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ABSTRACT

A documented shortage of technical leadership and top-tier performers in computer science jeopardizes the technological edge, security, and economic well-being of the nation. The 2005 President's Information and Technology Advisory Committee (PITAC) Report on competitiveness in computational sciences highlights the major impact of science, technology, and innovation in keeping America competitive in the global marketplace. It stresses the fact that the supply of science, technology, and engineering experts is at the core of America's technological edge, national competitiveness and security. However, recent data shows that both undergraduate and postgraduate production of computer scientists is falling. The decline is "a quiet crisis building in the United States," a crisis that, if allowed to continue unchecked, could endanger America's well-being and preeminence among the world's nations.

Past research on expert performance has shown that the cognitive traits of critical thinking, creativity, and problem solving possessed by top-tier performers can be identified, observed and measured. The studies show that the identified attributes are applicable across many domains and disciplines. Companies have begun to realize that cognitive skills are important for high-level performance and are reevaluating the traditional academic standards they have used to predict success for their top-tier performers in computer science.

Previous research in the computer science field has focused either on programming skills of its experts or has attempted to predict the academic success of students at the undergraduate level. This study, on the other hand, exam-

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The results of this study suggest a need to examine how critical-thinking abilities are learned in the undergraduate computer science curriculum and the need to foster these abilities in order to produce the high-level, critical-thinking professionals necessary to fill the growing need for these experts. Due to the fact that current measures of academic performance do not adequately depict students' cognitive abilities, assessment of these skills must be incorporated into existing curricula.

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CRITICAL THINKING TRAITS OF TOP-TIER EXPERTS AND IMPLICATIONS FOR COMPUTER SCIENCE EDUCATION

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Computer Science

---

by
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August 2007

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DEDICATION

This dissertation is dedicated to my wife Andrea and daughter Alison who were with me throughout this entire journey.

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Chapter 1

Introduction

The 2005 President's Information and Technology Advisory Committee (PITC) report on competitiveness in computer sciences highlights the major impact of science, technology, and innovation in keeping America competitive in the global marketplace, stressing that the supply of experts in these fields is at the core of America's technological edge, national competitiveness and security [Benioff and Lawzoska 2005]. Specifically, top-tier performers in computer science are essential to the success of business, according to a 2004 Computing Research Association (CRA) survey. Ninety-seven percent of the businesses surveyed said they could not compete or even exist without high performance computing [Vegso 2004]. However, the supply of these top performers is declining at the same time the demand is growing. The impact of declining numbers of experts in computer science is "a quiet crisis in the United States" that, if allowed to continue unchecked, could endanger America's well-being and adversely affect the nation's current leadership role [Jackson 2005].

According to a recent UCLA Higher Education Research Institute report, the percentage of incoming undergraduates at all degree-granting institutions, indicating they plan to major in computer science, declined by 70 percent between the Fall of 2000 and 2005 [Higher Education Research Institute 2006]. The number of new computer science majors in the Fall of 2005 was half the number of those in the Fall of 2000–7,952 in 2005 versus 15,958 in 2000. A United States Department of Education report notes that other nations; notably Australia, China, India, Singapore and South Korea; are strongly

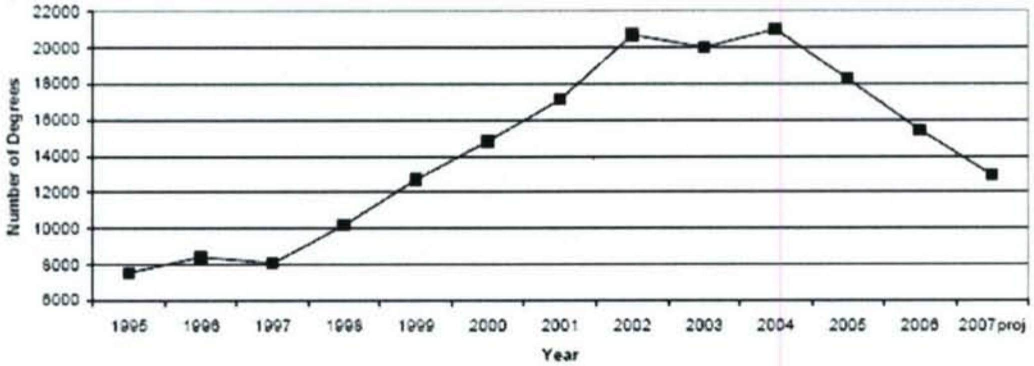


Figure 1.1: Decline in computer science bachelor's degree production [Zweben 2007]

supporting degrees in the Science, Technology, Engineering, and Mathematics (STEM) disciplines, especially in computer science, and investing heavily in them. At the same time, America's output of these graduates is declining [Freeman 2005]. This marked decline in undergraduate computer science majors weakens the talent pool of computer scientists. Figure 1.1 shows the decline in bachelor's degree production over the past 10 years. According to the most recent Taulbee CRA survey, bachelor's production declined by 15 percent in 2006, following a 13 percent decrease reported in 2005 [Zweben 2007]. One of many contributing factors to this decline is "doubts about the relevance of computing, particularly as it is taught" [McGettrick et al. 2007].

The decreased enrollment in the United States in computer science PhD programs is equally as alarming as the decline in undergraduate enrollment. The number of students entering computer science PhD programs in 2005 decreased 5 percent, following an 8 percent decrease in 2004 and a 5 percent decrease in 2003 [Vegso 2006]. According to CRA, the 849 doctoral degrees in computer science and computer engineering awarded in 2002 by United States institutions was the lowest since 1989 [Vegso 2004]. In 2006 the number

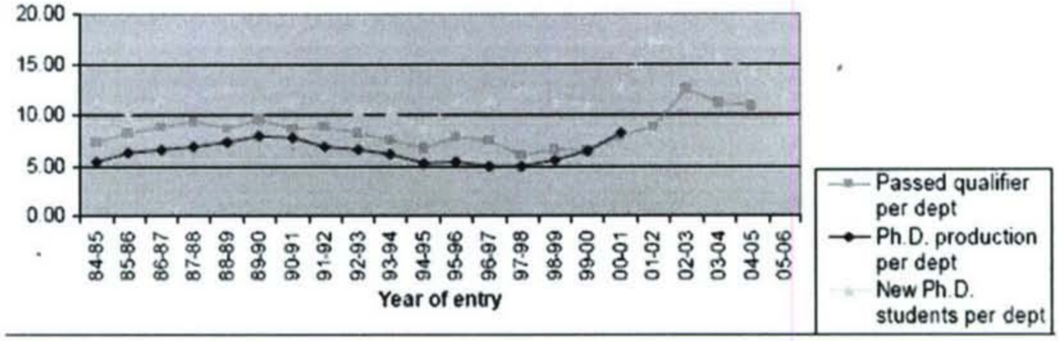


Figure 1.2: Decline in production pipeline of PhDs across the United States 1984-2006 [Zweben 2007]

of new PhD's granted hit an all-time high of 1499, however, the long term production of PhD's continues to be a concern. The latest CRA report shows, "The number of students who passed the qualifier declined 5%, and the total number of new Ph.D. students declined more than 6% (the fourth straight year of a decline in number of new students)" [Zweben 2007]. This overall downward trend of PhD candidates in the production pipeline is shown in Figure 1.2. This declined production potentially will have a negative impact on the talent pool of computer science experts.

Past research has identified specific traits and cognitive skills common among the top-tier performers or experts in their fields. However, traditional methods of identifying potential experts often rely solely on assessing subject-matter expertise and evaluating measures such as academic performance and technical skills. Some companies, however, have found that these methods do not necessarily predict success. For example, Intel and Google have found that successful and innovative employees did not necessarily have high grades in undergraduate computing courses, did not uniquely come from elite engineering institutions, and do not always have the widest array of programming skills and technical expertise [Colwell 2005]. On the other hand, more recent research,

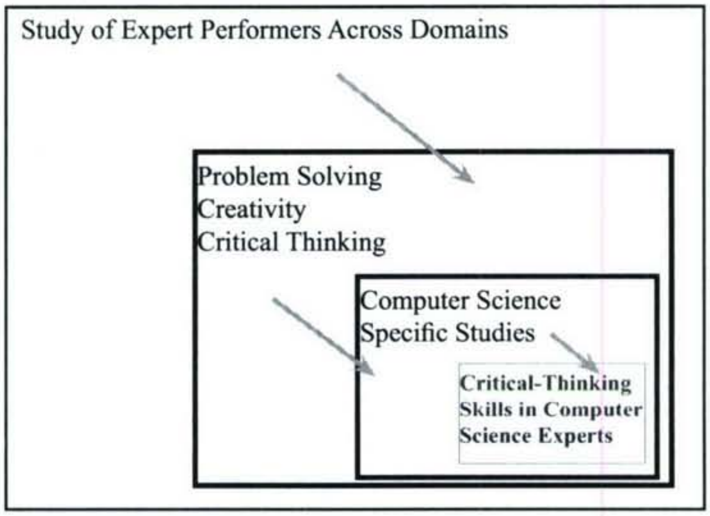


Figure 1.3: Study direction for critical-thinking skills in computer science as proposed in the research presented here

using other methods of identification, has shown that expert performers have strengths in the cognitive skills of problem solving, critical thinking and creativity [Sternberg 2003b; 2006; Ericsson 2003; Facione 2005; Chi and Glaser 1988].

These cognitive skills also have great significance for expert performance in computer science. Traditional computer science curriculum and undergraduate education focus on subject-matter knowledge as defined by The Joint Task Force on Computing Curricula [ACM and IEEE 2001; 1991]. Recent guideline recommendations by the Accreditation Board for Engineering Technology (ABET) Computing Accreditation Committee (CAC), however, have expanded the basic skill requirements, placing a new emphasis on critical-thinking and problem-solving skills. It requires accredited programs to equip graduates with "an ability to analyze a problem, and identify and define the computing requirements appropriate to its solution" and "an ability to design, implement and evaluate a computer-based system, process, component, or program to meet desired needs" [ABET 2007]. A recent report by the Computer Science Teachers Association has likewise stressed the importance of critical-thinking and problem-solving skills, listing among its 10 core principles of computer science education a "focus on teaching problem-solving methodologies and critical-thinking skills," and a need to "help students develop a wide range of cognitive capabilities and practical skills, independent of specific technologies" [CSTA Curriculum Improvement Task Force 2005].

Current studies have begun to evaluate the importance of critical-thinking skills in computer science and how they should be incorporated into specific core courses [M.R.K. Krishna Rao and Bagais 2006; Fagin et al. 2006]; however, a thorough review of these studies and of available computer science literature show that research into critical-thinking skills among computer professionals and experts and how to relate these skills to undergraduate education is lacking. One of the first steps in addressing this needed research is to compare and contrast the critical-thinking skills of top-tier professionals and undergraduate students, and to assess correlations between currently used measures of academic success and these skills, raising several questions reported in this study.

The first research question examines top-tier performers in computer science in an effort to identify the critical-thinking skills that have enabled them to become the experts. The study also examined college freshman and senior computer science students in order to answer additional research questions: "What critical-thinking abilities do freshmen have?"; "What are the critical-thinking abilities of senior computer science students?"; "How do the critical-thinking skills of the freshmen and senior computer science students

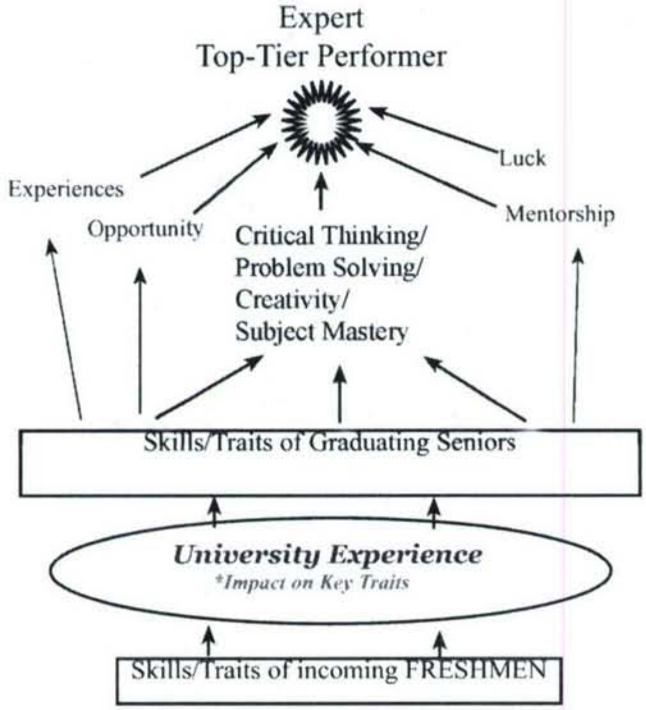


Figure 1.4: Educational impact of cognitive skills on expert performance

compare?", and "How do currently used measures of academic performance, such as grade-point average, correlate to this assessment of critical-thinking skills?" The results of these questions enabled the research to answer the final question, "What are the differences in critical-thinking skills between professionals and undergraduate computer science students?" Figure 1.4 graphically illustrates the role that educating college students in cognitive skills plays in equipping them to become those expert top-tier performers in their fields.

While traditional measures of academic success are important and underlying subject-specific skills are at the core of a computer science major, this study shows that critical-thinking skills do have implications for computer science education. It suggests a need to reevaluate the computer science curriculum in an effort to address the concerns caused by the growing demand for top-tier experts in the field.

Chapter 1 has included information related to the problem that prompted this research, a statement of that problem, and the significance of this study. Chapter 2 provides a foundation for this research by reviewing the background literature related to expertise, problem solving, critical thinking and creativity. Chapter 3 explains the research methodology used, and Chapter 4 analyzes the results. Chapter 5 concludes the dissertation with a summary of the study, its implications for computer science education, and suggested areas for future work.

