). I mentioned at the beginning of this paper that very good decision-making comprises frugality of thought. Neural efficiency is very similar to this idea. Neural efficiency is quite simply the hypothesis that highly able people use their brains more proficiently than less able people (Neubauer and Fink 2005). However, the question of what specific brain processes actually serve as evidence for the neural efficiency hypothesis has been challenging to answer. The challenge has arisen because some anticipated measures of neural efficiency such as evoked potentials (EP) latency (Deary and Caryl 1993; Neubauer 1997) and peripheral nerve conduction velocity (PNVC) have failed to show a reliable relationship to intelligent performance (Barrett, Daum, and Eysenck 1990; Reed and Jensen 1991, 1992). Nevertheless, more reliable measures have been found such as positron emission tomography (PET), which can be used to assess glucose metabolism rate (GMR).

3.1.1 Glucose metabolism rate (GMR)

Like other organs in the body, the human brain consumes energy in the face of environmental demands. More specifically, in cognitively difficult situations, the brain compensates for the loss of energy by metabolizing glucose (Haier et al. 1988; Neubauer and Fink 2005). To measure the GMR of the brain, neuroscientists inject a metabolic tracer into participating research subjects. During the uptake phase, the brain absorbs the tracer and the effects of cognitive activity on the GMR of different brain regions can be examined. The cognitive activity usually requires participants to solve the kinds of tasks found in traditional intelligence tests such as the Raven's Advanced Progressive Matrices. Below is an example of a matrix completion problem in which the participant must select from a set of options the one that will best complete the perceptual pattern:

Figure 1: An example of a matrix completion problem.



After the uptake phase and cognitive activity are completed, individuals are moved to the PET scanner where their GMR is measured. Negative relationships have been found between GMR and cognitive activity (Haier et al. 1988; Haier et al. 1992a, 1992b; Parks et al. 1988). For example, Haier et al. (1988) found that individuals with higher IQs (intelligence quotient) exhibited lower GMRs during performance on the Raven's Advanced Progressive Matrices than individuals with lower IQs (correlations between -.44 to -.84 for different brain regions).

3.1.2 Event-related desynchronization (ERD)

Another promising measure for establishing the relationship between neural efficiency and intelligence is the ERD or event-related desynchronization (Pfurtscheller and Aranibar 1977; Pfurtscheller and Lopes da Silva 1999) in the human electroencephalogram (EEG). Using this method, EEG background activity is assessed in two trials; one control trial involves no cognitive activity and the other activation trial involves cognitive activity where participants are asked to process task information. The task information presented to participants is again similar to tasks found in traditional intelligence tests. The ERD is measured by calculating the percentage of decrease in power from the control trial to the activation trial. With this approach, neuroscientists (Neubauer, Freudenthaler, and Pfurtscheller 1995; Neubauer, Sange, and Pfurtscheller 1999) have found that individuals with lower IQs were more likely to display stronger and relatively unspecific cortical activation (positive increase in ERDs) compared to individuals with higher IQs. Higher-IQ participants generally showed weaker, but specific, cortical activation on cognitive tasks such as the well-known sentence-verification task (Carpenter and Just 1975). Although the ERD seems to share a negative relationship with measured intelligence (weak but specific activation is associated with higher intelligence), it seems particularly related to individual differences in fluid rather than crystallized intelligence (Neubauer and Fink 2003) and in male cognitive activity rather than female cognitive activity (Neubauer and Fink 2003; Neubauer, Fink, and Schrausser 2002). Studies have found that although higher-ability males tend to show the weak but specific cortical activation associated with efficient neural processing, higher-ability females do not. Moreover, the strong but unspecific cortical activation associated with lower-ability individuals is observed with lower-ability males but not with lower-ability females. In other words, cortical activation has been found to be unrelated to ability in female participants. Other studies have also shown that males and females display distinct patterns of cortical activation on verbal, numerical and figural-spatial tasks (see Neubauer, Fink, and Schrausser, 2002).

In addition to the findings that higher measured intelligence is associated with greater neural efficiency, there is also evidence that higher measured intelligence is associated with stronger myelination of axons. Stronger myelination translates into higher speed of nerve conduction, less leakage and anatomically larger brains (Miller 1994). Other sources of evidence suggest that redundant synaptic connections (also referred to as deficiencies in neural pruning) are associated with lower measured intelligence (Haier 1993). Finally, there is some evidence that in adaptation to environmental demands, more efficient brains grow dendritic trees and axon branches compared to less efficient brains and these changes are again associated with differences in measured intelligence (see Garlick 2002).

3.2 Intelligence and Neural Plasticity

There is strong evidence for individual differences in neural efficiency and, in some cases, these differences predict performance on tests of intelligence. At a basic level, then, it might seem that what influences human capital is neural anatomy. However, the statistical relationship between neural efficiency and measured intelligence has some limitations. Although better problem-solvers appear to have more efficient neural systems, this could be the case for at least two different reasons (Hunt 2005). It could be the case that when faced with a problem to solve, better problem-solvers simply have more efficient (faster) neural processing and thus take advantage of this asset. Alternatively, better problem-solvers may simply have better-organized brain systems due to *unique learning patterns and opportunities*, such that less neural processing is required to achieve a solution to a task.

In an impressive review of the literature, Garlick (2002) explains this second alternative in depth. He claims that better-organized brain systems are likely to arise when young children are exposed to learning environments that challenge their developing brains to create highly efficient connections in adaptation to difficult tasks. Garlick proposes that *neural plasticity* is the most likely process responsible for individual differences in neural efficiency and measured intelligence. Neural plasticity involves “the processes that involve major connectional changes of the nervous system in response to experience and that are observed to cease to operate at maturity” (Garlick 2002, 120). He explains that neural efficiency naturally arises in (young) brains that have been exposed to a wide array of stimuli and have therefore been given the opportunity to create the optimal connections necessary to deal with an equally wide range of complex task situations. Integrating neuroscience and computer simulation studies, Garlick concludes that *these connections are largely generated during a critical period for intellectual development, starting at birth until age 15.* In support of this neural plasticity hypothesis, many cognitive skills such as learning a second language, playing a musical instrument and thinking in knowledge-intensive disciplines such as science and math have been found to be encountered and practiced early in life by those considered to be highly gifted in their performance (Albert 1978; Tomlinson-Keasey and Little 1990).

3.3 Policy Implications

What does this research imply for educational policy? For starters, outside of the obvious importance of prenatal precautions and care for brain development, Garlick indicates that valued forms of thinking, whether in science and math or music and art, should be introduced to students at a younger age than is currently the case in educational settings. More succinctly, Garlick states that "the educational system…presents these phenomena to people in college when they are past the critical period. It [educational system] is then surprised when these young adults cannot acquire these abilities" (127). The main implication of this research, then, is that if we want to enhance outputs of value in knowledge-intensive domains, the efforts must begin early by exposing young minds to the *variety of the knowledge and skills we deem valuable as a society*. Waiting until adulthood to create educational interventions to develop human capital may be too late (see Hansen, Heckman and Mullen 2004 for an econometrics approach to this argument).

The research on the neural basis of intelligence is important to review when considering human capital development. Consider that individual differences in measured intelligence have been found to predict school grades, occupational outcomes (Barrett and Depinet 1991; Ceci 2000) and job success, especially for knowledge-intensive occupations, including professional, scientific and upper management jobs (Schmidt and Hunter 2004). Although Sternberg (1999) claims that intelligence tests simply measure *one form* of expertise—performing well on (simple) inductive problems that resemble academic tasks—it is also the case that performance on these seemingly simple problems predicts a highly valued output for human capital development; that is, the management of knowledge. Leaving aside for a moment the neural processes implicated in measured intelligence, I now turn to a discussion of the most likely information-processing mechanism that translates measured intelligence into outputs of value. In the next section, I review the information-processing link between intelligence and skilled performance—working memory

4. Working Memory

Working memory is an integral component of the human information processing system. It is a temporary holding station for information required for a range of cognitive activities involving knowledge management, including language learning, reasoning and problem solving (Baddeley 2000, 2003). Working memory is used to rehearse, interpret and transform information so that it can be transferred into long-term memory (where it resides as permanent knowledge for later retrieval). Outside of being a location where information is managed and manipulated, working memory also maintains existing information as active while new information arrives via sensory channels or long-term memory (Baddeley 2000).

Working memory is such a central component of human information processing that some differential psychologists claim working memory and general intelligence are indistinguishable (Kyllonen 1996; Kyllonen and Christal 1990). In support of this claim, laboratory measures of working memory and intelligence have been found to be strongly correlated (.90 at the latent variable level between working memory and fluid intelligence, Kyllonen and Christal 1990; see also Engle et al. 1999; Hambrick, Kane, and Engle 2005).

Working memory is a limited-capacity system, where capacity refers to the quantity of information an individual can simultaneously and consciously attend to without becoming overloaded (Baddeley 2000; Nairne 2003; see also Ericsson and Simon 1993 for how working memory influences cognitive performance). Working memory is especially susceptible to overload when faced with new tasks or situations. Consider the first time you drove a car or visited a new city. The newness of the task or situation makes every detail relevant and it is impossible not to consciously attend to and evaluate every piece of information. When working memory is overloaded, there is a rapid decay in the information held, causing a breakdown in knowledge management. Thus, the information and any chance of successful performance are lost. Only when a task has been performed many times and is well learned to the point of being performed automatically (for example, driving after five years of experience), is working memory essentially bypassed and it no longer functions as a bottleneck. Working memory can be bypassed when conscious or controlled attention to task details is no longer required for successful performance.