Chapter 2

Background

2.1 Theories of Expert Performance

The study of expert performance, a widely researched subject in cognitive psychology, has found that expert performers possess certain common traits: a mastery of the subject content in which they are involved, and high-level strengths in 3 basic cognitive areas–problem solving, critical thinking and creativity. Figure 2.1 synthesizes these common traits as reported by top researchers:

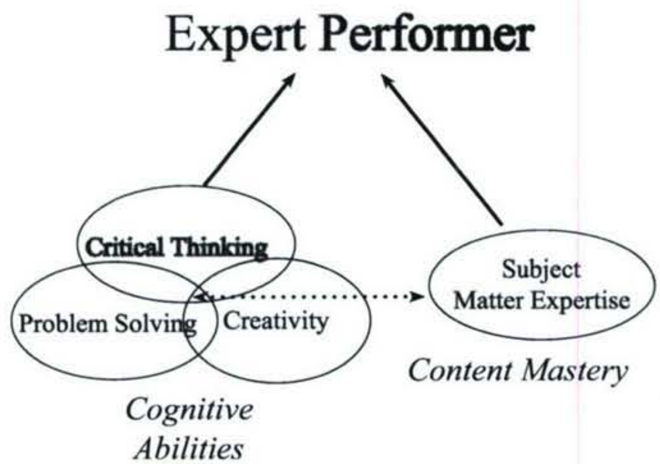


Figure 2.1: Factors that influence expert performance

Galton (1822-1911), one of the earliest pioneers in the study of traits of expert performers, stands out because he was the first to theorize and explore factors of expert performance, including an innate ability, eagerness to work, and "an adequate power of doing a great deal of very laborious work" [Ericsson and Charness 1994]. Although he considered the later 2 important, his research focused primarily on innate abilities and the role heredity plays in intelligence and expert performance. He theorized that innate abilities are necessary for excellence and that although practice is required, it alone cannot produce top performers. In *Hereditary Genius* (1869), he espouses his views that hereditary factors form the upper limit to maximal performance. He uses the example of beginning a new physical activity such as rowing, lifting weights, or running:

> So long as he is a novice, he perhaps flatters himself there is hardly an assignable limit to the education of his muscles; but the daily gain is soon discovered to diminish, and at last it vanishes altogether. His maximum performance becomes a rigidly determinate quantity.... There is a definite limit to the muscular powers of every man, which he cannot by any education or exertion overpass.

In extending these physical limits to the intellectual domain, he argues that "this is precisely analogous to the experience that every student has had of the working of his mental powers...." As the student matures, he reaches naturally inherited limits to his intellectual capacity and "when he reaches mature life, he is confident only within certain limits...." He "limits his undertakings to matters below the level of his reach and finds true moral repose in an honest conviction that he is engaged in as much good work as his nature has rendered him capable of performing" [Galton 1892].

Theorizing that excellence in diverse fields and domains has a common set of causes, Galton studied such characteristics as "height, body size, circumference of head, size of brain, weight of grey matter and number of brain fibers" in an attempt to find physiological differences between experts and novices [Simonton 2003]. His views of "maximum performance" based on genetic qualities, shaped much of the early debate and research on expertise and intelligence. "Galton's belief in the adaptive value of natural ability became thereby translated into widespread conviction that general intelligence provides the single most critical psychological factor underlying success in life" [Simonton 2003]. His study, "On Men of Science" (1874), in which he looks at both innate and environmental factors that shape excellence, further documents his belief and is particularly famous because it introduces the phrase, "nature and nurture," to describe interacting factors that promote high levels of human achievement or expertise. In Galton's words, nature is "all that a man brings into the world; nurture is every influence without that affects him since his birth" [Galton 1874]. Leading researchers continue to acknowledge the impact of his work on their studies.

Spearman (1863-1945), another researcher who recognized innate ability as being of primary importance in the development of an expert performer, "invented factor analysis, a method which permitted a rigorous statistical test of... Galton's hypothesis that a general mental ability enters into every kind of activity requiring mental effort" [Jensen 1999]. His g-theory, or the two-factor theory, divides expertise into two areas, the general or g factor, and the area more specific to a discipline, the s factor. For him, the general factor of "mental energy" determines individual differences in expertise. To make this relationship more quantifiable, Spearman developed a formula that combined general ability or intelligence (the g factor) with the specific factor (the s factor) in a particular venue to predict whether or not an individual can be an expert [Spearman 1904]. His findings that intelligent behavior arises from a "single metaphorical entity," forms the foundation for many theories of human intelligence [Jenson 1998]. His factor theory is considered by some to be "the most important psychometric construct in the study of individual differences in human cognitive abilities.... The g factor has become so firmly established as a major psychological construct in terms of psychometric and factor analytic criteria that further research along these lines is very unlikely either to disconfirm the construct validity of g or to add anything essentially new to our understanding of it" [Jensen 1999].

In contrast to Galton's theories of innate abilities, Binet's (1857-1911) seminal research at the turn of the twentieth century focused on developing an assessment to support his hypothesis that environmental factors play a larger role in intelligence and expertise than inherited abilities do. Binet's methods of diagnosing levels of intellect–the medical method (anatomical, physiological, and pathological signs of inferior intelligence), the pedagogical method (judging intelligence according to the sum of acquired knowledge), and the psychological method (observations and measurements of the degree of intelligence)–led to his development of several tests, including the Stanford-Binet intelligence test [Binet 1905] that assesses the natural intellectual abilities of individuals. Many of the current theories of intelligence arrive from the contributions of and theoretical differences between Galton and Binet [Sternberg 2003a]. Binet expanded his research with extensive studies of the cognitive abilities of chess experts laying the foundation for the studies of de Groot and others in the 1950's. He originally thought chess masters had superior memory and recall, but concluded that experience, imagination and memory play a large role in the level of expertise required in grand master chess [Binet 1894].

Whereas Binet and Spearman emphasized the innate abilities of expert performers, Poincaré (1854-1912) was one of the first researchers to emphasize the creative portion of the problem-solving and critical-thinking processes. His study of the role of creativity in solving problems laid the groundwork for his theory of the generation of creative ideas. The "appearance of sudden illumination is a manifest sign of long, unconscious prior work." Initial, intense, prior, conscious work on a problem is necessary to "unlock" relevant ideas from their "fixed positions so they are free to join during unconscious processing" [Poincaré 1907]. This process is initiated by conscious but unsuccessful efforts to solve a problem, followed by the unconscious phase that ultimately leads to a collection of potential solutions from which one solution emerges. On the other hand, to doubt everything or to believe everything are two equally convenient solutions; both ignore the necessity of reflection, the process that leads to the "Aha!" moment [Poincaré 1907].

Following the research and writings of Kant (1724-1804), Dedekind (1831-1916), and Brouwer (1881-1966), Poincaré considered mathematics as intuition, not pure logic. "It is by logic that we prove, but by intuition that we discover" [Poincaré 1905]. According to him, intuition is what "goes on in the very soul of the mathematician." In his work, *The Foundations of Science*, in which he relates his struggle to explain the mathematical Fuchsian function, he describes the creative component of the problem-solving process, positing that unconscious thought offers a "point of departure" from which the conscious mind can work out the argument in detail. The conscious mind, on the other hand, is capable of the strict discipline and logical thinking of which the unconscious is incapable [Poincaré 1908]. His theories added new insight to the scientific method described by Dewey laying the foundation for future studies in creativity and its role in the critical-thinking and problem-solving processes.

Dewey (1859-1952), agreeing with Poincaré, theorized that the problem-solving process involves both logic he termed "reflection", and intuition which he saw as "unconscious thought". Whereas Poincaré emphasis was on a more creative method of solving problems, Dewey saw the process from a more structured and classical "scientific method" [Deek et al. 1999]. According to Dewey, a critical thinker and problem solver must develop the habit of reflective thinking, as it forms the basis for critical inquiry; it leads somewhere, to a specific albeit initially unknown goal or conclusion; it is the ability to suspend judgment, to maintain a healthy skepticism, and to exercise an open mind. It is an "active, persistent, and careful consideration of any belief or supposed form of knowledge in the light of the grounds that support it and the further conclusions to which it tends" [Dewey 1910]. As this definition suggests, reflective and critical thought have both an intellectual and an emotional component.

Although best known as a philosopher and a pragmatist, Dewey made several seminal contributions as an educational theorist. The central concept of his view of education is that greater emphasis should be placed on the broadening of the intellect and the development of problem-solving and critical-thinking skills rather than on the memorization of lessons, a popular educational method of the time. Put simply, his theory promotes "learn by doing" rather than through practice and repetition [Dewey 1916]. His problem-solving step-by-step process ("active learning"), well known and often quoted, consists of the following steps:

- Definition and analysis of the problem
- Establishment of criteria for evaluating solutions
- Identification of possible solutions
- Selection of the best solution
- Testing of the selected solutions

Dewey's research into reflective thought; the basis for many theories of problem solving, critical thinking and creativity; influenced significantly the later works of Guilford (1950), Polya (1957), and Sternberg (1996, 1998, 2003). His book, *How We Think*, published in 1910 and revised in 1933 [Dewey 1910; 1933], establishes the framework for the study of top-tier performers in computer science reported in this dissertation.

The French mathematician, Hadamard (1865-1963), probably best known for proving the Prime Number Theorem, also drew upon Poincaré's problem-solving theories in his work, *The Psychology of Invention in the Mathematical Field* (1954). In it he discusses the creative process in the discovery segment of the problem-solving cycle, the unique process used by mathematicians, physicists and engineers. He observed that this creative process is composed largely of wordless mental images that form the entire solution set to the problem at hand [OConnor and Robertson 2003]. His four-step model (preparation, incubation, illumination and verification) stresses the importance of insights derived from the incubation portion of problem solving [Hadamard 1954].

Guilford (1897-1987) expanded the earlier work of Dewey and recognized fundamental traits of creativity. In his 1950 address to the American Psychological Association, he revitalized modern research into creativity and divergent thinking and emphasized the difference between convergent thinking, deriving the single best answer to a clearly defined problem, and divergent thinking, producing multiple or alternate answers from available information [Guilford 1950]. His theories emphasize the belief that the first step in the problem-solving process, analyzing the problem, requires creativity and divergent thinking to establish a series of possible solutions.

He also rejected the earlier notions of a two-factor theory of intelligence as proposed by Spearman. In a study of highly skilled personnel, he expresses his belief that "thinking abilities, which have played important roles in some definitions of intelligence, seemed to have been neglected; particularly abilities having to do with productive thinking" [Guilford 1956]. He believed that a general test, such as the Binet-Stanford Intelligence Test with a single score, can measure the variance of intelligence and expertise in only one or two factors. "Assessment of intellectual qualities should go much beyond present standard intelligence tests which seriously neglect important abilities that contribute to problem solving and creative performance in general" [Guilford 1968].

Guilford also popularized the structure of intelligence (SI) model, depicted in Figure 2.2. It provides for 120 different SI abilities that factor into intelligence and expert performance and includes components of divergent and convergent creativity [Kearsley 2004]. In it the interplay between convergent and divergent thinking is a key part of intellect.

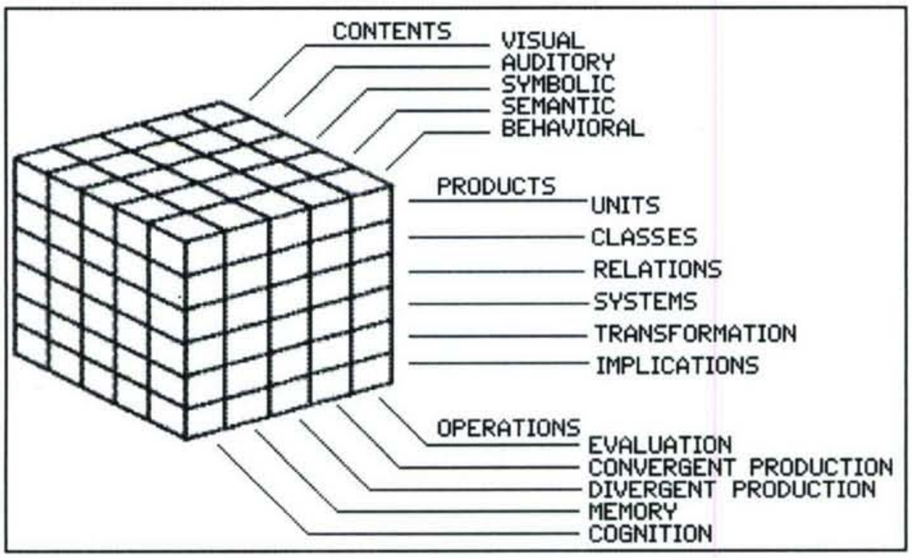


Figure 2.2: Structure of Intelligence model proposed by Guilford [Kearsley 2004]

He concluded that previous attempts to measure "the superior human adult," or expert, had a far too narrow scope and believed that "psychology and psychologists since Binet have taken a much too restricted view of human intelligence.... In attempting to fathom the nature of intellect, more attention should be given to the human adult, particularly the superior human adult. It is to such specimens that we must go, if we are to investigate intellectual qualities and functions in their greatest scope and variety" [Guilford 1956]. The consideration of divergent production is "anything but a minor innovation. Guilford brought within the realms of a problem not just a new idea, but the rest of the universe–or whatever part of it might be helpful at the time–in finding a creative solution, be this from the past, present, or future" [Richards 2001].

Building on the work of Dewey and Poincaré, Polya (1887-1985) devised steps in the problem-solving cycle [Polya 1957]:

- Understand the problem
- Find the connection between the data and the unknown
- Devise a plan and take action on a solution
- Examine the results obtained

His classic work on problem solving, *How to Solve It*, gives general heuristics for solving problems of all kinds and across all disciplines [Polya 1957]. In it he provides "a list of heuristics for understanding a problem and devising a plan to solve it, including making sure that the givens, the conditions, and the goal stated are understood; reformulating the problem; thinking of known analogous problems; making the problem more general; and breaking the problem into parts" [Frederiksen 1984]. This seminal work has had a major impact on the theory of problem solving across STEM disciplines.

In *Mathematics and Plausible Reasoning*, Volume I, Polya discusses inductive reasoning, reasoning from particular cases to the general rule in mathematics. In Volume II, he gives equal expression to his interests in mathematics, natural science and cognitive psychology [Polya 1954], and discusses more general forms of inductive logic. One of his central themes stresses the role of mathematical engagement, the active engagement of discovery, one that takes place in large measure by guessing. He argues that mathematics is not an entirely formal deductive discipline, but, like the sciences, it is an inductive discipline that requires conjecture, insight and discovery. His problem-solving theories are cited in journals such as *American Political Science Review, Annual Review of Psychology, Artificial Intelligence, Computers and Chemistry, Computers and Education, Discourse Processes, Educational Leadership, Higher Education, and Human Learning* [Schoenfeld 1992].

Building upon Binet's influence and his belief that human intelligence can be assessed, Piaget (1896-1980) developed a four-stage model of human intellectual development for use in classifying intellectual abilities. He sought to explain the stages of intellectual development, the top stage which he called "formal operational reasoning," and defined as "the ability to use abstract reasoning and deduction as well as to employ previous knowledge and experiences to less well-defined situations" [Piaget 1972]. The characteristics of this stage of development are "exhibited in an individual's ability to carry out combinatorial analysis, propositional logic..., proportional reasoning, and isolating and controlling relevant variables from among the set of identified possibilities the individual has generated" [Nurrenbern 2001]. Piaget also has had a considerable impact on the field of artificial intelligence. Seymour Papert, who saw Piaget as a "giant in the field of cognitive theory," [Papert 1999] used his work while developing the Logo programming language.

Although other researchers had developed their models for learning, Bloom (1913-1999) and his colleagues at Chicago University saw the need to obtain more reliable evaluations and to provide improved procedures in education. They were "interested in providing a useful practical tool that was congruent with what was understood at that time about the features of the higher mental processes" [Eisner 2000] and devised a system that consists of 6 levels of learning, each one building on the level below it and increasing in complexity [Bloom 1956]. The following is Bloom's definition of each level with sample learning objectives [Nilson 2003]:

- Knowledge is the recall of information previously learned, the foundation for the higher levels of thinking. "The student will be able to state Newton's Laws of Motion."