Increasing the capacity of working memory would be expected to improve performance on measures of intelligence and, in turn, performance on all the tasks that measures of intelligence seem to predict (for example school grades, occupational outcome). But how could working memory be increased? Much like an express cashier at a local grocery store – moving foods through as quickly as or even more quickly than the rate at which they are coming in – working memory can be increased by sheer practice. In the next section, I describe expertise and how deliberate practice increases working memory capacity.

4.1 Working Memory and Expert Problem-solving

Expertise is defined by Charness and Schultetus (1999) as “consistently superior performance on a set of representative tasks for the domain that can be administered to any subject” (58). Studies of expertise suggest that expert performance is a reliable phenomenon that can be measured using standard tasks or conditions for competition in laboratory settings (for a review, see Ericsson 1996). Identified experts within a domain seem to share a cluster of features about their training and performance. First, peak performance results after many years of intense preparation and practice within the domain – 10,000 hours, for example, are normally required to reach top-level performance within a domain (Charness and Schultetus 1999). Second, experts do not simply spend more "leisure" time in their respective domain in comparison to others, but rather spend more hours engaging in *deliberate* practice (Ericsson and Charness 1994). Deliberate practice normally involves solitary study with the purpose of improving knowledge management and performance.

Experts have been found to have an amplified working memory capacity in the domain of their expertise. This amplified capacity is the result of efficient organization and automation—experts organize their vast knowledge into *chunks of facts and strategies* in long-term memory and they practice accessing this knowledge repeatedly to the point of making information retrieval automatic (Chase and Simon 1973; de Groot 1965; Gobet 1997; for a review see Johnson 2003 and Leighton and Sternberg 2003). For example, their vast knowledge buys them the enviable skill of recognizing patterns (or chunks) of relevant and important features within a problem quickly (Allard and Starkes 1991; Chase and Simon 1973; de Groot 1965; Gobet 1997; Gobet and Simon 1996). These task features are interpreted, transformed and matched to previously learned and catalogued templates (schemas) in the expert's long-term memory.

This ability to match task features to previously catalogued templates allows experts to demonstrate extraordinary recall and management of information. For example, Gobet and Simon (1996) found that in contrast to less accomplished players, champion chess players could recall more than nine chess positions that had been presented to the players briefly and without breaks between presentations. Likewise, Allard and Starkes (1991) found that elite athletes were able to abstract and recall more information about game situations after a brief exposure than non-elite athletes. In other words, retrieval of accurate information is exceedingly efficient for experts because recall does not take place piecemeal. All the associated and relevant pieces of information come along with it in a chunk. Distilling these chunks of information allows experts to form highly complex representations of the problem situation, allowing them to integrate task information with background knowledge to select and evaluate courses of action (Charness and Schultetus 1999; Ericsson 1996; Ericsson and Charness 1994; Ericsson and Kintsch 1995; Ericsson and Smith 1991; Johnson 2003; Sternberg 1999).

Organizing knowledge into chunks effectively increases the capacity of working memory. Unlike novices within a domain, experts function as thriving businessmen and women, producing their outputs through *economies of scale*. When a maker of widgets first begins to make widgets, she will take time to ensure that the widgets are well crafted and even consider the different strategies to market and distribute them. After considerable time refining the production and distribution of widgets, however, and with sufficient market demand, the producer now has enough practice to automate the process. She can produce the widgets in large scale. One can see how this might extend to experts' thinking and performance. The vast knowledge and experience experts have allow them to automate much of their thinking within a domain, such that their performances become *performances of scale* – working memory is freed up to manage new, additional information because basic information processing has been refined and no longer takes time. Experts' organized knowledge therefore functions to increase working memory capacity because it (a) permits working memory to operate on chunks of information instead of on single pieces of information, and (b) often bypasses working memory entirely for basic information-processing, freeing the single-channel system to operate on other newer and relevant information.

Surprisingly, experts learn to manage or chunk their knowledge by sheer practice within their domains. In fact, in contrast to the popular opinion that skilled performance within a contextual domain originates solely from superior intelligence, research on expertise suggests the opposite. The main message from this line of research is that skilled and even exceptional performance develops largely, although not exclusively, from basic hard work, effort and intense preparation (Ericsson and Charness 1994; see also Johnson 2003). Studies of expertise are intriguing because they suggest that human cognitive abilities are flexible and can adapt to meet increasingly higher demands and expectations. Although studies of expertise have been carried out largely with a limited range of problem-solving tasks within laboratory settings (for example, Chase and Simon 1973; Chi, Glaser, and Farr 1988; de Groot 1965; Gobet 1997; Holding 1992), this line of research offers concrete avenues for developing human capital (see Ceci and Liker 1986a, 1986b; Ceci and Ruiz 1992, 1993). Increasing working memory capacity presents another opportunity for policy initiatives in human capital development.

4.2 Policy Implications

After reviewing numerous studies of expertise, Gobet (2005) has eight recommendations for educators to develop working memory and skilled performance in their students:

1. Devote time to task for the purpose of improving performance (essential to gaining knowledge).
2. Direct learners' attention to key features of the material to be learned (segment curriculum).
3. Provide feedback and highlight important features of a problem so as to focus the acquisition of correct knowledge.
4. Supplement the teaching of specific knowledge with the teaching of metaheuristics (or metacognitive)—strategies about how to learn, how to direct one's attention in novel domains and how to regulate memory.
5. Pay attention to the ordering of presented material to be learned by presenting simple material first, followed by more complex material (that builds on previously presented material), noting discriminative features or cues in the material that signal avenues for problem-solving.
6. Focus on the conditions for applying newly learned procedures.
7. Maintain variety in presentation by using many examples to show the parameters or underlying principles of the concept: "without variation, schemata [general principles] cannot be created" (197).

8. Avoid new technologies (for example, hypertexts) that “present distractions that interfere with what should ideally be learnt” (198).

These eight recommendations are designed to promote working memory and expert performance for individuals regardless of pre-existing differences in intelligence. In fact, Gobet (2005) (see also Bloom 1984) claims that pre-existing individual differences should be taken into account only to tailor teaching for expertise. He states that “first, while individual differences tend to be diluted by large amounts of practice, they play a large role in the early stages of studying a domain, which characterizes much of classroom instruction….taking into account individual differences may lead to better instruction, because instruction can be optimized for each student, including feedback on progress, organization of material, and choice of learning strategies to be taught” (199).

Training to become an expert in a knowledge-intensive domain should not only increase working memory capacity but should also boost measured intelligence to the extent that the tasks used in the training domain overlap with the kinds of tasks found on intelligence tests; namely, academic tasks (Ceci 2000; Sternberg 1999). In contrast, training to become an expert in a non-academic domain may improve working memory within that domain but will not likely boost performance on tests of intelligence because the tasks in the two domains would not share enough similarity (Beckmann and Guthke 1995; Ceci and Liker 1986a, 1986b; Ericsson, Krampe, and Tesch-Romer 1993; Funke 1995; Sternberg et al. 2001; see also Wenke, Frensch, and Funke 2005). For example, Ceci and Liker (1986a, 1986b) compared a group of experts and novices in their abilities to handicap horse races. The two groups were matched on many variables, such as their years of track experience, education and psychometric intelligence. The only variable on which the experts differed from novices was their ability to correctly predict the post-time odds (on the basis of a priori factual information) for the top three horses in ten real races. When experts and novices were asked to handicap 50 experimentally contrived races, there were significant differences between the two groups. In particular, experts used a sophisticated combination of variables (for example, lifetime speed of the horse, claiming price, track surface condition) in their handicapping compared to novices, suggesting increased working memory capacity to better manage their comprehension of task features and their relatedness. When numerical weights were assigned to the variables selected and combined by the experts, the weights correlated highly with handicapping performance but not with their measured IQ.

Research on expertise indicates that working memory can be reasonably enhanced at any age, thereby permitting experts to flourish within domains throughout the lifespan. In the next section, I describe the effects of knowledge and context and how these can be used to promote expert performance.

5. Developing Reuse and Transfer

So far in this discussion, I have identified two avenues for enhancing human capital: neural plasticity and working memory. Both of these avenues could lead to improvements in the outputs of value within a domain, albeit at different stages of development. On the one hand, improvements in neural plasticity function to develop human capital at very early stages of the individual lifespan (birth to age 15). On the other hand, increases in working memory function to develop human capital at any age. Both in academic and non-academic domains, working memory allows individuals to think efficiently and successfully within their domains by attending to specific perceptual cues and foregoing redundant information. Gobet (2005) calls this the expert's *professional eye,* and it seems to select successful courses of action instinctively by "allowing [experts such as nurses and firefighters] to be highly selective in their search and to solve routine problems without exploring many alternatives" (184).

However, we do not want to simply enhance neural plasticity and working memory to predict school grades and occupational outcomes. This is not the end goal. Part of the goal is also to enhance the performance of those already in knowledge-intensive occupations. So the question we must now ask is, What allows some experts to become *adaptive experts*; that is, individuals who reuse their knowledge and transfer their skills to new domains? We have seen that measured intelligence (via working memory) predicts acquired knowledge within academic domains and deliberate practice (via working memory) predicts acquired knowledge within all domains. But what predicts the reuse of knowledge and the transfer of skills? Gobet recognizes, as do others (for example, Sternberg 1999), that "transfer seems to be minimal from one domain of expertise to another" (184). Certainly this is an important question to ask for developing human capital. We must consider what information processes permit the expert firefighter to become the expert fire chief or the expert assembly worker to become the expert salesman. Especially in knowledge-intensive professions, experts who want to reuse their knowledge and transfer their skills must now push the envelope to broaden the flexibility of their knowledge management. In the next section, I explore the variables that must be considered if reuse and transfer are to occur.