- Comprehension is the ability to understand the meaning of what has been learned and the ability to interpret and explain it. The student will be able to describe the trends in the graph in her own words.

- Application is the ability to apply what has been learned in different situations. "The student will be able to determine the variables to be controlled for an experiment."

- Analysis is the ability to separate learned material into component parts and to show the relationships between those parts. "The student will be able to describe an experiment to test the influence of light and light quality on the Hill reaction of photosynthesis."

- Synthesis is the ability to put separate ideas or learned facts together to form them into new relationships and forms. "The student will be able to compose a logical argument on assisted suicide in opposition to personal opinion."

- Evaluation is the ability to assess the available information and to make appropriate judgments about it. "The student will be able to assess the validity of certain conclusions based on the data and statistical analysis."

Better known as "Bloom's Taxonomy," his model of the stages of learning in the cognitive domain is widely used, largely because it can be understood easily.

The top 3 levels–analysis, synthesis and evaluation–directly involve critical thinking and are characteristic of experts in all domains. All of the 6 levels, however, can apply to computer science education in general. The following sample assignments illustrate that fact [Scott 2003]:

- Knowledge: "Name the three kinds of looping structures in C++.... State 5 things that are true of a RISC architecture."
- Comprehension: "Indicate why more registers inside the CPU can make the processor faster."
- Application: "Demonstrate different programming constructs in 1 assignment."
- Analysis: "Compare RISC and CISC architectures."
- Synthesis: "Design samples of inheritance or polymorphism."
- Evaluation: "Organize a complete test plan for a programming assignment."

The theories of de Groot (1914-2006) also grew from and built upon those of earlier researchers. He applied Binet's assessment of intelligence and Piaget's model of learning to examine short-term recall and expertise of master chess players. In his groundbreaking study, he demonstrated the possibility of directly studying, under controlled laboratory conditions, the thought processes mediating the highest levels of performance of expert and master chess players. He instructed them to think aloud as they selected their next move for a series of chess positions taken from unfamiliar games by chess masters. Fundamentally, he showed that world-class players select better moves for chess positions than skilled club players do and provided initial insights into the processes mediating the difference [Ross 2006]. "We know that increasing experience and knowledge in a specific field (chess, for instance) has the effect that things (properties, for example) which, at earlier stages, had to be abstracted, or even inferred are apt to be immediately perceived at later stages. To a rather large extent, abstraction is replaced by perception.... A so-called 'given' problem situation is not really given since it is seen differently by an expert than it is perceived by an inexperienced person..." [de Groot 1965]. His findings on the structure of chess skill led to one of the first theories of expertise of chess players [Ericsson 2005].

Colleagues Chase and Simon (1973) have expanded on de Groot's work with chess players by proposing a 10-year rule for the development of chess expertise. They believe that one needs 4 hours of study a day for approximately a decade in order to acquire the necessary knowledge base for performing at high levels in any domain. They propose that with extended experience, experts acquire a larger number of increasingly complex patterns of chess pieces (chunks) and use them to retrieve moves (actions) when similar chess positions are encountered during subsequent chess playing [Ericsson 2005].

An important areas of research of cognitive abilities is the modeling of human expertise with computer systems [Feltovich et al. 2006]. Research in this area is a growing field including the work of Lenant on large knowledge-based models [Lenant and Guha 1990], the work of Mitchell on knowledge-based learning [Mitchell 1997], and the knowledge extraction work of Hammond and Davis [Hammond and Davis 2004]. Various researchers pioneered work in the area including Miller (1960), Reitman (1965), and Newell (1956, 1973) with their early works on artificial intelligence (AI) [Feltovich et al. 2006] that attempts to model intelligence by building computer programs able to exhibit intelligent behavior [Buchanan et al. 2006]. Turing considered the question, "Can machines think?" in his seminal work, "Computing Machinery and Intelligence."

> In about fifty years time it will be possible to program computers... to make them play the imitation game so well that an average interrogator will not have more than 70 per cent chance of making the right identification after five minutes of questioning. The original question, 'Can machines think?' I believe to be too meaningless to deserve discussion. Nevertheless, I believe that at the end of the century (twentieth) the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted [Turing 1950].

Research into developing systems that mimic expert behavior have sparked new questions into the study of expertise, such as, "Can expert-level performance be achieved by a computer program?"; "How can tacit knowledge be made explicit?", and "Are some types of knowledge more critical to high performance than others?" [Feltovich et al. 2006]. Attempts to model expert behavior and the problem-solving cycle by means of computer expert systems influenced the development of current theories dealing with cognitive abilities.

One of the most important initiatives by the early researchers of expert systems was the development of the "General Problem Solver" (GPS) by Newell and Simon, based on their earlier work, "Logic Theory Machine" (1956). The GPS used a "means-ends analysis," describing the desired goal state, looking at the present place in the problem-solving process, selecting a transition to a new state and, at the same time, remembering the final goal [Gardner 1985]. Newell stressed the resemblance between human and machine problem solving [Gardner 1985]. He believed that all intelligence involves the use and manipulation of various symbols and that "the profound similarities between the human mind engaged in solving a problem, and the computer programmed to solve the same problem, far overrode differences in hardware.... Both are simply systems that process information over time..." [Gardner 1985]. In *Human Problem Solving*, he outlines the steps he believes necessary for a computer to model human thought [Newell 1971]:

- "Discover and define a set of processes... of storing and manipulating patterns to perform complex nonnumerical tasks."
- "Construct an information-processing language, and a system for interpreting that language in terms of elementary operations."
- "Discover and define a program... capable of solving some class of problems that humans find difficult."
- "Obtain data... on human behavior in solving the same problems as those tackled by the program. Search for the similarities and differences between the behavior of program and human subject. Modify the program to achieve a better approximation to the human behavior."
- "Investigate a continually broadening range of human problem-solving and thinking tasks."
- "Construct more general simulation programs that can attack a whole range of tasks."

- "Examine the components of the simulation programs for their relation to the more elementary human performances that are commonly studied in the psychological laboratory: rote learning, elementary concept attainment, immediate recall, and so on. Draw inferences from simulations to elementary performances, and vice versa, so as to use standard experimental data to test and improve the problem-solving theories."

- "Search for new tasks... that might provide additional arenas for testing the theories."

- "Use neurophysiological evidence to improve the problem-solving theories."

- "Draw implications from the theories for the improvement of human performance, for example, the improvement of learning and decision making."

- "Review progress."

Other innovations in artificial intelligence and expert systems have had equally profound affects on cognitive research and the study of expert performance. John McCarthy at M.I.T. (1962) developed a list-processing programming language, LISP, to mimic the "mental steps of problem solving.... He believed the route to making machines intelligent is through a rigorous formal approach in which the acts that make up intelligence are reduced to a set of logical relationships or axioms that can be expressed precisely in mathematical terms" [Gardner 1985]. Minsky at M.I.T. saw human thought and intelligence as multifaceted functions interacting with each other to perform complex tasks. In his book, *Perceptron* (1969), he theorized that computing machines at the time were built upon erroneous concepts and that it was necessary to provide the system with informative feedback about successes and failures. This line of research led to his seminal study of artificial neural networks.

At the same time that AI research and the study of expert systems was exploring the problem-solving process from a logical viewpoint, Torrance (1915-2002) was conducting research into the more human, creative side of thinking and critical thought. He defined creative thinking as "the process of sensing difficulties, problems, gaps in information, missing elements, something askew; making guesses and hypotheses about the solution of these deficiencies; evaluating and testing these hypotheses; possibly revising and restating them; and finally communicating the result" [Shaughnessy 1998]. He believed that when one confronts a problem for which there is no learned and practiced solution, some creativity is necessary. As a result, in 1974, he produced the Torrance Tests of Creative Thinking and suggested that intelligence can be measured in ways other than with an IQ test. The tests built on the work of Guilford and his belief that the first step in the problem-solving process, analyzing the problem, requires creativity and divergent thinking.

According to Ericsson, this creative aspect of expert performance is not an innate talent unique to select individuals, but one that can be learned and enhanced through "deep knowledge of the domain (that) will allow successful contributors to direct their efforts with greater effectiveness" [Ericsson 1999]. He expanded on Watson's theory that expertise can be obtained in any domain after many hours of practice and his belief that "with a dozen healthy young infants well-formed, and my own specified world to bring them up in..., I'll guarantee to take any one at random and train him to become any type of specialist I might select" [Watson 1919]. To Ericsson, expert performance, even elite performance, in any domain is not related to innate talent or ability but can be acquired by anyone through focused effort and hard work. He believes

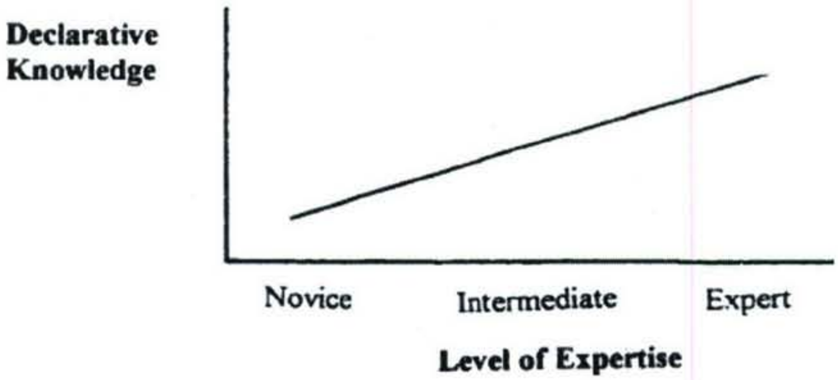


Figure 2.3: Model of linear progression of expert performance [Wood 2000]

that in most fields, 5 to 10 years of experience is a necessary precondition for becoming a master or expert; although, attainment is highly dependent on the nature of experiences one receives in that time period. He and his colleagues argue that the key activity in the acquisition of expertise is deliberate practice. He says that deliberate practice requires "appropriately challenging tasks that are chosen with the goal of improving a particular skill. As such, deliberate practice can be contrasted with activities such as work and competitive performance in which task demands and goals may vary greatly in difficulty and fall beyond ones control, or play in which the task is relatively easy and is performed with minimal regard for accuracy or the improvement of ones ability" [Ericsson and Charness 1994].

To Ericsson, expert performance is not linear (see Figure 2.3); instead, the 10-year progression toward expert performance follows the path illustrated in Figure 2.4. He and Chase argue that experts acquire long-term memory encoding and retrieval skills and that these skills expand the functional capacity of working memory. Organization of knowledge allows for retrieval rates typically associated with short-term memory. The crux of his skilled memory theory is that "skilled memory enables experts to rapidly encode, store, and retrieve

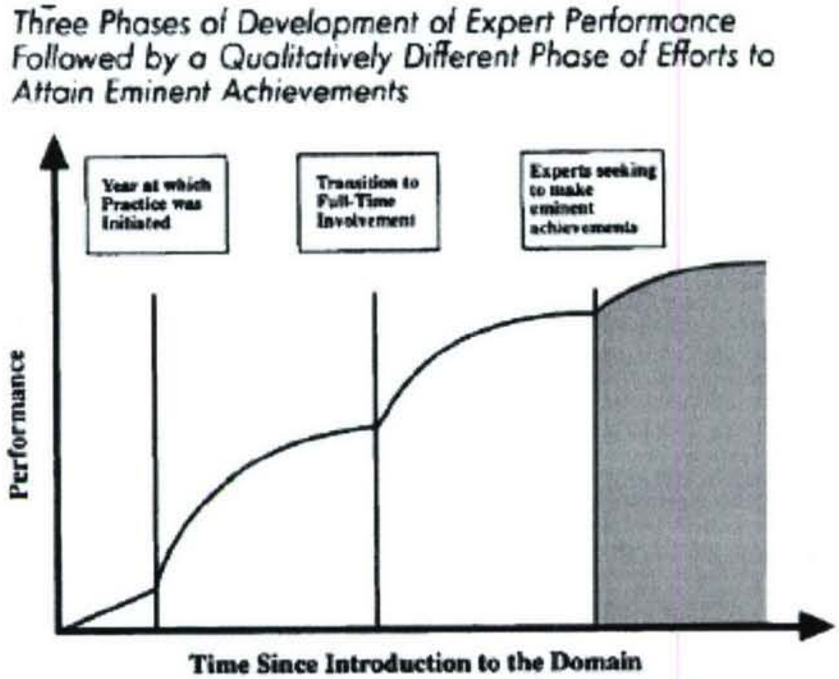


Figure 2.4: Actual path or phases of expert performance as defined by Ericsson [Ericsson and Charness 1994]

information within the domain of their expertise and thereby to circumvent the capacity limitations that typically constrain novice performance" [Ericsson and Staszewski 1989].

Unlike Ericsson, Sternberg disagrees with Watson's deliberate practice theory. He says that practice alone cannot account for a Mozart or a Picasso, that practice is only one part of the picture. He believes instead that various traits and abilities along with practice lead to expertise [Sternberg 1996]. In addition to other traits and abilities, he ties the cognitive skills of problem solving, critical thinking and creativity into his model of expertise. His model includes the following stages: recognize or identify the problem; define or represent the problem mentally in different ways; develop a solution strategy (closely related to divergent thinking as defined by Guilford); organize knowledge about the problem; allocate mental or physical resources to solve the problem; monitor progress (a form of metacognition), and evaluate the solution. The following variables influence expert performance in Sternberg's model [Sternberg 2003b]:

- Knowledge or perspective: the ability to see patterns and to frame problems
- Cognitive processes and strategies: the differing experiences and schemas a person brings to the task
- Individual abilities and strategies: divergent thinking, openness, tolerance of ambiguity, and intrinsic motivation
- External factors: the social context in which the problem is framed

Gardner (1943-) investigates how human beings think. In contrast to Spearman's more narrow view, he believes that intelligence is not a "single entity," and unlike Binet, believes that an IQ test alone cannot measure the multitude of factors involved. He also builds on the cognitive development work of Piaget and is not ready to abandon the generalist approach. Instead, he posits that intelligence is multifaceted and that independent traits of cognitive development should be explored.

> In the heyday of the psychometric and behaviorist eras, it was generally believed that intelligence was a single entity that was inherited; and that human beings... could be trained to learn anything.... Nowadays an increasing number of researchers believe precisely the opposite; that there exists a multitude of intelligences, quite independent of each other... and that it is unexpectedly difficult to teach things that go against early "naïve" theories that challenge the natural lines of force within an intelligence and its matching domains [Gardner 1993].

Gardner believes that a person has many intelligences that blend together to make each individual unique. In *Frames of the Mind* (1983), he formulated a list of 7 intelligences [Gardner 1993]:

- Linguistic intelligence is the ability to learn language and to use it to attain goals.