5.1 The Effect of Knowledge and Context

Knowledge mobilizes reasoning and problem-solving skills (Barnett and Ceci 2005; Cosmides 1989; Leighton and Sternberg 2003, 2004; Nickerson 2004). Unless a person thinks they have adequate knowledge and skills to solve a task, he or she will not be able to solve it successfully. Alternatively, constantly developing new knowledge and skills to tackle new problems that resemble old problems is inefficient. Davenport (2005) adds that "in many cases the goal is to reuse knowledge more effectively. We can greatly improve performance by having a lawyer reuse knowledge created in another case, or having a programmer employ a subroutine that someone else created" (71). The issue then is how to make tasks more accessible for the reuse of knowledge (Cheng and Holyoak 1985, 1989; Cosmides 1989) and how to help individuals see the similarities between new and old tasks so that their background knowledge mobilizes the transfer of skills.

Investigations of abstract and logical reasoning have underscored the importance of task presentation and the presence of relevant knowledge to "kick start" the use of appropriate reasoning and problem-solving skills (for a review see Leighton and Sternberg 2003). Studies of college students who are asked to solve the so-called Wason selection task (see Figure 2), a reasoning task named after the famous British psychologist Peter Wason (Wason 1966), demonstrated how miserably they could perform when the task was framed in an unfamiliar context (see Leighton and Sternberg 2003, 2004 for reviews):

Figure 2: Adaptation of the Wason Selection Task (see Leighton and Sternberg 2003)

Consider the rule: If there is a vowel on one side of the card, then there is an even number on the other side. Now examine the four cards below, each of which has either a letter or number on one of the sides. Choose the fewest numbers of cards that can test the truth or falsity of the rule.

E	K	4	7

Only 10 percent of college students normally select the appropriate cards, which happen to be the E and the 7. Students' poor performance in these studies was not due to their inherent deficiencies in information processing. The participants in most of these studies were college students. In fact, the most likely reason for students' poor performance was that most of them had never taken a course in symbolic logic (Girotto 2004; Stenning and Yule 1997) and thus had no idea how to interpret the conditional rule formally, let alone the instructions for "testing the truth or falsity" of a rule.

The Wason task might seem at first glance to be no more than a toy problem. However, consider that student performance on more-familiar versions of the Wason task predict performance on the SAT, a measure of college readiness (a correlation of .47), statistical reasoning (.26) and the ability to evaluate arguments (.31). In other words, when the Wason task is presented in a format that permits individuals to reuse their knowledge, the task can be used to discriminate abstract thinkers from not-so-good abstract thinkers (Stanovich, Sá, and West 2004; Stanovich and West 1998). Consider a more familiar version of the Wason task (adapted from Cosmides 1989):

Figure 3: An adaptation of the thematic version of the Wason Selection Task for Social Contract Theory (see Cosmides 1989; reviewed by Leighton and Sternberg 2003)

Your job is to enforce the following law: If you take the benefit, then you must pay the cost.

The cards below have information about four people. Each card represents one person. One side of the card tells whether a person accepted the benefit, and the other side of the card tells whether the person paid the cost. Indicate only those card(s) that definitely need to be turned over to see if any of these people are breaking the law.

Benefit Accept	Benefit Not Accept	Cost Paid	Cost Not Paid

When college students were asked to solve the familiar task shown in Figure 3, approximately 75 percent of them selected the correct cards, the Benefit Accepted and Cost Not Paid cards. Although the framework of this new, more thematic task is similar to the traditional Wason task, more able students solved it correctly because the familiar context facilitated their reuse of existing knowledge (for example, Cosmides 1989). Most people learn extensively about rule enforcement from an early age, and therefore have the necessary background knowledge about potential rule violators. Participants who have this background knowledge recognize quickly which cards must be chosen to ensure that potential cheaters are identified and punished.

The context of a task can be manipulated in many ways to promote the reuse of previously learned knowledge (Girotto 2004; Leighton 2004; Newell and Simon 1972; Sperber, Cara, and Girotto 1995). For example, some studies have found that depending on the *perspective* individuals are asked to adopt on a reasoning task (such as whether they stand to gain or lose), their performance can be manipulated in predictable ways (see cheating detection theory, Gigerenzer and Hug 1992; Manktelow and Over 1991; Manktelow et al. 2000). The *instructions* participants receive prior to a task have also been found to influence their performance. For instance, instructing participants about the importance of searching for alternative solutions to a problem has been shown to improve their reasoning on categorical syllogisms (Cheng and Holyoak 1985; Cosmides 1989; Cosmides and Tooby 1996; Liberman and Klar 1996; Newstead and Evans 1993; Pollard and Evans 1987).

In general, persons' *perceived relevance* of a task, which determines whether they will entertain the prospect of solving it, is based on their background knowledge. After examining the experimental literature on the Wason task and conducting several studies where perceived relevance was manipulated, Sperber et al. (1995) concluded that people gauge the benefits and costs (effort) of solving a task. A task is perceived as increasingly relevant the more its benefits outweigh its costs. Moreover, Sperber et al. explain that perception of task relevance is related to background knowledge. Individuals who believed they were knowledgeable about the task perceived it as less effortful and more relevant than those individuals who believed they were not knowledgeable enough to solve the task.

When we consider how knowledge and skills relate to outputs of value, it is useful to consider how best to invoke that knowledge and those skills on a given task, so as to fairly judge what people can maximally or optimally produce. Otherwise we risk underestimating what people are capable of producing and contributing to the creation of valued goods. Our understanding of the specific variables that promote knowledge management in the service of skilled reasoning and problem-solving is still in its infancy, prompting Barnett and Ceci (2002, 2005) to suggest that we need a *theory of context* in order to understand the interaction of person-based and environmental variables that affect successful performance in a variety of contexts. In the effort to contribute to a theory of context, there are person-based variables or dispositions that correlate with successful performance in a variety of domains.

5.2 Effect of Person-based Variables

Nickerson (2004, p. 415) has identified the following abilities, qualities and propensities that good reasoners tend to possess: intelligence, domain-specific knowledge, general knowledge about human cognition, knowledge of common limitations, foibles and pitfalls, self-knowledge, knowledge of tools of thought, ability to analyze and evaluate arguments, good judgment, ability to estimate, sensitivity to missing information, ability to deal effectively with uncertainty, ability to take alternate perspectives, ability to reason counterfactually, ability to manage own reasoning, reflectiveness, curiosity and inquisitiveness, strong desire to hold true beliefs and willingness to work at reasoning. Nickerson argued that these abilities and qualities "are supportive of good reasoning independently of who does it or the subject on which it is focused. They do not guarantee that one will reason well, but they increase the likelihood" (414). Other investigators have also identified similar abilities and qualities (Kuhn 2001; Norris, Leighton, and Phillips 2004; Perkins 1995; Stanovich and West 2000; Sternberg and Ben-Zeev 2001).

In answer to the question of how best to promote the individual abilities and qualities associated with successful knowledge management and performance, we turn not to a theory of context but rather to a *theory of mind* (Wellman and Lagattuta 2004). The term theory of mind refers "to our everyday understanding of persons in terms of their inner psychological states" (Wellman and Lagattuta 2004, 479). An important aspect of theory of mind for our purposes is its relationship with metacognition (or metaheuristics, see section 4.2) – how a child views the use of the mind to memorize facts, learn knowledge, and use strategies effectively in learning contexts (Adams, Treiman, and Pressley 1998). Increasingly, research studies show (see Dunn et al. 1991; Meins et al. 2003) that children who are adept at providing *psychological explanations* for a person's actions or experiences as the cause or consequences of their mental states tend to also make more references to underlying causal mechanisms.

After reviewing experimental studies where children are asked to provide explanations for characters' actions and situations, Wellman and Lagattuta (2004) concluded that children who are asked to provide causal explanations also improve their perspective-taking and knowledge of the tasks presented to them. In their words, explanations are critical to learning because "attempting to better explain such anomalous behaviour (including seeking and receiving explanations from others), causes children to develop further, deeper conceptualizations. Regardless of differing theoretical emphases, empirically the data are clear: explanations have a special role in theory of mind development" (491). The ability to generate causal explanations for events within domains promotes the successful transfer of skills across domains (Chi, Feltovich, and Glaser 1981). The types of underlying principles used to generate causal explanations are precisely those that are used to map meaningful relations across seemingly disparate domains (Dunbar 1995; Loewenstein, Thompson, and Gentner 1999; Rattermann and Gentner 1998).

5.3 Policy Implications

Although there is need to conduct more research to identify the best methods to cultivate abilities and qualities that will promote knowledge management, practices that facilitate knowledge acquisition such as directing learners' attention to key features of the material to be learned, and providing feedback and highlighting important features of a problem so as to focus the acquisition of correct knowledge (see Gobet 2005, section 4.2), should increase the perceived relevance of a task and the likelihood that background knowledge will be reused in solving it. Moreover, encouraging children to provide explanations for physical and social phenomena and to comment on others' explanations is an important teaching tool for stimulating meaningful learning (see Chi et al. 1994; Pine and Siegler 2003; Siegler 2002). In fact, the payoffs of teaching children about the use of explanations may be a key to promoting *adaptive expertise* and, ultimately, both the reuse of knowledge and the transfer of skills. The reason for this is that experts who can adapt their skills most readily to new situations are those who understand the underlying principles for using rules in particular situations. Davenport (2005) comments on this capacity by sharing the comments of one high-performing project manager: "I learned management not from a class, but through reflecting on my past experiences of being managed, through simple trial and error, and through conscious observation and reflection on the acts of other managers" (149). An individual's theory of mind can be used to promote the learning of underlying principles and causal mechanisms of a domain, which, in turn, can promote the flexible, theory-based reasoning shown by adaptive experts in response to new situations.

6. Adaptive versus Routine Expertise

Ensuring that the knowledge and skills people learn in one domain are applicable to other domains is an essential part of developing human capital and outputs of value. Investigators of problem-solving agree that managing knowledge and having the skills to solve tasks across conceptually similar domains is the hallmark of adaptive thinking, broadly conceived (Anderson 1983; Barnett and Ceci 2005; Bransford and Stein 1984; Ericsson 1996; Holyoak 1991; Johnson-Laird 1999; Leighton and Sternberg 2003, 2004; Newell and Simon 1972; Roberts and Newton 2005). But transfer of knowledge does not occur spontaneously (Adey and Shayer 1994; Nickerson 2004; Salomon and Perkins 1989; Sternberg and Ben-Zeev 2001). For example, the knowledge people learn in a mathematics class is often not used to solve problems in a symbolic logic class, even though the underlying structure of problems in the two contexts may have similarities. This lack of reuse and transfer underscores the domain-specific nature of most of human learning. However, deficiencies in the reuse of knowledge and transfer of skills can be minimized so as to avoid having individuals continually relearning concepts and skills previously acquired. For example, Davenport (2005) claims that continually relearning how to make sense of and solve organizational tasks limits the optimization of output. Output is limited because the individual is constantly bogged down with basic information and cannot focus on new, advanced information about the domain.

6.1 Theory-based Reasoning

One area of research that stands to inform the reuse of knowledge and transfer of skills distinguishes the learning patterns of two kinds of experts: adaptive and routine (Hatano 1982, 1988; Hatano and Inagaki 1984, 1986; Holyoak 1991; see also Barnett and Koslowski 2002). The difference between adaptive and routine expertise involves, fundamentally, the ability to reuse knowledge and transfer skills to novel tasks within conceptually similar domains. Holyoak (1991) summarizes the distinction succinctly: “Whereas routine experts are able to solve familiar types of problems quickly and accurately, they have only modest capabilities in dealing with novel types of problems. Adaptive experts, on the other hand, may be able to invent new procedures derived from their expert knowledge” (310). Holyoak claims that routine experts are proficient skill-learners but are essentially algorithmic in their understanding of a domain. These are the individuals who know a lot about what they do and can solve many problems as long as they have learned a rule for it (Barnett and Koslowski 2002). In contrast, adaptive experts do not only know how to apply the rules of their field effectively but they also have the depth of knowledge in the form of underlying principles to understand what makes the domain “tick.” They often invent their own successful rules for solving problems if previously learned rules are ineffective. Davenport (2005) claims these high performers to be “intentional, flexible, and proactive learners over time” (145). Adaptive experts are believed to hold the key to knowledge reuse and transfer of skills because they are practiced at using what they already know to solve novel, yet conceptually similar tasks successfully.

In a study examining important group differences in knowledge reuse and transfer of skill, Barnett and Koslowski (2002) had two expert groups and one novice group read a story about a hypothetical restaurant. The groups included general business consultants, restaurant managers and a group of novices (non-business graduates). The groups of business consultants and restaurant managers were matched in age (approximately 35 years) and number of years of formal education (approximately 16.5 years). However, the groups differed on other variables. The business consultants had all earned business degrees, whereas only 42 percent of the restaurant managers had done the same. In addition, the business consultants had an average of six years of consulting experience but no restaurant experience, whereas the restaurant managers had no experience consulting but had an average of eight years of restaurant experience. The novice group was generally younger, at 20 years of age, and had 14 years of education and no business education, consulting experience or restaurant experience. Using individual interviews, Barnett and Koslowski posed four open-ended questions to the participants within each group, asking them to identify possible solutions to challenges facing the hypothetical restaurant.

After conducting individual interviews, the interviews were transcribed and then given to "super-expert" referees. These super-experts were university professors whose research focused on restaurant management in a faculty department specializing in the hotel and restaurant business. These super-experts also had previously managed restaurants and also had broader consulting experience. In essence, these super-experts represented the combination of skills possessed by both business consultants and restaurant managers in the study. The super-experts coded the interviews, without knowing from which group they originated, for whether participants mentioned the optimal solution to the hypothetical restaurant challenge, and for whether participants expressed extraneous solutions that would not address the challenge. In the analysis of responses, business consultants were found to provide more optimal solutions (average score of 41 percent) than restaurant managers (average score of 24 percent) or novices (average score of 20 percent). Even though the scores of the business consultants were generally below 50 percent, they were still better than the other two groups (see Leighton 2006 for a discussion of expertise in novel domains and its impact on performance).

After reviewing the interviews for optimal solutions, a second analysis was conducted to examine the knowledge management and problem-solving skills of business consultants. Using a combination of qualitative and quantitative analytical methods, Barnett and Koslowski found that even though business consultants *had no restaurant experience*, they engaged in deep, *theory-based reasoning* in response to the challenge faced by the hypothetical restaurant. In particular, the consultants made use of theory-based reasoning, including the reuse of previously learned theoretical concepts, and the transfer of causal reasoning skills, causally-supported solutions and complementary alternatives in their thinking compared to restaurant managers and the novice students. Theory-based reasoning is believed to facilitate knowledge reuse and transfer to novel tasks because it provides an organizing framework with which to make sense of novel information in a conceptually similar domain (see also Dunbar 1995; Gentner 1999; Newell and Simon 1972). The organizing framework highlights what might be relevant in the problem and the main goals for task solution (see Carpenter, Just, and Shell 1990; Kuhn 2001). Knowing and understanding the theory-based reasons for organizing problem-solving skills, including the fundamental principles at work within a domain, helps to distinguish experts who perform well within *narrow* domains based on algorithmic knowledge from those who can perform well within *broadly* defined domains based on adaptive thinking (see Kuhn 2001).

Consider the reasoning of one business consultant in response to the problem of having one of the roads leading to the hypothetical restaurant becoming a one-way street, without parking:

> …depending on which way the one way is, it would be busy in one rush hour and not busy in another rush hour, so the road heading to town from suburbia would be busy in the morning and the other at night…
>
> …so if it turned out that it didn't matter and this was a destination decision I wouldn't worry about it, if there was significant impulse traffic I would be concerned and then I'd look into options such as a sign on the other road, billboard on the road 'make a right turn for Luigi's'. (245)

According to Barnett and Koslowski, the business consultant who provided this answer considered the alternative of having different kinds of customers stop by the restaurant, such as customers who planned in advance to eat at the restaurant and other (impulse) customers who might stop in by chance. The consequences of the one-way road were considered for both kinds of customers. In contrast, restaurant mangers often leapt to a conclusion and then used the available evidence to rationalize it:

> …put in their ads a reasonable place to park that is not too far away, advertise the fact that it is still very accessible for people, and that it is still very much worth coming to.

Recommendations were sometimes justified, and typically these justifications came after the recommendation:

> …it would definitely affect the restaurant because people don't want to go too much out of their way unless it's a special occasion or they really, really like it there.

In a final set of analyses, Barnett and Koslowski examined possible answers to the question of why some experts, such as the group of business consultants, make use of theoretical reasoning more often than others, and what types of experiences encourage the formation of these theoretical perspectives. In search of answers, they looked at participants' backgrounds, comparing their age, years of education, the presence or absence of business education, and number of years of experience in restaurant management and business consulting. The analyses revealed that the only characteristic predicting both the amount of theory-based reasoning and overall performance was *consulting experience*. None of the other background characteristics (for example, age, years of formal education) predicted use of theory-based reasoning or performance on the task. Although consulting experience was found to be the most influential predictor of performance, the investigators acknowledged that they were unable to examine pre-existing differences in ability or intelligence among the participants. This is a limitation with most studies of expertise (Gobet 2005). Although Barnett and Koslowski examined whether the Grade Point Average (GPA) of students in the novice group was associated with better problem-solving, they found no effect of GPA. This finding suggests that successful knowledge management across domains does not simply result from proximal academic success (GPA), seniority (age) or even years of formal education, but rather, is also a result from a method of thinking that involves in large part managing the reuse of theoretical concepts learned previously and the transfer of causal reasoning skills (for example, Wellman and Lagattuta 2004).

6.2 Policy Implications

Barnett and Koslowski's study is one of the few expert studies (however, see also Alexander et al. 2004; Barnett and Ceci 2005; Leighton 2006 for examples) to examine the differences between algorithmic and adaptive expertise and the form of thinking that characterizes the latter. Until recently, most research in skilled performance has not addressed this difference, focusing instead on simple comparisons between experts and novices (see for example, Chi, Feltovich, and Glaser 1981; Johnson et al. 1982) without distinguishing among different kinds of experts and their respective methods to manage knowledge.