- Logical-mathematical intelligence "entails the ability to detect patterns, reason deductively and think logically" [Gardner 1993]. It is usually associated with scientific and mathematical thinking.

- Musical intelligence involves skills in all areas of music including composition and performance.

- Bodily-kinesthetic intelligence involves solving problems by using the mind or mental abilities in coordination with body movements.

- Spatial intelligence is the ability to recognize and use patterns found in spaces of varying sizes and shapes.

- Interpersonal intelligence enables a person to work well with others and to recognize and understand the driving forces within them.

- Intrapersonal intelligence is the ability to understand self to the point of being able to appreciate and regulate one's life.

He says that schools too often take a single approach to educating children, usually geared to successful completion of uniform tests and typically measure students' linguistic and mathematical intelligences at the exclusion of teaching the high-order thinking skills. He promotes the concept of "education for understanding" in which students are taught to think critically and to apply their knowledge to new situations. In *Five Minds for the Future* (2007), he delineates cognitive abilities that lead to desirable expert performance. He emphasizes the disciplinary mind, the person who has mastery of areas such as science, mathematics and history, and of at least one professional skill; the synthesizing mind, one who can form ideas from various disciplines into a logically consistent whole and then communicate the process to others; and the creating mind, one who is able to recognize and clarify new issues [Gardner 2007].

Chi, another current researcher in the area of expertise, has studied the domain knowledge of experts in a variety of fields, including computer science. She has determined that experts not only possess a large amount of knowledge in their domains, but they are also able to uniquely organize, utilize and structure the knowledge in a useful manner. One of her important studies deals with how the experts apply their domain-specific knowledge to be critical thinkers and problems solvers [Chi and Bedard 1992]. She has found that the problem-solving strategies used by experts vary greatly from those of the novices. The experts are more adept at representing the problem with more detail, exploration of given facts, possible limitations and other implications. They use different problem-solving strategies, tending to work forward from the given information, searching for facts that can be gleaned from the variables presented. Novices, on the other hand, tend to work backward to the given problem statement with a goal in mind.

In further studies, she has expanded her research and examined the characteristics of experts, including computer programmers [Chi and Glaser 2003]. Among computer professionals, the experts have the ability to notice useful patterns, and they can "recall key programming language words in meaningful clusters" [Chi and Glaser 2003]. They are able to represent the problem at a detailed level, whereas the novices represent problems at a superficial level.

She has further determined that expert programmers sort problems by categorizing them by the algorithms needed, while novices sort them by areas of application. In agreement with her previous work, she has also found that experts spend more time at the beginning of the problem-solving process and use greater critical-thinking skills in trying to understand and to analyze the problem; whereas, novices tend to spend little time in the beginning phases of the process and prefer to generate a solution with equations and algorithms immediately.

Chi's studies have looked directly at how an expert performs, but according to her, this type of research may bring up questions concerning ways to classify an individual as an expert: "How does one define an expert?", "What qualities make a person an expert?", "What distinguishes that person from the masses?", "Who determines the 'expert' population versus the 'normal' population?". She sees the need for a ranking or a measurement as a way to classify the study groups and to answer some of the questions; thereby, she has developed her own classification system for identifying the different levels of skills leading to expertise [Chi 2006]:

- Naïve: one who is totally ignorant of the domain
- Novice: one who is new to the domain
- Initiate: a novice with initial training
- Apprentice: a student working with a person skilled at the task
- Journeyman: one able to perform daily tasks unsupervised
- Expert: a distinguished or brilliant journeyman having special skills or knowledge derived from extensive experience with the subject matter

- Master: an expert qualified to teach those at a lower level and regarded by other experts as "the expert," especially regarding subject-matter knowledge

Chi believes that it is important for scientists and researchers studying expertise and expert performance to be clear about what they are studying and points out two methods of research. The absolute method explicitly studies how true experts perform using a classification system such as hers. The relative method, on the other hand, studies the differences between experts and novices. This type of research, according to Chi, allows for a much looser interpretation and definition of "expert." "Proficiency level can be grossly assessed by measures such as academic qualifications (undergraduates versus graduate students), seniority or years performing the task, or consensus among peers.... Thus, the goal of studying relative expertise is not merely to describe and identify the ways in which experts excel. Rather, the goal is to understand how experts become that way so that others can learn to become more skilled and knowledgeable" [Chi 2006]. The study presented in this dissertation follows the relative method described above, exploring different groups of populations delineated by characteristics such as position, rank and education and how they perform in relation to each other.

2.2 Critical Thinking in Computer Science

The importance of teaching critical-thinking skills has lately been re-energized and brought to the forefront in educational studies. A consensus of higher education associations in 2004 highlighted critical thinking as one of the 6 major intellectual and practical skills all college students should develop [NSB 2006; Office of Outcomes Assessment 2006]. Also in 2004, the President of

Harvard reported that over 90 percent of the faculty consider critical thinking as the most important part of education. Nevertheless, many faculty members "spend most of the time in their curricular reviews arguing over which courses to offer and which to require. Researchers, in contrast, find that the arrangement of courses per se has little effect on the development of critical thinking" [Bok 2005]. An academic profile produced by the Education Testing Service in 2003-2004 revealed that only 6 percent of college seniors rated "proficient" in critical-thinking skills while the vast majority, 77 percent, rated "not proficient" [AAC 2004], and a 2006 "No Child Left Behind" report stated that "70 percent of employers said that high school graduates were deficient in critical-thinking... skills" [Thompson and Barnes 2006]. In spite of the general consensus that critical-thinking skills are important, high school and undergraduate students still lack mastery of those skills.

Likewise, those in the STEM disciplines recognize the development of critical-thinking skills as one of the most important objectives of undergraduate education [Yuritech 2004]. Educational leaders and researchers in some of the STEM disciplines have recognized that the development of critical-thinking skills in students is important. However, based on a comprehensive literature review, no research specifically into the critical-thinking skills of computer professionals and experts and the impact upon undergraduate computer science education has been found, possibly due to the absence of a clear understanding of exactly what critical thinking is as it relates to computer science. Many terms including "problem-solving skills," "cognitive abilities," "higher-order thinking skills," "creative-thinking abilities" and "critical-thinking skills" have often been used interchangeably. Because this research specifically uses the term "critical thinking," highlighting some of its most prominent definitions is important. Critical thinking is

- an "active, persistent, and careful consideration of any belief or supposed form of knowledge in the light of the grounds that support it and the further conclusions to which it tends" [Dewey 1910];

- the mental processes, strategies and representations people use to solve problems, make decisions and learn new concepts [Sternberg 1986];

- "the intellectually disciplined process of actively and skillfully conceptualizing, applying, analyzing, synthesizing, and/or evaluating information gathered from, or generated by, observation, experience, reflection, reasoning, or communication, as a guide to belief and action" [Scriven and Paul 2006];

- an ability to evaluate information and opinions in a systematic, purposeful, efficient manner [Hill 2007];

- "an essential tool of inquiry; purposeful, self-regulatory judgment that results in interpretation, analysis, evaluation, and inference, as well as explanation of the evidential, conceptual, methodological, criteriological, or contextual considerations upon which that judgment is based" [Insight Assessment 2007].

The CCTST assessment tool and its definition of critical thinking, the final definition above, is the one used in this study (see Appendix C for details)

"While there is a great deal of latitude in regard to definitions of critical thinking and how those definitions are applied, several commonalities exist. Throughout the literature, critical thinking is defined as an active process which goes beyond basic acquisition and memorization of information in that critical thinking requires the ability to recognize and rationally consider multiple concepts or elements" [Office of Outcomes Assessment 2006]. A person with the ability to think critically is "habitually inquisitive, well-informed, trustful of reason, open-minded, flexible, fair-minded in evaluation, honest in facing personal biases, prudent in making judgments, willing to reconsider, clear about issues, orderly in complex matters, diligent in seeking relevant information, reasonable in the selection of criteria, focused in inquiry, and persistent in seeking results which are as precise as the subject and the circumstances of inquiry permit" [Facione 1990]. These skills are essential for computer scientists.

Three aspects of critical thinking that specifically apply to computational science are clarity, the ability to understand the facts; accuracy, the ability to understand the relationship between the facts and reality; and relevance, the ability to identify only relevant information and deductions [Fagin et al. 2006]. In other words, in addition to having the knowledge and an understanding of the methods and techniques specific to the domain, a top-tier performer in computer science must be a critical thinker; therefore, a computer science degree program needs to teach critical thinking, must require the students to understand their thoughts, and to be able to express them in a way that a computer can use them. Programming a computer requires the following steps, each one requiring critical-thinking skills [Pamula 2007]:

- "Before one can write a computer program to do something, one must understand what the program is supposed to accomplish. Since the intended objectives of a software system are described in English, significant critical-thinking skills are required simply to understand what is to be done. ... Software developers are required to interview the intended users of the system to try to determine what really is needed. This is often an extraordinarily difficult job, which requires quite sophisticated critical-thinking skills."

- "Students must determine, in precise detail, how the objective determined by the previous step may be accomplished."
- "Students must express the required steps as a computer program. A computer program is a text in an unforgiving language, a programming language. Programming languages are interpreted more formally and literally than virtually any other language in existence. Syntax and semantics are rigidly defined. Everything must be correct for the program to operate properly."

Being successful in these steps requires sharp and wise critical-thinking skills that are imperative for students of computer science to have so they will be equipped to become experts, the top-tier performers in the field.

2.3 Previous Studies in Computer Science Expert Performance

For the most part, previous studies on expert performance in computer science concentrated on undergraduate students and on predicting their course grade. Prior to 1975, many of the research projects on the subject of computer science and expert performance tended to explore the demographic background and the high school achievements of the participants. These studies had limited predictive power. Between 1975 and 1981 attention focused on specific programming aptitude tests (PATs) such as IBM's PAT. From 1981 to 1990, most studies explored various learning styles necessary for the expert performance in computer science [Evans and Simkin 1989].

Wood (2000) notes that one of the major limitations on previous studies of expertise in computer science was in obtaining large enough sample sizes

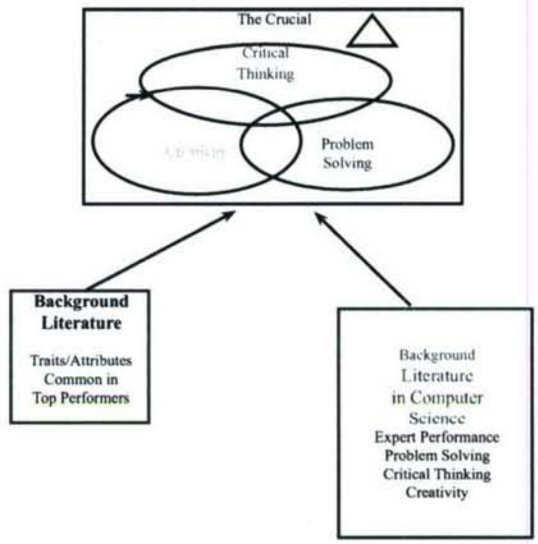


Figure 2.5: Review of background literature and previous studies on the factors in expert performance

for data analysis. She examined 36 studies from 1976 to 1999 and found that the "expert" group averaged only 10 participants. Only 8 had more than 20 participants in the control group, and the novice group averaged only 13. She identified the following variables: dependent variables–memory (6 studies), knowledge structures (10 studies), comprehension (6 studies), and problem solving (6 studies). Expertise was the sole independent variable in a majority of the studies [Wood 2000].

In an attempt to find a research project that dealt specifically with the critical-thinking skills of expert performers in top-tier computer science professionals and that compared their assessment scores with the same scores of undergraduate students (see Figure 2.5), the researcher conducted a comprehensive literature review (see the projects listed in Appendix D).

This review of the research suggests that past studies in expert performance in computer science focused primarily on the technical skills of programmers and on predicting academic success and achievement at the undergraduate level. The researcher found no studies that specifically assessed the critical-thinking skills of top-tier performers in computer science and compared their scores with those of undergraduate students. Considering the growing need for computer science graduates with cognitive-thinking skills compounded by the decline in enrollment in computer science programs across the nation, the specific critical-thinking skills characteristic of expert computer science professionals merit study. One of the first steps in addressing this need is to compare and contrast the critical-thinking skills of top-tier professionals and undergraduate students, and to assess correlations between currently used measures of academic success and these skills.

Chapter 3

Methodology

The study's hypothesis is that top-tier computer science professionals have demonstrable, critical-thinking abilities that are superior to those of undergraduate students. The importance of this primary hypothesis is that critical-thinking abilities are a learned behavior and not "naturally" present. In spite of the large amount of literature related to this subject, this relationship has yet to be validated. In order to test the veracity of this hypothesis, the research presented here tested a random sample of students, both freshmen and seniors, and compared the assessment scores of these two samples with each other and with those of the experts. The hypothesis is considered confirmed if the professionals are statistically better than the students.

The study reported here addresses the following related research questions that represent critical elements of the primary hypothesis:

1. What critical-thinking abilities do top-tier professionals exhibit?

2. What are the critical-thinking abilities of freshmen students?

3. What are the critical-thinking abilities of senior computer science students?

4. How do the critical-thinking skills of the freshmen and senior computer science students compare?

5. How do currently used measures of academic performance, such as grade point average, correlate to this assessment of critical-thinking skills?

6. What are the differences in critical-thinking skills between computer science professionals and undergraduate computer science students?

Figure 3.1 shows the process used to answer these questions and to meet the research objectives. To achieve the overall objective, a series of "sub-studies" produced data to evaluate the main hypothesis. Study 1 addresses the critical-thinking abilities of top-tier performers, the experts as defined by their position, responsibility, recognition, or rank, and is used to establish a benchmark of these abilities of top performers in computer science. Study 2 is the assessment of the critical-thinking abilities of freshmen and senior college students at Clemson University. To see if these abilities are currently being measured, study 3 tests the data for a correlation between these abilities and grade-point average, SAT scores, and credit hours earned. Study 4 is the comparison of the critical-thinking scores of the students to those of the expert groups assessed. Each arrow is substantiated through either background literature, observations, or testing.

The remainder of this chapter details this plan including a description of its implementation, the assessment tool used to answer the research questions, and the participants assessed. It also explains the data collection procedures, including the relevant variables, and the statistical tests used to analyze the data.

3.1 Population and Samples

This research project tested 6 different population samples, college freshmen and seniors, faculty members in the STEM disciplines, computer professionals in industry and in the military, and a group of military officers with non-technical backgrounds representing non-industry professionals outside the

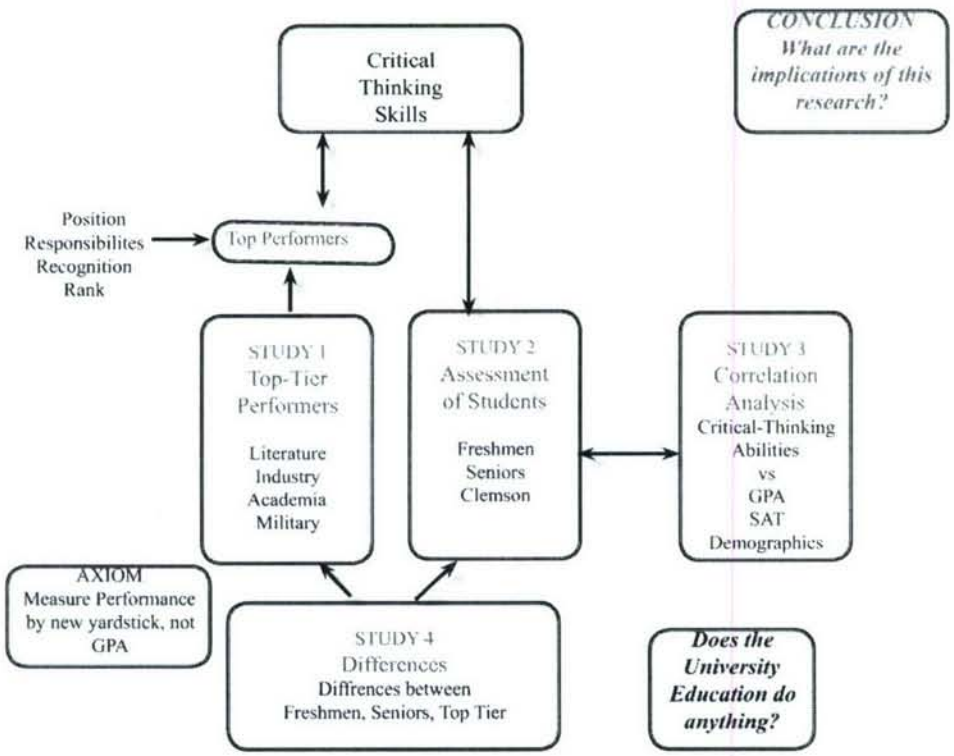


Figure 3.1: Research plan of attack

STEM disciplines. Participation in the study was voluntary, and a Clemson Institution Review Board (IRB) (# 06-IRB-226) reviewed and approved it before it commenced (see Appendix H).

All undergraduate participants, both the freshmen and seniors, were full-time students at Clemson University during the Spring of 2007. Class presentations to 5 first-year computer science classes and 4 first-year ROTC leadership classes resulted in the 51 freshman volunteers. This sample represented a wide range of students in their first year of college intending to major in various areas, primarily in STEM disciplines. Specifically, the sample included 15 majoring in computer science, 3 in mathematics, 2 in physics, 2 in chemistry, 2 in civil engineering, 3 in biology, 4 in the behavioral sciences, 2 in mechanical engineering, 10 in general engineering, 2 in business, 3 in foreign studies, 1 in history, and 2 in political science. The 14 female and 41 male participants included 4 Asians, 2 African-Americans, 40 Caucasians, and 6 who elected not to identify their ethnic backgrounds. The mean age of these freshman volunteers was 19.43 years, with the youngest being 17 and the oldest 43.

In-class presentations to computer science majors and an email announcement sent to senior math and engineering majors obtained the senior participants. The majority of the resulting sample were computer science majors enrolled in senior-level computer science courses. They consisted of 27 computer science majors, 2 mathematical science majors, and 1 electrical engineering major. The 6 female and 24 male participants included 1 Asian, 3 African-Americans and 26 Caucasians. The mean age of these senior participants was 21.93 years, with the youngest being 20 and the oldest 26.

The faculty participants were professors in computer science and related STEM disciplines from several major universities solicited via an email announcement. The expertise level of faculty members was difficult to gauge;

therefore, all were automatically considered expert participants, regardless of school or academic rank. The participants consisted of 9 computer science faculty, 3 faculty members from mathematical science, 3 of physics, 2 of computer engineering, 1 of systems engineering, 1 of industrial engineering and 1 of chemistry. The 6 female and 14 male faculty included 2 African-Americans, 2 Caucasians, and 2 who chose not to reveal their ethnic backgrounds. The mean age of the faculty members was 45.3 years, with the youngest being 22 and the oldest 67.

To obtain industry participants, a facilitator in each of 6 different computer-related companies was contacted and sent an informational packet and on-line testing procedures as well as a set of user names and passwords to distribute to the volunteers within their organizations. This group consisted of 1 female and 18 male volunteers including 1 Hispanic, 2 Asians, 1 African-American, 12 Caucasians and 2 who chose not to identify their ethnic backgrounds. The mean age of the participants was 33.06 years with the youngest being 24 and the oldest 55.

The United States Air Force participants were from computer and communication disciplines and from the Defense Information Systems Agency (DISA) (see Appendix F.1). Subjects primarily consisted of field grade officers in the communications field, and included signal officers, automators, engineers, and communications-computer officers. The United States Air Force communications officers were chosen as expert participants in this study because they demonstrate high levels of achievement and are representatives of an elite performing group. They are all specialists in their field and were hand-selected for their assignments. They are mainly field-grade officers with 10 or more years of experience in high-tech leadership positions. This group included 4 females and 23 males including 2 African-Americans, 23 Caucasians, and 2 who chose

Table 3.1: Mean age of sample groups in current study

Group	n	Mean Age	StDev	Min	Max
Freshmen	54	19.43	4.12	17	43
Senior	29	21.93	1.93	20	26
Faculty	20	45.35	14.29	22	67
Industry	18	33.06	9.41	24	55
Air Force	27	38.07	6.59	27	50
Army	31	33.00	6.23	23	50

not to reveal their ethnic backgrounds. The mean age of the participants from the Air Force was 38.07 years with the youngest being 27 and oldest 50.

The final group of participants was from the United States Signal Corps Army Officers located at Fort Gordon, Georgia (see Appendix F.2). This group represents officers in a first-level information technology school, all have 4-year college degrees and are experienced Army officers. It consisted of 2 females and 29 males including 7 African-Americans, 4 Asians, 5 Hispanic-Americans, 11 Caucasians, and 3 who chose not to reveal their ethnic backgrounds. The mean age of the participants from Fort Gordon was 33.00 years, with the youngest being 23 and the oldest 50.

3.2 Measurements and Instrumentation

A study of creativity skills was initially considered for this research; however, most tests had objective grading criteria and many required the grader to attend training in order to interpret the results. None had creativity questions relating specifically to computer science, and generating them would have required their being somehow validated. Some of these tests had varying options, but with limitations (see Appendix A).

Instead of creativity, critical thinking was chosen as the focus of this study and the California Critical Thinking Skills Test (CCTST) version 2000, developed by Peter Fracione, was selected as the assessment tool [Facione 1990; Insight Assessment 2007].In addition to the CCTST, several other critical-thinking assessments were considered for this research. The following criteria were established in selecting an appropriate assessment:

- A nationally validated test
- Capable of measuring subcategories of critical thinking
- Requiring no special training to grade and interpret results
- Administered on-line
- Can be completed in approximately 45-minutes or less

The CCTST, a 34-question, multiple-choice, on-line assessment, allows for immediate feedback to the test-taker on 5 areas of critical thinking: inductive reasoning, deductive reasoning, analysis, inference, evaluation, and total critical-thinking score. It is time efficient, convenient, and can be easily accessed by all participants as well as by the researcher, and, according to Insight Assessment, the KR-20 alphas range from 0.78 to 0.84, indicating a high level of internal consistency. Appendix C provides details about the test including sample questions.

3.3 Data Collection

The researcher used on-line testing procedures to assess the student participants. He emailed each student a cover letter and an instruction sheet, including a login name and password pair (see Appendix G). Testing began on

January 12, 2007, and all tests were completed on or before May 1, 2007. The assessment was untimed, and volunteers took the test when and where they chose.

3.4 Variables

In comparing the difference of means between samples (research questions 1-4 and 6) the sole independent variable: study population represents class year for student participants and professional group for military and industry participants. The independent variables used in this study for research question 5 and listed in Table 3.2 are

- Math SAT is the participant's score on the mathematical section of the Scholastic Aptitude Test. This score was not always available.
- Verbal SAT is the participant's score on the verbal section of the Scholastic Aptitude Test. This score was not always available.
- Current GPA is the current grade point average for the student participants.
- Gender is voluntary information requested on the student survey.
- Age
- Race is the ethnicity of the participant, obtained from voluntary information on the participant survey.
- University
- Major is the major or intended major of the undergraduate participant.

- Study Population is the participant's population: freshman, senior, faculty, industry, air force, or army.

- Group is a subjective grouping of the participants based on the field of work for industry and military professionals or academic major for the student participants.

Table 3.2: Independent variables for research question 5

Name	Description	Source
Math SAT	Continuous - Scholastic Aptitude Test Math Score	Registrar
Verbal SAT	Continuous - Scholastic Aptitude Test Verbal Score	Registrar
Current GPA	Continuous - Current GPA of student participants	Registrar
Gender	Dichotomous - Gender of participant	Participant survey
Age	Discrete - Age of participant	Participant survey
Race	Nominal - Ethnicity of participant	Participant survey
University	Nominal - Undergraduate college of participant	Participant survey
Major/intended Major	Nominal - Undergraduate major	Participant survey
Study Population	Discrete - Population sample of participant	Assigned
Group	Nominal - Main area of work or major of participant	Assigned

The dependent variables used in this study and listed in Table 3.3 are

- CCTST Induction Score represents the participant's score on the inductive reasoning portion of the CCTST, which has a maximum score of 17.

- CCTST Deduction Score represents the participant's score on the deductive reasoning portion of the CCTST, which has a maximum score of 17.

- CCTST Analysis Score represents the score on the analysis portion of the CCTST, which has a maximum score of 7.

- CCTST Inference Score represents the participant's score on the inference portion of the CCTST, which has a maximum score of 16.

- CCTST Evaluation Score represents the participant's score on the evaluation portion of the CCTST, which has a maximum score of 11.

- CCTST Total Score represents the participant's total critical-thinking score on the CCTST, which has a maximum score of 34.

Table 3.3: Dependent Variables for all research questions

Variable Name	Description	Source
CCTST Induction Score	Discrete variable representing CCTST score	CCTST
CCTST Deduction Score	Discrete variable representing CCTST score	CCTST
CCTST Analysis Score	Discrete variable representing CCTST score	CCTST
CCTST Inference Score	Discrete variable representing CCTST score	CCTST
CCTST Evaluation Score	Discrete variable representing CCTST score	CCTST
CCTST Total Score	Discrete variable representing CCTST score	CCTST

3.5 Data Analysis

The statistical software package Minitab version 15.1 [1][Minitab Inc. 2007], performed data analysis and produced textual and graphical models. The researcher used the following statistical tests, all using a 0.05 level of significance, to analyze the data [Brown 2007]:

1. Computing means and standard deviations for each area measured by the CCTST assessment generated a benchmark for the critical-thinking skills of professionals (Research Question 1).

2. Means and standard deviations determined critical-thinking abilities of freshmen and seniors (Research Questions 2 and 3).

3. A one-way analysis of variance (ANOVA) determined if significant differences in critical-thinking skills exist between freshmen and seniors, between freshmen and experts, and between seniors and experts. Additionally, Hsu's Comparison test identified factor levels that are the best,

[1] Available at www.minitab.com

are insignificantly different from the best, and are significantly different from the best [Minitab Inc. 2007]. Hsu's comparison creates a confidence interval for the difference between each level mean and the best of the remaining level means. An interval that has zero as an end point indicates a statistically significant difference between the corresponding means. Specifically [Hsu 1996]:

- Confidence interval contains zero - No difference
- Confidence interval entirely above zero - Significantly better
- Confidence interval entirely below zero - Significantly worse

(Research Questions 4 and 6).

4. Computation of a Pearson Product-Moment correlation tested the null hypothesis that no significant correlation exists between student GPA, SAT and critical-thinking skills (Research Question 5).

Chapter 4

Experimental Results

This study used the assessment tool CCTST by Insight Assessment to evaluate the hypothesis that computer science experts have exceptional critical-thinking skills greater than those of undergraduates. It focuses on addressing the data relevant to the research questions posed in Chapter 3 concerning the assessment and comparison of critical-thinking skills of top-tier computer science performers and college freshmen and seniors. Section 4.1 reports the response rates of the various populations to the requests for participation in the survey. Section 4.2 addresses the survey findings as they relate to the research questions and concludes with additional information supported by the data collected from the surveys.

4.1 Response rate

In order to obtain a sufficient sample size for each of the populations, a large number of students, faculty members, industry experts and military personnel received inquiries about participating in the survey. As reported in previous study's [Wood 2000], finding volunteer participants is one of the greatest obstacles encountered when conducting this type of research. The overall response rate to this study's request for participation was 47.29% (166 out of 351).

The response rate of undergraduate students to the initial request was 3.03% (5 out of 165) with no incentives offered. With an incentive of drink and food coupons or small amounts of extra credit, the response rate improved significantly. Of the 120 freshmen contacted, 55 participated for a 45.83%

response rate, and 30 of the 45 seniors contacted participated for a 66.67% rate.

The response rate for the faculty was much lower. In answer to the 36 email announcements sent, only 4 individuals responded and participated in the survey for a response rate of 11.11%. The additional faculty volunteers came from an email solicitation sent to the contacts on a STEM-interest email list.

The response rates for industry participants was also low. Out of several companies contacted, only 6 responded and requested assessment surveys. Of the 60 surveys distributed, 18 returned for a response rate of 30%. Two companies required a non-disclosure statement, and all chose not to be individually identified in the study.

Military personnel and leadership were, for the most part, eager to help with the study and to participate. The United States military is actively interested in critical-thinking skills, and this research particularly interested the leadership and personnel at the agencies contacted. Of the 45 surveys distributed to the United States Air Force Communications Officers, 28 returned for a response rate of 62.22%. The response rate from the United States Army Signal Corps was similar to that of the Air Force with 45 surveys distributed and 31 returned for a response rate of 68.89%.

4.2 Findings

4.2.1 Experts' Critical-Thinking Scores

The following data is in response to Research Question 1 concerning the critical-thinking abilities, as measured by the CCTST, of top-tier performers, the experts.

Table 4.1: Mean total scores for the expert populations

GROUP	n	Mean	StDev	Min	Med	Max
Faculty	20	26.100	4.191	17	26	32
Industry	18	25.278	3.268	20	26	31
Air Force	27	26.556	4.003	12	27	31
Air Force[a]	25	27.480	2.143	24	28	31

[a]Air Force scores with outliers removed

The average mean score on the CCTST of each of the 3 expert populations, is significantly above the average mean score of 16.801 reported by Insight Assessment (N=2061, SD=5.062) (see Appendix J). No statistical difference showed between the 3 groups at the 0.05 level. Table 4.1 shows the mean total critical-thinking score for each of the 3 expert populations as measured by the assessment.