From a policy perspective, then, what prompts knowledge reuse and the transfer of skill in the form of theoretical-based reasoning? Again, there is research suggesting that the *breadth* of an individual's prior experience may be the key to the development of deep, theory-based reasoning in the service of knowledge reuse and transfer of skill (Brown 1989; Catrambone and Holyoak 1989; Cummins 1992; Dunbar 1995; Gick and Holyoak 1983; Hatano 1982; Holyoak 1991; Leighton and Bisanz 2003). In addition to the research and recommendations already discussed by Garlick (2002), Gobet (2005), and Wellman and Lagattuta (2004), Brown (1989) found that four-year- old children who were trained with a broad range of distinct examples to illustrate mimicry-like defence mechanisms in animals (such as playing dead or changing shape) were more likely to reuse their knowledge to a new situation than children who were presented with a single type of example (ways to look dangerous). This is also supportive of Garlick's (2002) contention that variety or breadth (see section 3.2) in the tasks presented during a child's intellectual critical period is a key to maximizing neural plasticity and the connections for complex problem-solving (see also Gobet 2005 in section 4.2). In a similar vein, Dunbar (1995) discovered in his work with real scientists in microbiology laboratories that the collective span of relevant experience possessed by the scientists in the lab was a major determinant of their rate of effective problem solving leading to new discoveries.

Overall, the substantive variety in an expert's background experience appears to be associated with forms of flexible thinking that focus on underlying principles that can be used to make sense of new problems in conceptually similar domains. Again this is reminiscent of Gobet's (2005) recommendations for educators (see section 4.2). Activities that promote learning for meaning should be encouraged because they influence the ability to acquire flexible forms of thinking that make adaptive expertise possible. In short, there is strong evidence that exposing children to a variety of educational stimuli during their intellectual critical period, presenting them with stimulating problems and fostering them to seek deep, theory-based explanations for the occurrences they see in their environments, leads children to *learn for meaning* because they can abstract general principles about phenomena and understand (through explanations) why these principles exist. These general principles then facilitate the reuse of knowledge and transfer of skill by making visible the relational similarities in conceptually new domains (Dunbar 1995; Gentner 1999; Loewenstein, Thompson, and Gentner 1999; Rattermann and Gentner 1998).

7. Summary and Discussion

To conclude, I provide summary answers to the questions posed at the beginning of this paper:

1. *What does existing research in psychology tell us about the factors that influence human capital development?* The factors that influence human capital development are (a) *measured intelligence* because it predicts school grades and occupational outcomes in knowledge-intensive domains, (b) *neural efficiency* and *neural plasticity* because they predict measured intelligence, (c) *working memory* because it predicts knowledge management within academic and non-academic domains, (d) *knowledge (expertise)* and *context* because individuals who can use what they know in familiar contexts can solve problems more successfully and view problem-solving tasks as more relevant, and (e) *learning for meaning* through variety, explanations and discriminating features so that emerging experts can reuse their knowledge and transfer their skills to conceptually new domains.

2. *Which causal connections are well established, and which are more speculative? Which influences have the greatest impact?* Although *causal* connections are not fully established at the present time, there are predictive relationships that are well established: (a) Measured intelligence predicts schools grades and occupational outcomes in knowledge-intensive domains; this means that anything we can do to meaningfully boost measured intelligence in children will have payoffs for human capital development. Garlick (2002) suggests (see section 3.2) that we can do this by introducing valued forms of thinking (for example, theory-based reasoning in order to *learn for meaning*) to students at a younger age than is currently the case in educational settings. (b) Deliberate training within a domain to become an expert is associated with increases in working memory capacity and skilled performance; this means that anything we can do to meaningfully boost deliberate training for children and adults with have payoffs for human capital development. As mentioned previously, Gobet (2005) has eight recommendations (see section 4.2) that include spending a lot of time on training (so that individuals can acquire basic knowledge), using a variety of exemplars in teaching so as to promote the abstraction of general, underlying principles and pointing out key discriminating features in the material learned so that students learn the proper frameworks essential in the domain and can reuse their knowledge and transfer their skills to conceptually similar domains. In other words, one cannot simply hope that students will pick up the right knowledge, but rather, one has to make sure it is taught and students have the opportunity to learn. (c) Teaching and modeling the use of explanations promotes learning and performance in knowledge-intensive domains. Wellman and Lagattuta (2004; see section 6.2) as well as others (for example, Siegler 2002) have shown that children's ability to explain or try to explain phenomena in a variety of domains enhances their understanding of underlying principles within those domains; this means that creating conditions within the classroom and the home that highlight the definition and importance of understanding a concept and *knowing when something is known* is related to successful performance in knowledge-intensive domains and is most likely the mechanism by which adaptive experts are created.

3. *What key questions are not being answered or asked? What new ways of framing the issues might be worth exploring?* The key questions that are being asked but, as yet, not being answered interface with educational, sociological and health interests:

   (a) Using micro-level quasi-experimental and experimental research designs, are educational interventions able to improve children's learning and performance during a child's critical period for intellectual development? What are the specific subject topics that are most complementary to *early instruction* during a child's critical period for intellectual development?

   (b) What are the best methods to follow in maximizing the use of exemplars in teaching students so that they will learn underlying, explanatory principles about the domain?

   (c) Do large-scale assessments such as the PISA include test items that attempt to measure adaptive expertise and, if so, what are the effects of student characteristics on their performance?

   (d) What family or school characteristics promote or hinder the development of adaptive expertise?

   (e) How does socioeconomic status (SES) moderate the development of adaptive expertise? Does a low SES minimize the variety of educational experiences required to abstract underlying, explanatory principles in a domain?

   (f) Using longitudinal studies, how do prenatal and postnatal health relate to school grades, post-secondary participation, and labour market participation and/or occupational outcomes?

   (g) What are the effects of early educational and psychological interventions on postnatal health, school grades, post-secondary participation, and labour market participation/occupational outcomes?

Other key questions interface with social-organizational and economic interests, such as:

   (a) What are the effects of credentialing (versus education) in today's colleges and universities on innovative, adaptive expert thinking?

   (b) If knowledge creation and innovation respond to economic incentives, what are the incentives that could be offered to educational systems in experimenting with more inventive approaches to student education?

4. *How can we look beyond conventional disciplinary boundaries? Where could those boundaries be breached in the most interesting, creative and useful manner, in terms of subject matter, methodology, or in any other respect?* At least in some Canadian jurisdictions, there are few opportunities to engage in the kind of research that might begin to seriously answer some of these key questions. In part, this is the case because in order to answer some of these questions, psychologists must have access to children and student populations in classroom settings. None of this research is possible without the full help of school districts and personnel. However, access to schools and children is increasingly more difficult to obtain because research takes time and teachers and other school officials,

> for understandable reasons particularly pertaining to the need to cover curriculum and other activities, are unwilling to provide the necessary time and conditions to conduct intervention studies and other studies examining pedagogy. However, unless we are able to bridge this gap, these studies will not be conducted by Canadian researchers and instead will be conducted by others (for example, Americans) who have access to what are known as partnership programs between schools and universities (also known as university laboratory schools). For example, through the National Network of Partnership Schools at Johns Hopkins University, researchers, educators, parents, students and community members work together to develop and maintain effective academic and other programs at the elementary, middle and high school level to study and modify student learning and success.

The research findings reported in this paper provide compelling evidence for (a) introducing valued forms of thinking such as theory-based reasoning at earlier ages in the individual lifespan and (b) emphasizing deliberate and sustained practice with the effort to improve working memory and performance for individuals of varying levels of intelligence across the lifespan. In sum, these research findings suggest that, across the lifespan, we can improve the odds for developing human capital. Ideally, we should start early in a child's life and continue our efforts. However, to be successful in our aims we must shift our standards and our expectations of students, increasing and widening what we see as possible for all members of society. Initiatives to understand and develop human capital must aim also to bring together those individuals who teach future workers and those individuals who can apply systematic methods for examining the best way to teach thinking, skilled performance and adaptive expertise. Otherwise, we cannot successfully address ways to develop what Davenport (2005) calls the single most important capability for knowledge workers: the management of personal information and the knowledge environment.

References

Adams, M.J., R. Treiman, and M. Pressley. 1998. "Reading, Writing, and Literacy." In *Handbook of Child Psychology: Vol. 4. Child Psychology in Practice*, edited by W. Damon, I. Sigel, and K. Renninger. New York: Wiley, 275-355.

Adey, P.S. and M. Shayer. 1994. *Really Raising Standards: Cognitive Intervention and Academic Achievement*. New York: Routledge.

Albert, R.S. 1978. "Observations and Suggestions Regarding Giftedness, Familial Influence and the Achievement of Eminence." *The Gifted Child Quarterly* 22: 201-211.

Alexander, P.A., C.T. Sperl, M.M. Buehl, H. Fives, and S. Chiu. 2004. "Modeling Domain Learning: Profiles from the Field of Special Education." *Journal of Educational Psychology* 96: 545-557.

Allard, F. and J.L. Starkes. 1991. "Motor-Skill Experts in Sports, Dance, and Other Domains." In *Toward a General Theory of Expertise: Prospects and Limits*, edited by K. Anders Ericsson and Jacqui Smith. New York: Cambridge University Press, 126-152.

Anderson, J.R. 1983. *The Architecture of Cognition*. Cambridge: Harvard University Press.

Baddeley, A.D. 2000. "The Episodic Buffer: A New Component of Working Memory?" *Trends in Cognitive Sciences* 4: 417-423.

____. 2003. "Working Memory and Language: An Overview." *Journal of Communication Disorders* 36: 189-208.

Barnett, S.M. and S.J. Ceci. 2002. "When and Where Do We Apply What We Learn? A Taxonomy for Far Transfer." *Psychological Bulletin* 128: 612-637.