Figure 4.1 shows a normal distribution (A-Squared = 0.46, P-Value = 0.231) with a median of 26 (M=26.10) for the total critical-thinking scores for the faculty population.

Figure 4.2 shows the results of the critical-thinking scores for the industry participants. Their scores also show a normal distribution (A-Squared = 0.43, P-Value = 0.273), with a median of 26 (M=25.28).

Figure 4.3 shows the results of the critical-thinking scores for the Air Force expert participants, including 2 outlying scores as calculated by Minitab. The median score for these participants is 27 (M=26.56). Figure 4.4 shows the results of the scores for the Air Force expert participants with the outlying scores removed. The Anderson-Darling Normality Test shows that this is a normal distribution (A-Squared = 0.52, P-Value = 0.169) with a median score of 28 (M=27.48). The Air Force experts' raw score was higher than the scores of the other experts; however, there is no measurable statistical difference.

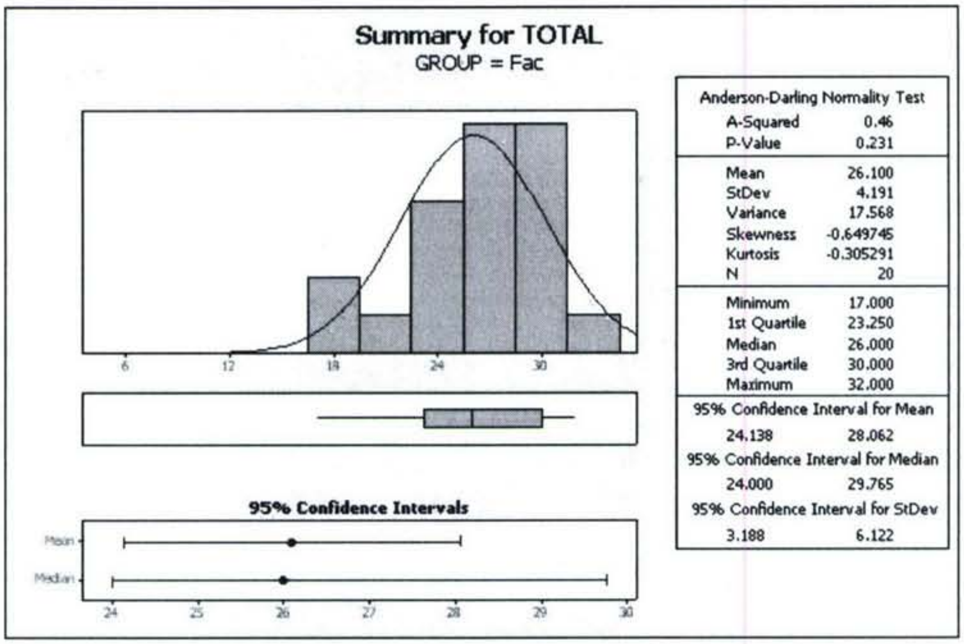


Figure 4.1: Mean total score for the faculty population

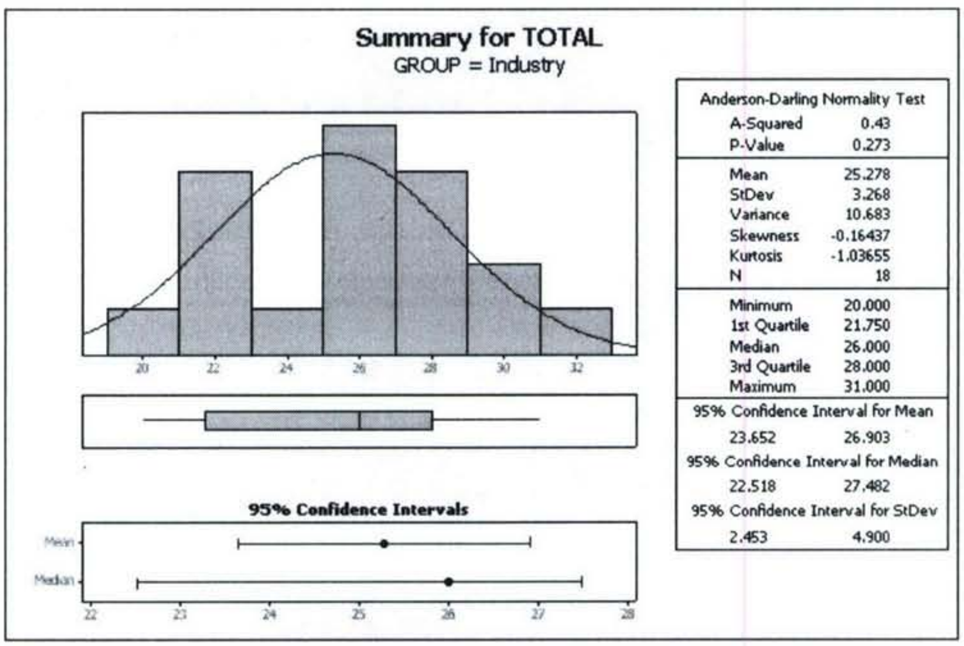


Figure 4.2: Mean total score for the industry participants

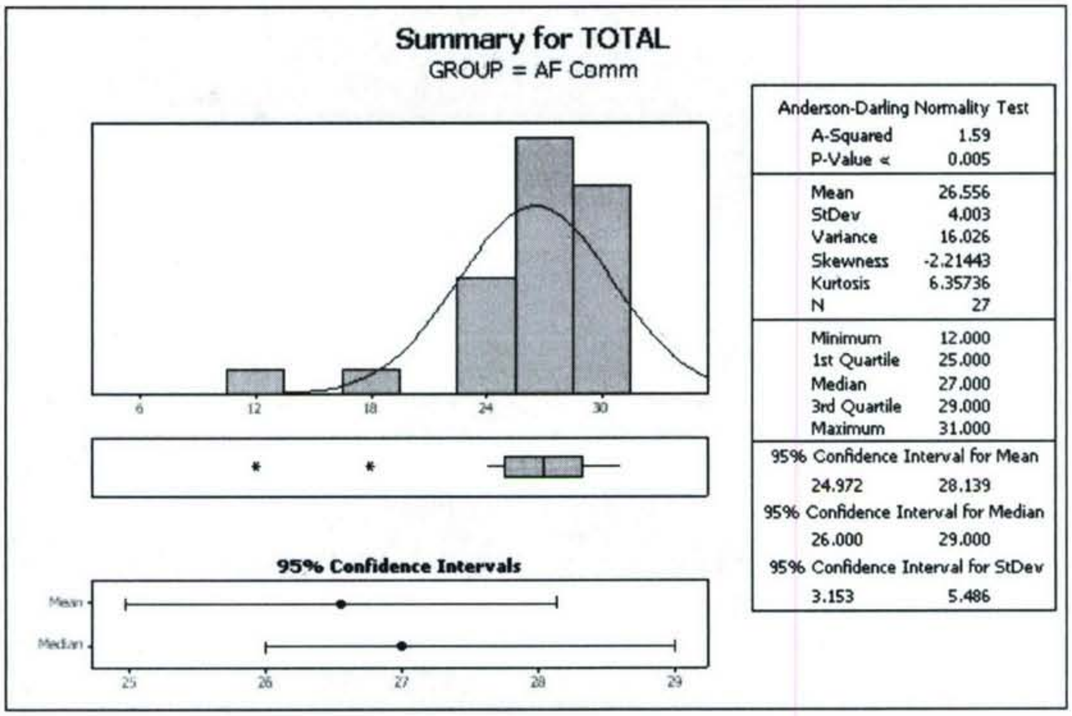


Figure 4.3: Mean total score for Air Force participants with outlying scores indicated by * at the 12 and 18 levels

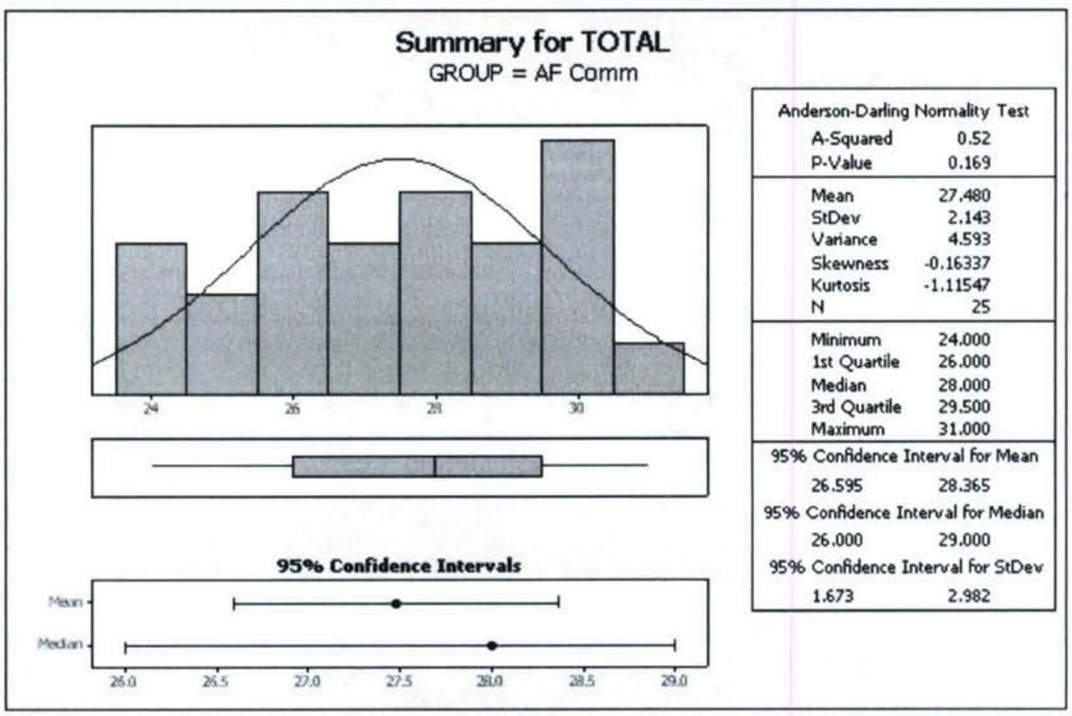


Figure 4.4: Mean total score for the Air Force participants with outlying scores removed

Table 4.2: Mean total scores in the sub-categories for the expert populations

GROUP	Ind(17)	Ded(17)	Anl(7)	Inf(16)	Eval(11)	Tot(34)
Faculty	13.90	12.20	6.35	12.10	7.65	26.10
Industry	12.61	12.67	5.67	12.61	7.00	25.28
Air Force	13.59	12.89	5.93	12.63	8.11	26.56
Air Force[a]	14.04	13.36	6.04	13.00	8.56	27.48

[a]AF expert population with outliers removed
The number in the parenthesis indicates the maximum possible score

Table 4.2 shows the results for each of the expert populations in the critical-thinking sub-categories: induction, deduction, analysis, inference, evaluation, and the total as reported by Insight Assessment. There is no statistical difference in any of the categories between the scores of the expert populations sampled.

4.2.2 Students' Critical-Thinking Scores

The following data is in response to Research Questions 2, 3, and 4 concerning the critical-thinking skills of students.

Table 4.3 shows the data collected in the sub-categories of the critical-thinking abilities of freshmen. The mean score of the freshmen participants, 20.981 (SD=5.023, N=54), was significantly higher than the average score reported by Insight Assessment (M=16.801, N=2061, SD=5.062)(see Figure 4.5).

The data collected in response to Research Question 3 concerning the critical-thinking abilities of seniors, shows that the mean score of the senior participants, 24.931 (SD=4.869, N=29), was also significantly higher than the average score reported by Insight Assessment (M=16.801, N=2061, SD=5.062) (see Figure 4.6). Table 4.4 shows the total scores in the critical-thinking sub-categories for the senior participants as reported by Insight Assessment.

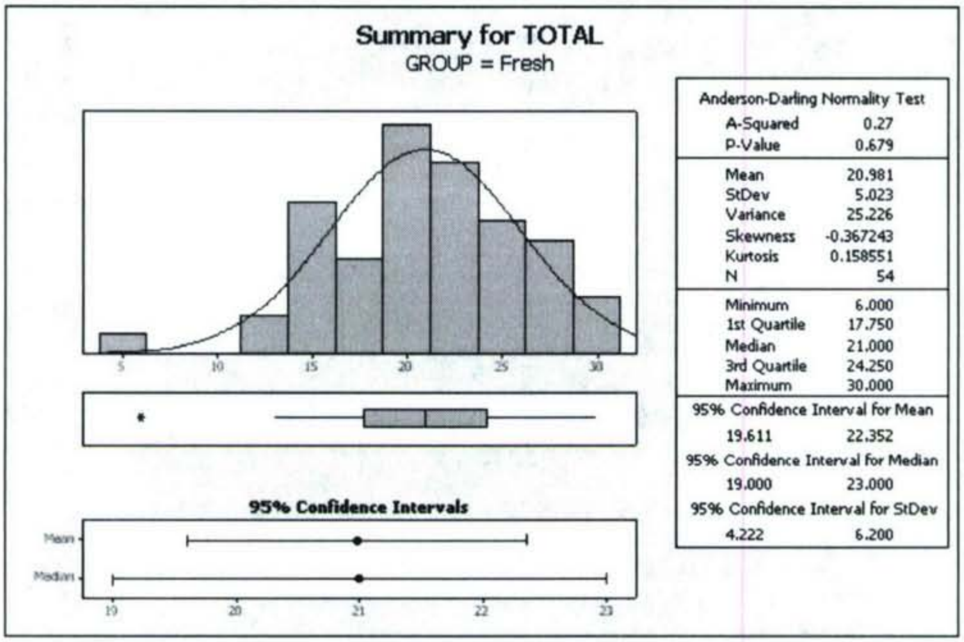


Figure 4.5: Mean total scores for the freshmen participants

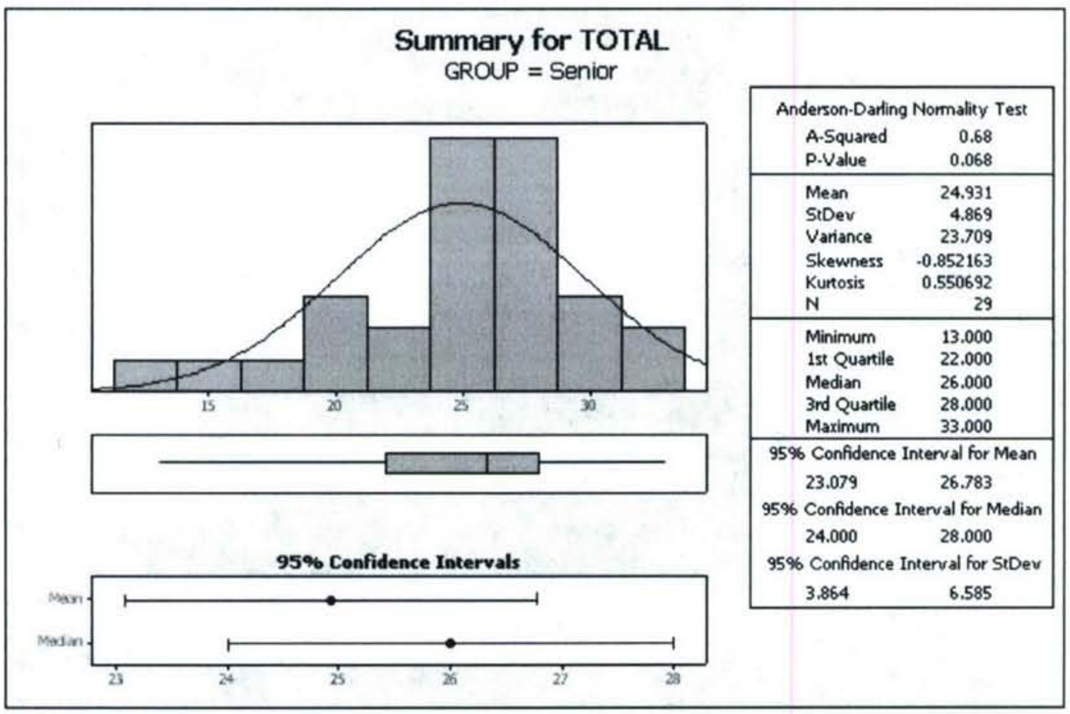


Figure 4.6: Mean total score for the senior participants

Table 4.3: Mean total scores in the sub-categories for the freshmen participants

Variable	n	Mean	StDev	Var	Min	Med	Max
Induction	54	11.074	2.433	5.919	4	11	13
Deduction	54	9.907	3.217	10.35	2	10	12
Analysis	54	5.019	1.407	1.981	1	5	6
Inference	54	10.074	2.906	8.447	3	10	11
Evaluation	54	5.889	1.959	3.836	2	6	8
TOTAL	54	20.981	5.023	25.226	6	21	26