____. 2005. "The Role of Transferable Knowledge." In *Cognition &Iintelligence*, edited by R.J. Sternberg and J.E. Pretz. Cambridge, UK: Cambridge University Press, 208-224.

Barnett, S.M. and B. Koslowski. 2002. "Adaptive Expertise: Effects of Type of Experience and the Level of Theoretical Understanding It Generates." *Thinking and Reasoning* 8: 237-267.

Barrett, P.T., I. Daum, and H.J. Eysenck. 1990. "Sensory Nerve Conduction and Intelligence: A Methodological Study." *Journal of Psychophysiology* 4: 1-13.

Barrett, G.V. and R.L. Depinet. 1991. "A Reconsideration of Testing for Competence Rather than Intelligence." *American Psychologist* 46: 1012-1024.

Beckmann, J.F. and J. Guthke. 1995. “Complex Problem Solving, Intelligence, and Learning Ability.” In *Complex Problem Solving. The European Perspective*, edited by P.A. Frensch and J. Funke. Hillsdale, NJ: Erlbaum, 3-25.

Bloom, B.S. 1984. “The 2-Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-One Tutoring.” *Educational Researcher* 13: 4-16.

Bransford, J.D. and B.S. Stein. 1984. *The Ideal Problem Solver: A Guide for Improving Thinking, Learning, and Creativity*. New York: Freeman.

Brown, A.L. 1989. “Analogical Learning and Transfer: What develops?” In *Similarity and Analogical Reasoning*, edited by S. Vosniadou and A. Ortony. Cambridge, UK: Cambridge University Press, 369-412.

Carpenter, P.A. and M. Just. 1975. “Sentence Comprehension: A Psycholinguistic Processing Model of Verification.” *Psychological Review* 82: 45-73.

Carpenter, P.A., M.A. Just, and P. Shell. 1990. “What One Intelligence Test Measures: A Theoretical Account of Processing in the Raven’s Progressive Matrices Test.” *Psychological Review* 97: 404-431.

Carroll, J.B. 1993. *Human Cognitive Abilities*. Cambridge, UK: Cambridge University Press.

Catrambone, R. and K.J. Holyoak. 1989. “Overcoming Contextual Limitations on Problem-Solving Transfer.” *Journal of Experimental Psychology: Learning, Memory, and Cognition* 15: 1147-1156.

Cattell, R.B. 1971. *Abilities: Their Structure, Growth, and Action*. Boston: Houghton Mifflin.

Ceci, S. J. (2000). So near and yet so far: Lingering questions about the use of measures of general intelligence for college admission and employment screening. *Psychology, Public Policy, and Law, 6, 233-252.*

Ceci, S.J. and J. Liker. 1986a. “A Day at the Races: IQ, Expertise, and Cognitive Complexity.” *Journal of Experimental Psychology: General* 115: 255-266.

____. 1986b. “Academic Versus Non-Academic Intelligence: An Experimental Separation.” In *Practical Intelligence: Nature and Origins of Competence in the Everyday World*, edited by R.J. Sternberg and R.K. Wagner. New York: Cambridge University Press, 119-142.

Ceci, S.J. and A. Ruiz. 1992. “The Role of General Ability in Cognitive Complexity: A Case Study of Expertise.” In *The Psychology of Expertise*, edited by R. Hoffman. New York: Springer-Verlag, 218-230.

____. 1993. “Transfer, Abstractness, and Intelligence.” In *Transfer on Trial: Intelligence, Cognition, and Instruction*, edited by D.K. Detterman and R.J. Sternberg. Norwood, NJ: Ablex, 168-191.

Charness, N. and R.S. Schultetus. 1999. "Knowledge and Expertise." In *Handbook of Applied Cognition*, edited by F.T. Durso, R.S. Nickerson, R.W. Schvaneveldt, S.T. Dumais, D.S. Lindsay, and M. Chi. Chichester, NY: Wiley, 57-81.

Chase, W.G. and H.A. Simon. 1973. "Perception in Chess." *Cognitive Psychology* 4: 55-81.

Cheng, P.W. and K.J. Holyoak. 1985. "Pragmatic Reasoning Schemas." *Cognitive Psychology* 17: 391-416.

____. 1989. "On the Natural Selection of Reasoning Theories." *Cognition* 33: 285-313.

Chi, M.T.H., N. de Leeuw, M.H. Chiu, and C. LaVancher. 1994. "Eliciting Self-Explanations Improves Understanding." *Cognitive Science* 18: 439-477.

Chi, M.T.H., P. Feltovich, and R. Glaser. 1981. "Categorization and Representation of Physics Problems by Experts and Novices." *Cognitive Science* 5: 121-152.

Chi, M.T.H., R. Glaser, and M.J. Farr, eds. 1988. *The Nature of Expertise*. Hillsdale, NJ: Lawrence Erlbaum Associates.

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. and J. Tooby. 1996. "Are Humans Good Intuitive Statisticians After All? Rethinking Some Conclusions from the Literature on Judgement under Uncertainty." *Cognition* 58: 1-73.

Cummins, D.D. 1992. "Role of Analogical Reasoning in the Induction of Problem Categories." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 18: 1103-1124.

Davenport, T.H. 2005. *Thinking for a Living*. Boston: Harvard Business School Press.

Deary, I.J. and P.G. Caryl. 1993. "Intelligence, EEG, and Evoked Potentials." In *Biological Approaches to the Study of Human Intelligence*, edited by P.A. Vernon. Norwood, NJ: Ablex, 259-315.

de Groot, A.D. 1965. *Thought and Choice in Chess*. The Hague: Mouton.

Dunbar, K. 1995. "How Scientists Really Reason: Scientific Reasoning in Real-World Laboratories." In *The Nature of Insight*, edited by R.J. Sternberg and J.E. Davidson. Cambridge, MA: MIT Press, 365-395.

Dunn, J., J. Brown, C. Slomkowski, C. Tesla, and L. Youngblade. 1991. "Young Children's Understanding of Other People's Feelings and Beliefs: Individual Differences and Their Antecedents." *Child Development* 62: 1352-1366.

Duncan, J., P. Burgess, and H. Emslie. 1995. “Fluid Intelligence After Frontal Lobe Lesions.” *Neuropsychologia* 33: 261-268.

Duncan, J., R.J. Seitz, J. Kolodny, D. Bor, H. Herzog, A. Ahmed, F.N. Newell, and H. Emslie. 2000. “A Neural Basis for General Intelligence.” *Science* 289: 457-460.

Engle, R.W., S.W. Tuholski, J.E. Laughlin, and A.R.A. Conway. 1999. “Working Memory, Short-Term Memory, and General Fluid Intelligence: A Latent Variable Approach.” *Journal of Experimental Psychology: General* 128: 309-331.

Ericsson, K.A. 1996. “The Acquisition of Expert Performance.” In *The Road to Excellence*, edited by K.A. Ericsson. Mahwah, NJ: Lawrence Erlbaum Associates.(pp. 1-50)

Ericsson, K.A. and N. Charness. 1994. “Expert Performance: Its Structure and Acquisition.” *American Psychologist* 49: 725-747.

Ericsson, K.A. and W. Kintsch. 1995. “Long-Term Working Memory.” *Psychological Review* 102: 211-245.

Ericsson, K.A., R.T. Krampe, and C. Tesch-Romer. 1993. “The Role of Deliberate Practice in the Acquisition of Expert Performance.” *Psychological Review* 100: 363-406.

Ericsson, K.A. and H.A. Simon. 1993. *Protocol Analysis*: *Verbal Reports As Data*. Cambridge, MA: MIT Press.

Ericsson, K.A. and J. Smith, eds. 1991. *Toward a General Theory of Expertise: Prospects and Limits*. New York: Cambridge University Press.

Fiez, J.A. 2001. “Bridging the Gap between Neuroimaging and Neuropsychology: Using Working Memory as a Case Study.” *Journal of Clinical and Experimental Neuropsychology* 23: 19-31.

Funke, J. 1995. “Experimental Research on Complex Problem Solving.” In *Complex Problem Solving. The European Perspective*, edited by P.A. Frensch and J. Funke. Hillsdale, NJ: Erlbaum, 243-268.

Garlick, D. 2002. “Understanding the Nature of the General Factor of Intelligence: The Role of Individual Differences in Neural Plasticity as an Explanatory Mechanism.” *Psychological Review* 109: 116-136.

Gentner, D. 1999. “Analogy.” In *The MIT Encyclopedia of the Cognitive Sciences*, edited by R.A. Wilson and F.C. Keil. Cambridge, MA: MIT Press, 17-19.

Gick, M.L. and K.J. Holyoak. 1983. “Schema Induction and Analogical Transfer.” *Cognitive Psychology* 15: 1-38.

Gigerenzer, G. and K. Hug. 1992. "Domain-Specific Reasoning: Social Contracts, Cheating, and Perspective Change. *Cognition* 43:127-171.

Gigerenzer, G., P.M. Todd, and the ABC Research Group, eds. 1999. *Simple Heuristics That Make Us Smart*. New York: Oxford University Press.

Girotto, V. 2004. "Task Understanding." In *The Nature of Reasoning*, edited by J.P. Leighton and R.J. Sternberg. New York: Cambridge University Press, 103-128.

Gladwell, M. 2005. *Blink: The Power of Thinking without Thinking*. New York: Little Brown.

Gobet, F. 1997. "A Pattern-Recognition Theory of Search in Expert Problem Solving." *Thinking and Reasoning* 3: 291-313.