Table 4.4: Mean total scores in the sub-categories for the senior participants

Variable	n	Mean	StDev	Var	Min	Med	Max
Induction	29	13.138	2.279	5.195	6	13	16
Deduction	29	11.793	3.353	11.241	5	12	17
Analysis	29	5.517	1.379	1.901	1	6	7
Inference	29	11.690	2.620	6.865	6	11	16
Evaluation	29	7.724	2.016	4.064	1	8	11
TOTAL	29	24.931	4.869	23.709	13	26	33

Table 4.5 shows the data collected in response to Research Question 4 concerning the comparison of critical-thinking skills of the freshmen and senior participants. The two-tailed T-Test shows that the seniors had statistically higher scores than the freshmen (P-Value=0.001, DF=58). Figure 4.7 shows the mean total scores for freshmen and seniors.

In response to Research Question 5, Pearson's Correlation tests determined the relationship between currently used measures of academic performance and the CCTST. A correlation of 0.696 with a P-value of 0.000 indicates a positive

Table 4.5: Two-tailed T test of freshmen vs. seniors

GROUP	N	Mean	StDev	SE Mean
Freshmen	54	20.98	5.02	0.68
Seniors	29	24.93	4.87	0.90

Difference = μ (Fresh) - μ (Senior)
Estimate for difference: -3.95
95% CI for difference: (-6.22, -1.68)
T-Test of diff=0: T-Val=-3.48 P-Val=0.001 DF=58

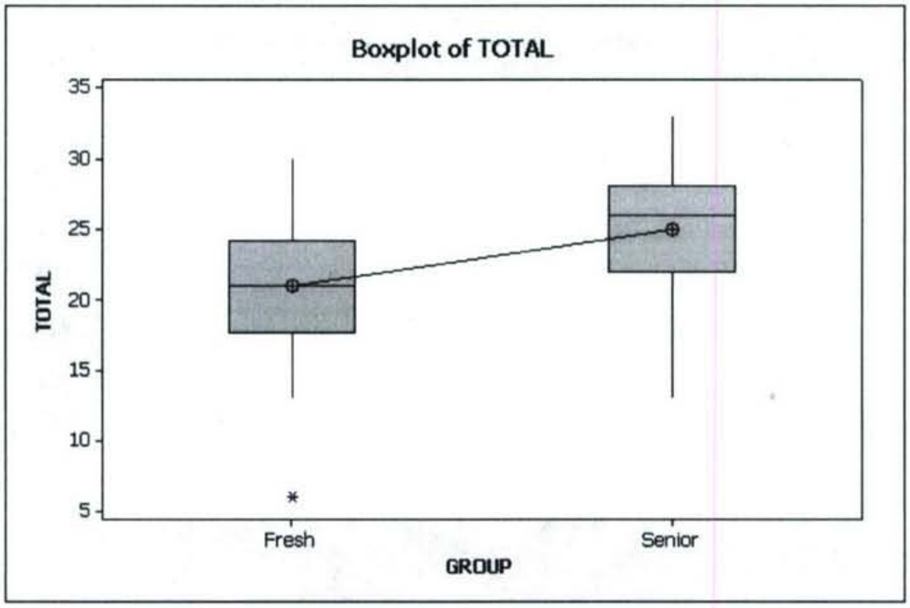


Figure 4.7: Mean total scores for freshmen and senior participants; the boxes represent the first quarter through the third quarter scores, with a line depicting the mean score

correlation between total and verbal SAT scores for the student participants (see Figure 4.8). Likewise a correlation of 0.693 with a P-value of 0.000 shows a positive relationship between total and math SAT scores (see Figure 4.9).

Figure 4.10 shows the correlation between total scores and grade point average, termed grade point record (GPR) at Clemson University (GPR and GPA are used interchangeably in this study). The Pearson's Correlation of 0.301 with a P-value of 0.062 indicates insufficient statistical evidence to show any correlation between total critical-thinking scores and GPA.

Figure 4.11 shows the correlation between total score and cumulative hours earned. The Pearson's Correlation of 0.297 and a P-value of 0.066 shows insufficient statistical evidence of any correlation between the total critical-thinking scores and cumulative hours earned.

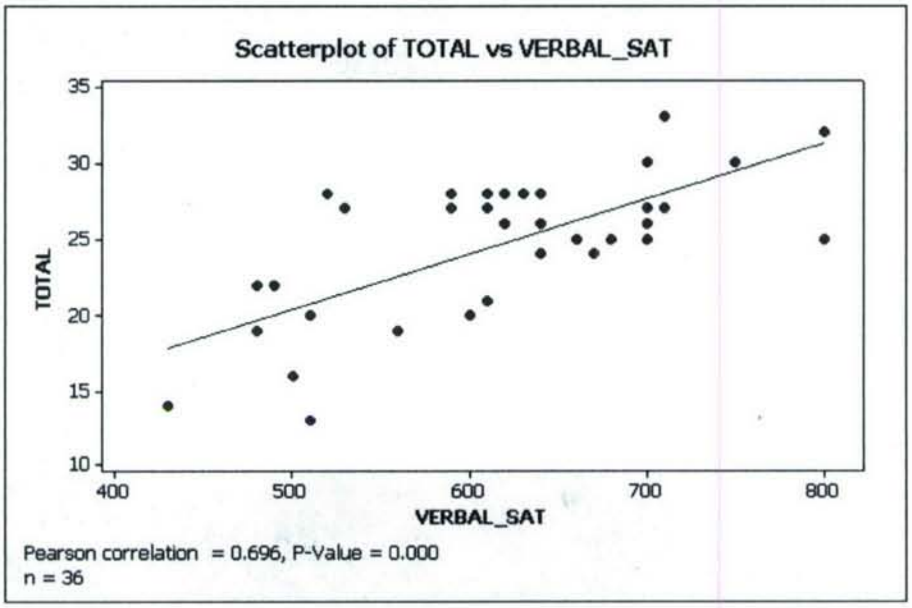


Figure 4.8: Correlation between total and verbal SAT scores

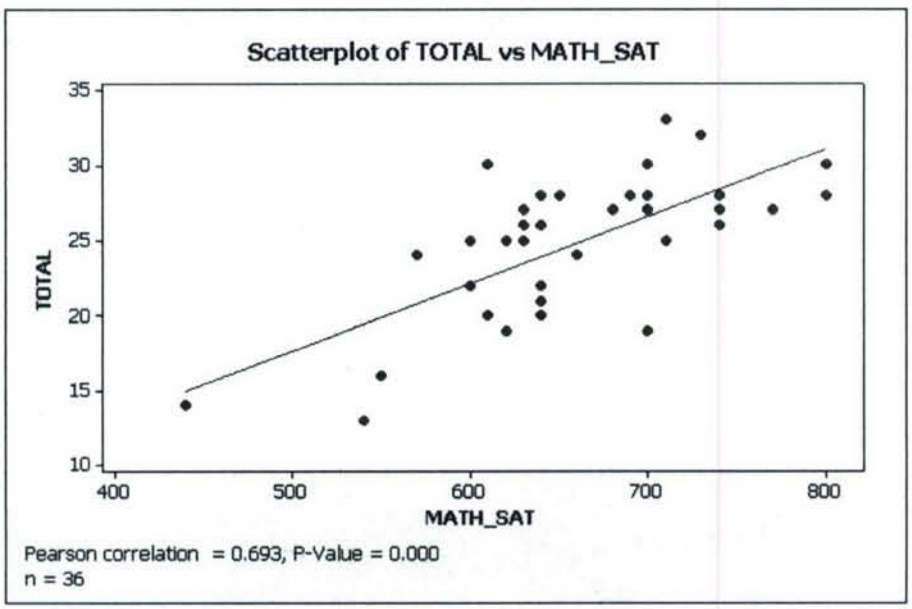


Figure 4.9: Correlation between total and math SAT scores

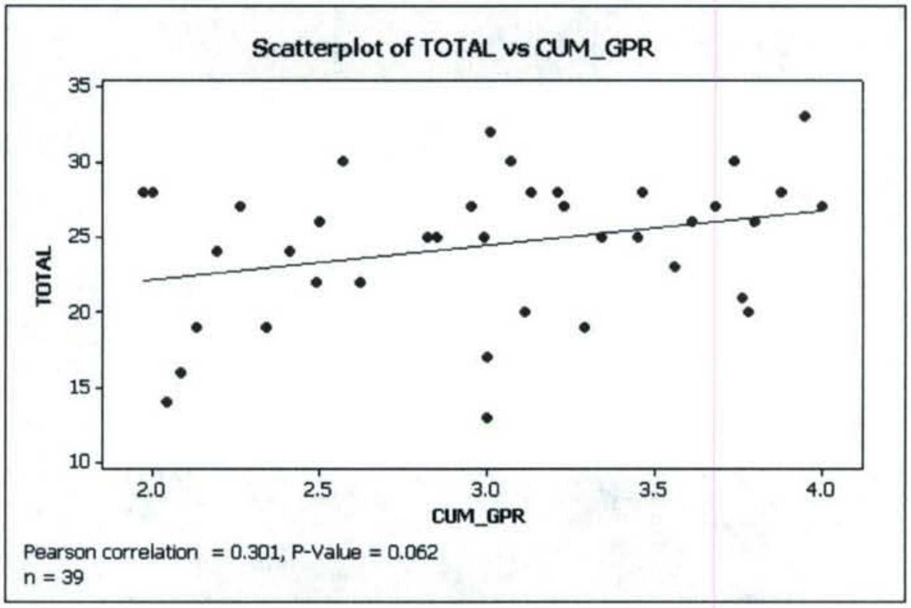


Figure 4.10: Correlation between total scores and cumulative grade-point average

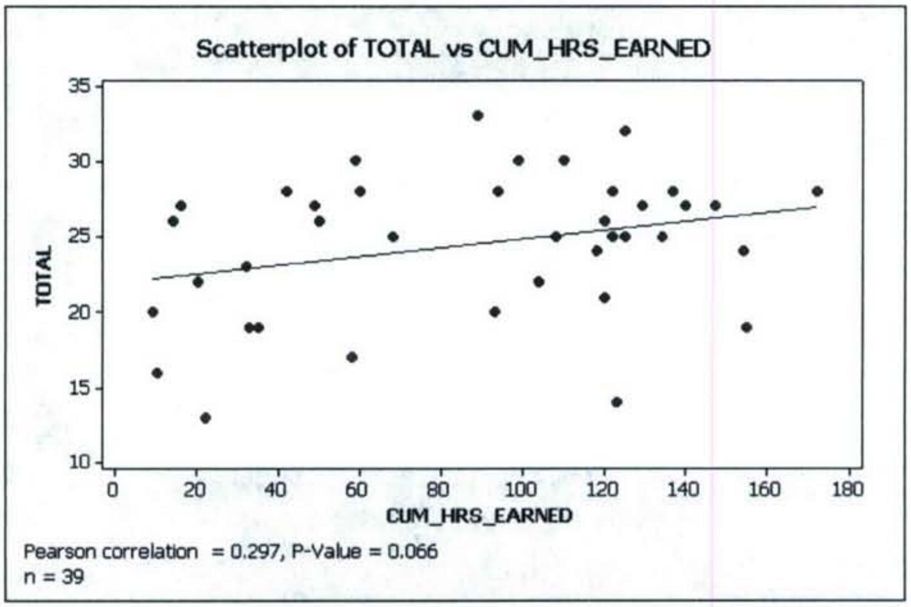


Figure 4.11: Correlation between total scores and cumulative credit hours earned

Table 4.6: Pearson's Correlation data as published by Insight Assessment, and as found in this study

Stat	IA	**Study**
SAT Verbal	0.55 - 0.62	**0.70**
SAT Math	0.44 - 0.48	**0.69**
Age	0.006	**0.13**
College GPA	0.20 - 0.29	**0.30**

Table 4.6 shows the correlation between critical-thinking skills and academic measures of success as reported by Insight Assessment [Insight Assessment 2007] and by this study. Both results show a positive correlation between SAT verbal and math scores and a low correlation between college GPA and critical-thinking scores, showing that there is not a strong link between GPA and critical-thinking ability.

4.2.3 Comparison of Experts' and Students' Critical-Thinking Scores

In response to Research Question 6 concerning the comparison of the critical-thinking skills of professionals with the scores of undergraduate computer science students, ANOVA tests and Hsu's Multiple Comparisons determined differences between the populations, by comparing each mean with the best (largest), as shown in Figure 4.12. The analysis shows a significant difference between the scores of the Air Force and those of the Army and Freshmen; however, no statistical difference showed between the scores of senior, faculty, industry, and Air Force participants.