____. 2005. "Chunking Models of Expertise: Implications for Education." *Applied Cognitive Psychology* 19: 183-204.

Gobet, F. and H.A. Simon. 1996. "Templates in Chess Memory: A Mechanism for Recalling Several Boards." *Cognitive Psychology* 31: 1-40.

Haier, R.J. 1993. "Cerebral Glucose Metabolism and Intelligence." In *Biological Approaches to the Study of Human Intelligence,* edited by P.A. Vernon. Norwood, NJ: Ablex, 317-332.

Haier, R.J., B.V. Siegel, K.H. Nuechterlein, E. Hazlett, J.C. Wu, J. Paek, H.L. Browning, and M.S. Buchsbaum. 1988. "Cortical Glucose Metabolic Rate Correlates of Abstract Reasoning and Attention Studied with Positron Emission Tomography. *Intelligence* 12: 199-217.

Haier, R.J., B.V. Siegel, A. MacLachlan, E. Soderling, S. Lottenberg, and M.S. Buchsbaum. 1992a. "Regional Glucose Metabolic Changes after Learning a Complex Visuospatial/Motor Task: A Positron Emission Topographic Study." *Brain Research* 570: 134-143.

Haier, R.J., B. Siegel, C. Tang, L. Abel, and M.S. Buchsbaum. 1992b. "Intelligence and Changes in Regional Cerebral Glucose Metabolic Rate Following Learning." *Intelligence* 16: 415-426.

Hambrick, D.Z., M.J. Kane, and R.W. Engle. 2005. "The Role of Working Memory in Higher-Level Cognition." In *Cognition & Intelligence*, edited by R.J. Sternberg and J.E. Pretz. Cambridge, UK: Cambridge University Press, 104-121.

Hansen, K.T., J.J. Heckman, and K.J. Mullen. 2004. "The Effect of Schooling and Ability on Achievement Test Scores." *Journal of Econometrics* 121: 39-98

Hatano, G. 1982. "Cognitive Consequences of Practice in Culture Specific Procedural Skills." *The Quarterly Newsletter of the Laboratory of Comparative Human Cognition* 4: 15-18.

____. 1988. "Social and Motivational Bases for Mathematical Understanding." In *Children's Mathematics*, edited by G.B. Saxe and M. Gearhart. San Francisco: Jossey-Bass, 55-70.

Hatano, G. and K. Inagaki. 1984. “Two Courses of Expertise.” *Research and Clinical Center for Child Development (Annual Report)* 83: 27-36.

____. 1986. “Two Courses of Expertise.” In *Child Development and Education in Japan*, edited by H.W. Stevenson and H. Azuma. New York: W.H. Freeman & Co., 262-272.

Haverty, L., K.R. Koedinger, D. Klahr, and M.W. Alibali. 2000. “Solving Inductive Reasoning Problems in Mathematics: Not-So-Trivial Pursuit.” *Cognitive Science* 24: 249-298.

Holding, D.H. 1992. “Theories of Chess Skill.” *Psychological Research* 54: 10-16.

Holyoak, K.J. 1991. “Symbolic Connectionism: Toward Third-Generation Theories of Expertise.” In *Toward a General Theory of Expertise: Prospects and Limits*, edited by K.A. Ericsson and J. Smith. New York: Cambridge University Press, 301-335.

Horn, J.L. and J. Noll. 1994. “A System for Understanding Cognitive Capabilities: A Theory and the Evidence on which It Is Based.” In *Current Topics in Human Intelligence: Vol. 4. Theories of Intelligence*, edited by D. Detterman. Norwood, NJ: Ablex, 151-204.

Hunt, E. 2005. “Information Processing and Intelligence.” In *Cognition & Intelligence*, edited by R.J. Sternberg and J.E. Pretz. Cambridge, UK: Cambridge University Press, 1-25.

Jensen, A.R. 2005. “Mental Chronometry and the Unification of Differential Psychology.” In *Cognition & Intelligence*, edited by R.J. Sternberg and J.E. Pretz. Cambridge, UK: Cambridge University Press, 26-50.

Johnson, A. 2003. “Procedural Memory and Skill Acquisition.” In *Experimental Psychology*, volume edited by A.F. Healy and R.W. Proctor, in *Handbook of Psychology, Volume 4*, editor-in-chief I.B. Weiner. New York: Wiley, 499-523.

Johnson, P.E., F. Hassebrock, A.S. Duran, and J.H. Moller. 1982. “Multimethod Study of Clinical Judgement.” *Organizational Behavior and Human Decision Processes* 30: 201-230.

Johnson-Laird, P.N. 1999. “Deductive Reasoning.” *Annual Review of Psychology* 50: 109-135.

Kessels, R.P.C., A. Postma, E.M. Wijnalda, and H.F. de Haan. 2000. “Frontal-Lobe Involvement in Spatial Memory: Evidence from PET, fMRI, and Lesion Studies.” *Neuropsychology Review* 10: 101-113.

Kuhn, D. 2001. “How Do People Know?” *Psychological Science* 12: 1-8.

Kyllonen, P.C. 1996. “Is Working Memory Capacity Spearman’s g?” In *Human Abilities: Their Nature and Measurement*, edited by I. Dennis and P. Tapsfield. Mahwah, NJ: Erlbaum, 49-75.

Kyllonen, P.C. and R.E. Christal. 1990. “Reasoning Ability Is (Little More Than) Working-Memory Capacity?” *Intelligence* 14: 389-433.

Leighton, J.P. 2004. "The Assessment of Logical Reasoning." In *The Nature of Reasoning*, edited by J.P. Leighton and R.J. Sternberg. New York: Cambridge University Press, 291-312.

____. 2006. "Teaching and Assessing Deductive Reasoning Skills." *Journal of Experimental Education* 74: 109-136.

Leighton, J.P. and G.L. Bisanz. 2003. "Children's and Adults' Knowledge and Models of Reasoning about the Ozone Layer and Its Depletion." *International Journal of Science Education* 25(1): 117-139.

Leighton, J.P. and R.J. Sternberg. 2003. "Reasoning and Problem Solving." In *Experimental Psychology*, volume edited by A.F. Healy and R.W. Proctor, in *Handbook of Psychology*, *Volume 4*, editor-in-chief I.B. Weiner. New York: Wiley, 623-648.

____. 2004. *The Nature of Reasoning*. New York: Cambridge University Press.

Liberman, N. and Y. Klar. 1996. "Hypothesis Testing in Wason's Selection Task: Social Exchange, Cheating Detection, or Task Understanding." *Cognition* 58: 127-156.

Loewenstein, J., L. Thompson, and D. Gentner. 1999. "Analogical Encoding Facilitates Knowledge Transfer in Negotiation." *Psychonomic Bulletin & Review* 6: 586-597.

Manktelow, K.I., N. Fairley, S.G. Kilparick, and D.E. Over. 2000. "Pragmatics and Strategies for Practical Reasoning." In *Deductive reasoning and strategies*, edited by W. Schaeken, G. De Vooght, and G. d'Ydewalle. Mahwah, NJ: Lawrence Erlbaum Associates, 23-48.

Manktelow, K. I. and D.E. Over. 1991. "Social Roles and Utilities in Reasoning with Deontic Conditionals." *Cognition* 39: 85-105.

Meins, E., C. Fernyhough, R. Wainright, M.D. Gupta, E. Fradley, and M. Tuckey. 2003. "Maternal Mind-Mindedness and Attachment Security as Predictors of Theory of Mind Understanding." *Child Development* 73: 1715-1726.

Miller, E.M. 1994. "Intelligence and Brain Myelination: A Hypothesis." *Personality and Individual Differences* 17: 803-832.

Nairne, J. 2003. "Sensory and Working Memory. In *Experimental Psychology*, volume edited by A.F. Healy and R.W. Proctor, in *Handbook of Psychology*, *Volume 4*, editor-in-chief I.B. Weiner. New York: Wiley, 423-444.

Neubauer, A.C. 1997. "The Mental Speed Approach to the Assessment of Intelligence." In *Advances in Cognition and Educational Practice: Reflections on the Concept of Intelligence*, edited by J. Kingma and W. Tomic. Greenwich, CT: JAI Press, 149-174.

Neubauer, A.C. and A. Fink. 2003. "Fluid Intelligence and Neural Efficiency: Effects of Task Complexity and Sex." *Personality and Individual Differences* 35: 811-827.

____. 2005. “Basic Information Processing and the Psychophysiology of Intelligence.” In *Cognition & Intelligence*, edited by R.J. Sternberg and J.E. Pretz. Cambridge, UK: Cambridge University Press, 68-87.

Neubauer, A.C., A. Fink, and D.G. Schrausser. 2002. “Intelligence and Neural Efficiency: The Influence of Task Content and Sex on the Brain-IQ Relationship.” *Intelligence* 30: 515-536.

Neubauer, A.C., H.H. Freudenthaler, and G. Pfurtscheller. 1995. “Intelligence and Spatio-Temporal Patterns of Event-Related Desynchronization.” *Intelligence* 20: 249-267.

Neubauer, A.C., G. Sange, and G. Pfurtscheller. 1999. “Psychometric Intelligence and Event-Related Desynchronization During Performance of a Letter Matching Task.” In *Event-Related Desynchronization (ERD) and Related Oscillatory EEG Phenomena of the Awake Brain. Handbook of EEG and Clinical Neurophysiology, Revised Series*, edited by G. Pfurtscheller and F.H. Lopes da Silva. Amsterdam: Elsevier, vol. 6: 219-231.

Newell, A. and H.A. Simon. 1972. *Human Problem Solving*. Englewood Cliffs, New Jersey: Prentice-Hall.

Newstead, S.E. and J.St.B.T Evans. 1993. “Mental Models As an Explanation of Belief Bias Effects in Syllogistic Reasoning.” *Cognition* 46: 93-97.

Nickerson, R. 2004. “Teaching Reasoning.” In *The Nature of Reasoning*, edited by J.P. Leighton and R.J. Sternberg. New York: Cambridge University Press, 410-442.

Norris, S.P., J.P. Leighton, and L.M. Phillips. 2004. “What Is at Stake in Knowing the Content and Capabilities of Children’s Minds? A Case for Basing High Stakes Tests on Cognitive Models.” *Theory and Research in Education* 2: 283-308.

Parks, R.W., D.A. Loewenstein, K.L. Dodrill, W.W. Barker, F. Yoshii, J.Y. Chang, A. Emran, A. Apicella, W.A. Sheramata, and R. Duara. 1988. “Cerebral Metabolic Effects of a Verbal Fluency Test: A PET Scan Study.” *Journal of Clinical Experimental Neuropsychology* 10: 565-575.

Perkins, D.N. 1995. *Outsmarting IQ: The Emerging Science of Learnable Intelligence*. New York: The Free Press.

Pfurtscheller, G. and A. Aranibar. 1977. “Event-Related Cortical Desynchronization Detected by Power Measurements of Scalp EEG.” *Electroencephalography and Clinical Neurophysiology* 42: 817-826.

Pfurtscheller, G. and F.H. Lopes da Silva. 1999. “Event-Related EEG/EMG Synchronization and Desynchronization: Basic Principles.” *Clinical Neurophysiology* 110: 1842-1857.

Pine, K.J. and R.S. Siegler. 2003. “The Role of Explanatory Activity in Increasing the Generality of Thinking.” Paper presented at the Biennial Meeting of the Society for Research in Child Development, Tampa, FL.

Pollard, P. and J.St.B.T. Evans. 1987. "Content and Context Effects in Reasoning." *American Journal of Psychology* 100: 41-60.

Prabhakaran, V., J.A.L. Smith, J.E. Desmond, H. Glover, and J.D.E. Gabrieli. 1997. "Neural Substrates of Fluid Reasoning: An fMRI Study of Neocortical Activation during Performance of the Raven's Progressive Matrices Test." *Cognitive Psychology* 33: 43-63.

Priest, A.G. and R.O. Lindsay. 1992. "New Light on Novice-Expert Differences in Physics Problem Solving." *British Journal of Psychology* 83: 389-405.

Rattermann, M. and D. Gentner. 1998. "More Evidence for a Relational Shift in the Development of Analogy: Children's Performance on a Causal-Mapping Task." *Cognitive Development* 13: 453-478.

Reed, T.E. and A.R. Jensen. 1991. "Arm Nerve Conduction Velocity (NCV), Brain NCV, Reaction Time, and Intelligence." *Intelligence* 15: 33-48.

____. 1992. "Conduction Velocity in a Brain Nerve Pathway of Normal Adults Correlates with Intelligence Level." *Intelligence* 16: 259-272.

Roberts, M.J. and E.J. Newton, eds. 2005. *Methods of Thought: Individual Differences in Reasoning Strategies.* New York, Psychology Press.

Salomon, G. and D.N. Perkins. 1989. "Rocky Roads to Transfer: Rethinking Mechanisms of a Neglected Phenomenon." *Educational Psychologist* 24: 113-142.

Schmidt, F.L. and J. Hunter. 2004. "General Mental Ability in the World of Work: Occupational Attainment and Job Performance." *Journal of Personality and Social Psychology* 86: 162-173.

Siegler, R.S. 2002. "Microgenetic Studies of Self-Explanation." In *Microdevelopment: Transition Processes in Development and Learning*, edited by N. Granott and J. Parziale. New York: Cambridge University Press, 31-58.

Sperber, D., F. Cara, and V. Girotto. 1995. "Relevance Theory Explains the Selection Task." *Cognition* 57: 31-95.

Stanovich, K.E., W.C. Sá, and R.F. West. 2004. "Individual Differences in Reasoning." In *The Nature of Reasoning*, edited by J.P. Leighton and R.J. Sternberg. New York: Cambridge University Press, 375-409.

Stanovich, K.E. and R.F. West. 1998. "Individual Differences in Rational Thought." *Journal of Experimental Psychology: General* 127: 161-188.

____. 2000. "Individual Differences in Reasoning: Implications for the Rationality Debate?" *Behavioral and Brain Sciences* 23: 645-726.

Stenning, K. and P. Yule. 1997. "Image and Language in Human Reasoning: A Syllogistic Illustration." *Cognitive Psychology* 34: 109-159.

Sternberg, R.J. 1999. "Intelligence As Developing Expertise." *Contemporary Educational Psychology* 24: 359-375.

Sternberg, R.J. and T. Ben-Zeev. 2001. *Complex Cognition: The Psychology of Human Thought*. New York: Oxford University Press.

Sternberg, R.J. and E.L. Grigorenko, eds. 2002. *The general factor of intelligence*. Mahwah, NJ: Erlbaum.

Sternberg, R.J., C. Nokes, P.W. Geissler, R. Prince, F. Okatcha, D.A. Bundy, and E.L. Grigorenko. 2001. "The Relationship between Academic and Practical Intelligence: A Case Study in Kenya." *Intelligence* 29: 401-418.

Sternberg, R.J. and J.E. Pretz, eds. 2005. *Cognition and Intelligence*. New York: Cambridge University Press.

Tomlinson-Keasey, C. and T.D. Little. 1990. "Predicting Educational Attainment, Occupational Achievement, Intellectual Skill, and Personal Adjustment among Gifted Men and Women." *Journal of Educational Psychology* 82: 442-455.

Vernon, P.A., ed. 1987. *Speed of Information Processing and Intelligence*. Norwood, NJ: Ablex.

Wason, P.C. 1966. "Reasoning." In *New Horizons in Psychology*, edited by B.M. Foss. Oxford Penguin.

Wellman, H.M. and K.H. Lagattuta. 2004. "Theory of Mind for Learning and Teaching: The Nature and Role of Explanation." *Cognitive Development* 19: 479-497.

Wenke, D., P.A. Frensch, and J. Funke. 2005. "Complex Problem Solving and Intelligence." In *Cognition & Intelligence*, edited by R.J. Sternberg and J.E. Pretz. Cambridge, UK: Cambridge University Press, 160-187.

Our Support

Funding for this project was provided by:

- Alberta Human Resources and Employment
- Canada Millennium Scholarship Foundation
- Canadian Council on Learning
- Human Resources and Skills Development Canada
- Ontario Ministry of Training, Colleges and Universities

Donations:
BCE Inc.
Power Corporation of Canada
Purpleville Foundation
Scotiabank
SNC-Lavalin Group Inc.

Members of the Board of Directors, Campaign Committee and management team
Many *e-network* subscribers and friends of CPRN

Project Funding:
***Corporations**:*
Bell Canada
Business Development Bank of Canada
CIBC
Ekos Research Associates Inc.
First Plazas Inc.
Home Depot Canada
RBC Financial Group
TD Bank Financial Group

Federal Government Departments, Agencies and Commissions:
Canada Mortgage and Housing Corporation
Canadian Heritage
Canadian Institutes of Health Research
Citizenship and Immigration Canada
Health Canada
Human Resources Skills Development Canada
Infrastructure Canada
International Development Research Centre
Law Commission of Canada
Office of Nursing Policy
Privy Council Office
Social Development Canada

***Provincial Governments*:**
Alberta
- Alberta Human Resources and Employment

British Columbia
- Ministry of Skills Development and Labour

Manitoba
- Department of Family Services and Housing
- Ministry of Advanced Education and Training
- Ministry of Education, Citizenship and Youth

New Brunswick
- Department of Training and Employment Development

Nova Scotia
- Department of Community Services
- Department of Education
- Department of Environment and Labour

Ontario
- Ministry of Children and Youth Services
- Ministry of Community and Social Services
- Ministry of Labour
- Ministry of Training, Colleges and Universities
- Ministry of Training, Colleges and Universities – Postsecondary Review Secretariat
- Ontario Women's Health Council
- Strategic Planning and Elementary/Secondary Programs

Prince Edward Island
- Department of Education

Quebec
- Commission des normes du travail

Saskatchewan
- Department of Community Resources and Employment
- Ministry of Labour
- Department of Learning

Foundations:
The Bertelsmann Foundation
Bronfman Foundation
Community Foundations of Canada
Walter and Duncan Gordon Foundation
Fondation Roaster's Foundation
Pierre Elliott Trudeau Foundation
William and Nancy Turner Foundation
R. Howard Webster Foundation
The Wilson Foundation

Associations and Other Organizations:
Association of Colleges of Applied Arts and Technology of Ontario
Atlantic Centre of Excellence for Women's Health
Canadian Centre for Philanthropy
Canadian Institute for Health Information
Canadian Labour Congress
Canadian Medical Association
Canadian Public Health Association
Centre of Excellence for Children and Adolescents with Special Needs
Centre of Excellence for Youth Engagement
Conference Board of Canada
McGill University
McMaster University
Modernizing Income Security for Working Age Adults
Organisation for Economic Co-operation and Development
Nuclear Waste Management Organization
Parliamentary Centre of Canada
Public Health Agency of Canada
Queen's University
Social and Enterprise Development Innovations
Task Force Two: A Physician Human Resource Strategy for Canada
University of Alberta
University of Toronto