4.2.4 Additional Findings

Figure 4.13 shows ANOVA and Hsu's comparisons of the data categorized by ethnicity. The majority of the participants were Caucasian, and the sample

```
One-way ANOVA: TOTAL versus GROUP

Source   DF      SS     MS      F      P
GROUP     5  2692.3  538.5  23.63  0.000
Error   173  3942.5   22.8
Total   178  6634.7

S = 4.774   R-Sq = 40.58%   R-Sq(adj) = 38.86%

                                  Individual 95% CIs For Mean
Level       N    Mean  StDev  ------+---------+---------+---------+---
Fresh      54  20.981  5.023                 (--*---)
Senior     29  24.931  4.869                          (---*----)
Fac        20  26.100  4.191                            (----*-----)
Industry   18  25.278  3.268                          (----*-----)
Air Force  27  26.556  4.003                              (---*----)
Army       31  15.419  5.801  (----*---)
                              ------+---------+---------+---------+---
                                  16.0      20.0      24.0      28.0

Hsu's MCB (Multiple Comparisons with the Best)

Intervals for level mean minus largest of other level means

Level         Lower   Center  Upper  --------+---------+---------+---------+-
Fresh        -8.163   -5.574  0.000                (----*----------)
Senior       -4.562   -1.625  1.313                      (-----*-----)
Fac          -3.696   -0.456  2.785                        (-----*------)
Industry     -4.620   -1.278  2.065                      (-----*------)
Air Force    -2.785    0.456  3.696                         (------*-----)
Army        -14.028  -11.136  0.000  (-----*---------------------)
                                     --------+---------+---------+---------+-
                                          -10.0      -5.0       0.0       5.0
```

Figure 4.12: Comparison of total scores for all populations

Table 4.7: Mean total scores on CCTST for all participants

GROUP	n	Mean	StDev	Var	Min	Max
Freshmen	54	20.98	5.02	25.22	6	30
Senior	29	24.93	4.87	23.71	13	33
Faculty	20	26.10	4.19	17.57	17	32
Industry	18	25.28	3.27	10.68	20	31
Air Force	27	26.56	4.00	16.03	12	31
Army	31	15.42	5.80	33.65	7	28

Table 4.8: Base line results in the sub-categories for all participants

Variable	n	Mean	StDev	Var	Min	Med	Max
Induction	179	11.888	3.037	9.223	3	12	17
Deduction	179	10.603	3.634	13.207	2	11	17
Analysis	179	5.263	1.478	2.183	1	6	8
Inference	179	10.648	3.245	10.533	2	11	16
Evaluation	179	6.609	2.406	5.790	0	7	11
TOTAL	179	22.503	6.105	37.274	6	24	33

Table 4.9: Two-tailed T test of women's scores and men's

GROUP	N	Mean	StDev	SE Mean
Women	32	21.75	6.02	1.11
Men	147	22.67	6.37	0.51

Difference = μ (Women) - μ (Men)
Estimate for difference: -0.92
95% CI for difference: (-3.29, 1.46)
T-Test of diff=0: T-Val = -0.78 P-Val = 0.441 DF = 46

sizes for the other groups were too small to draw any statistical conclusions. Table 4.9 shows no statistical difference between men's and women's scores (P-value=0.441, DF=46).

In Figure 4.14, ANOVA and Hsu's comparisons of total scores based on the main area of the participants show a statistically significant difference in the scores of the STEM disciplines when compared to the scores of other participants; however, senior STEM scores showed no difference from those of the STEM professionals.

In Figure 4.15, ANOVA and Hsu's comparison tests of total scores based on education levels of participants show a significant difference between the scores of the participants with the highest mean average (those with PhDs) and those with bachelor degrees and the freshmen. No statistical difference showed between the scores of those with PhDs and the scores of senior participants.

One-way ANOVA: TOTAL versus Ethnicity

```
Source      DF      SS     MS      F      P
Ethnicity    5  1873.7  374.7  13.62  0.000
Error      173  4761.1   27.5
Total      178  6634.7

S = 5.246   R-Sq = 28.24%   R-Sq(adj) = 26.17%
                                                Individual 95% CIs For Mean
Level                     N    Mean  StDev  -----+---------+---------+---------+---
Asian                    11  17.000  5.983     (--------*-------)
African American         18  16.333  6.472     (------*------)
Hispanic                  6  16.167  6.882      (------------*-----------)
I Choose not to provide   9  19.889  8.085                (---------*---------)
Other                     6  19.333  2.733           (-----------*-----------)
Caucasian               129  24.457  4.755                                  (--*-)
                                             -----+---------+---------+---------+---
                                               14.0      17.5      21.0      24.5

Hsu's MCB (Multiple Comparisons with the Best)
Family error rate = 0.05
Critical value = 2.33

Intervals for level mean minus largest of other level means

Level                Lower  Center  Upper  --+---------+---------+---------+-------
Asian              -11.304  -7.457  0.000     (------*-----------)
African American   -11.206  -8.124  0.000      (------*-----------)
Hispanic           -13.406  -8.291  0.000   (-------*-------------)
I Choose not        -8.791  -4.568  0.000         (------*-------)
Other              -10.239  -5.124  0.000      (-------*--------)
Caucasian            0.000   4.568  8.791                  (-------*------)
                                           --+---------+---------+---------+-------
                                          -12.0      -6.0       0.0       6.0
```

Figure 4.13: Comparison of mean total score and ethnicity

One-way ANOVA: TOTAL versus MAIN AREA

```
Source      DF      SS     MS      F      P
MAIN AREA    4  2273.6  568.4  22.68  0.000
Error      174  4361.2   25.1
Total      178  6634.7

S = 5.006   R-Sq = 34.27%   R-Sq(adj) = 32.76%

                                Individual 95% CIs For Mean
Level         N    Mean  StDev  ------+---------+---------+---------+---
Beh Sci/Man  23  18.130  6.525  (-----*------)
Other        50  18.600  5.890     (----*----)
Fresh STEM   24  22.500  4.520              (------*------)
Senior STEM  24  25.708  4.515                        (------*-----)
STEM         58  26.276  3.712                            (----*---)
                                ------+---------+---------+---------+---
                                   18.0      21.0      24.0      27.0

Hsu's MCB (Multiple Comparisons with the Best)

Intervals for level mean minus largest of other level means

Level          Lower  Center  Upper  -------+---------+---------+---------+--
Beh Sci/Man  -10.879  -8.145  0.000  (------*-------------------)
Other         -9.863  -7.676  0.000    (-----*------------------)
Fresh STEM    -6.469  -3.776  0.000            (------*--------)
Senior STEM   -3.260  -0.568  2.125                    (------*-----)
STEM          -2.125   0.568  3.260                       (-----*------)
                                     -------+---------+---------+---------+--
                                          -8.0      -4.0       0.0       4.0
```

Figure 4.14: Comparison of mean total scores of participants' main areas

One-way ANOVA: TOTAL versus Education level

```
Source           DF      SS     MS     F      P
Education level   7  1045.7  149.4  4.57  0.000
Error           171  5589.0   32.7
Total           178  6634.7

S = 5.717   R-Sq = 15.76%   R-Sq(adj) = 12.31%

                                   Individual 95% CIs For Mean
Level       N    Mean  StDev  --------+---------+---------+---------+-
HSGrad      1  13.000      *  (---------------*---------------)
Freshman   54  20.479  4.851                            (-*--)
Senior     32  24.037  5.396                                 (--*--)
Bachelors  28  19.393  7.238                          (--*--)
Masters    43  23.605  6.532                                (--*-)
PhD        21  26.429  3.400                                   (---*--)
                              --------+---------+---------+---------+-
                                    7.0      14.0      21.0      28.0

Hsu's MCB (Multiple Comparisons with the Best)

Intervals for level mean minus largest of other level means

Level        Lower   Center  Upper  --------+---------+---------+---------+-
HSGrad     -27.691  -13.429  0.833  (--------------*-------------)
Freshman   -10.554   -5.949  0.000                 (----*-----)
Senior      -7.252   -2.392  1.663                     (----*---)
Bachelors  -11.876   -7.036  0.000                (----*------)
Masters     -7.468   -2.824  0.886                     (---*---)
PhD         -5.022    1.429  6.446                       (-----*----)
                                    --------+---------+---------+---------+-
                                          -20       -10         0        10
```

Figure 4.15: Comparison of mean total scores based on education level

4.3 Summary

This data shows that expert computer science professionals have exceptional critical-thinking abilities and scored well above the national average. The freshmen and the seniors also scored above the national average, with the seniors scoring statistically higher than the freshmen. The experts scored significantly higher than the freshmen; although, there was no statistical difference between the scores of the experts and the seniors. Although a positive correlation was found between critical-thinking and SAT scores for both student populations, no correlation showed between critical-thinking scores and grade-point average.

Chapter 5

Conclusions and Recommendations

A "quiet crisis" is growing in America because of the discrepancy between the increasing need for top-tier performers in computer science and the declining number of college graduates available to fill these positions. In addition to the need for more computer science graduates, these students must be equipped with exceptional critical-thinking abilities, beyond subject matter content, exemplified by top-tier performers in the industry. This study addressed that growing concern by assessing and comparing the critical-thinking abilities of top-tier computer science professionals and college freshmen and seniors in the STEM disciplines.

Section 5.1 provides a summary of the research including the problem addressed, the background literature and the findings of the study. Section 5.2 draws conclusions based on the findings of the research questions followed by a discussion of them in Section 5.3. Section 5.4 concludes the chapter with recommendations for practice and for future areas of research.

5.1 Study Summary

Highly skilled top-tier performers in computer science are essential to America's business success and are at the core of America's technological edge, national competitiveness and security. While the need for these skilled computer science professionals is increasing, the supply of potential computer science experts is declining. Adding complexity to this issue, many companies have found that subject matter knowledge and academic record are not necessarily good indicators of the traits that enable newly hired employees to become top-tier performers. Research in expertise also supports this conclusion, finding that expert performers have cognitive skills that are more likely to predict success than do traditional measures of academic merit. Additionally, recent guidelines of the computer science accreditation board imply the need to incorporate critical-thinking skills into the curriculum [ABET 2007].

The purpose of this study was to assess the critical-thinking abilities of top-tier computer science performers from college faculties, industry and the military, and of undergraduate freshmen and seniors in the STEM disciplines. The core hypothesis is that 1) top-tier performers in computer science have highly developed critical-thinking abilities and 2) that college students in the STEM disciplines lack these abilities. The data supports the first element of the hypothesis, but it does not support the second. Guiding the research to establish this argument were the following areas of inquiry:

- The critical-thinking abilities of top-tier professionals
- The critical-thinking abilities of freshmen students
- The critical-thinking abilities of senior computer science students
- The comparison of the critical-thinking skills of college freshmen with those of senior computer science students
- The comparison between currently used measures of academic performance, such as grade point average, and critical-thinking skills
- The differences in critical-thinking skills between computer science professionals and the student populations tested

To assess the critical-thinking abilities of volunteers from different populations, this study used the California Critical Thinking Skills Test (CCTST).

An analysis of the data collected from these assessments shows the following:

- The mean total critical-thinking score on the CCTST of expert populations from academia, industry and the military is significantly above the national average.
- Both student populations scored higher than the national average.
- The senior computer science students scored significantly higher than the freshmen students.
- Although the analysis revealed a positive correlation between the students' scores on the verbal and the math SAT's, there was little correlation found between critical-thinking abilities and grade point average.
- The seniors scored as well as those in the expert populations with the exception of the Air Force, with outlying scores removed, who scored significantly higher than the seniors.

5.2 Conclusions

Data presented in Chapter 4 shows that highly developed critical-thinking skills are characteristic of expert top-tier performers in computer science. It also shows that these experts score significantly higher on critical-thinking abilities, as measured by the CCTST, than do the freshmen, suggesting that critical thinking is a learned skill.

The current study also shows that the seniors do have high levels of critical-thinking, as measured by the CCTST; in fact on a statistical level equivalent to the defined "experts." At the same time the seniors scored significantly higher than the freshmen, which on the surface at least, seems to demonstrate a progression of critical-thinking abilities - suggesting the undergraduate curriculum

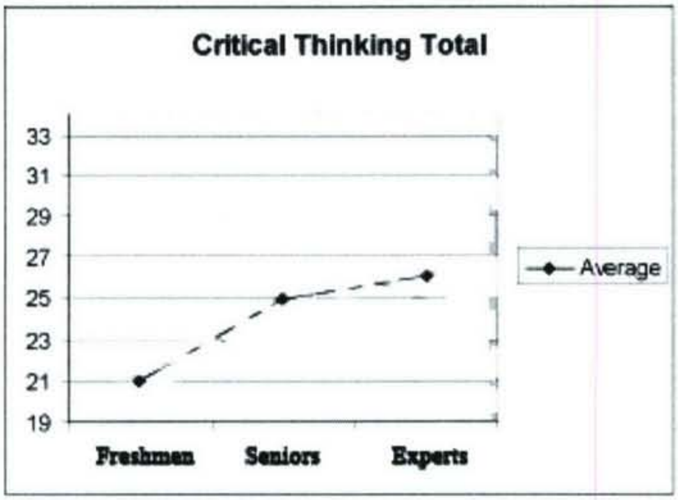


Figure 5.1: Critical thinking scores of the sample populations tested showing a significant difference between the scores of the freshmen and those of the seniors and experts and no statistical difference between the scores of the seniors and those of the experts.

does have an impact on the development of critical-thinking skills of computer science students. However, how and when these skills are developed is unclear from this work and remains an area for future research. Figure 5.1 shows the progression of these scores. Intermediate scores between freshmen and senior levels were not assessed, and the uncertainty of the shape and nature of the change that occurs during an undergraduate computer science education raises many questions for future research.

Industry research indicates that students with high grade-point averages do not necessarily have high levels of critical-thinking ability and that students who score low on tests and projects may, in fact, have high critical-thinking abilities [Colwell 2005]. This earlier finding is supported by the current study in that the data shows little relationship between grade-point average, the assumed measure of academic success, and critical-thinking abilities.

5.3 Discussion

Unlike past studies that focused primarily on the academic success of undergraduates to predict expert performance, this research took a different approach by identifying the presence of critical-thinking skills of top-tier performers, those in the computer science profession with 5 to 10 years of experience. Their critical-thinking scores can serve as a benchmark of critical-thinking skills, red a standard that can be compared to the scores of undergraduate students, and can be used to guide the development of curriculum and course modules that stress the development of these cognitive skills.

The current work demonstrates that critical-thinking abilities of computer science students improve from the freshmen to the senior year, that is those who choose computer science as a major and survive to graduation do gain some measure of critical-thinking skills. How such enhancement occurs and when it happens is unclear but suggests such questions as: Do those with high levels of critical-thinking abilities survive in the computer science discipline, indicating a need for this skill when entering as freshmen, or do students develop critical-thinking skills while in the computer science discipline? A longitudinal study measuring critical-thinking abilities throughout an undergraduate career would help to answer these questions.

It is generally accepted that the needs of the computer science industry require that the computer science curriculum have a particular interest in and emphasis on the development of these skills; however, this current research does not investigate how critical-thinking skills are enhanced and what experiences create the atmosphere for improving these abilities at the undergraduate level. Significant questions remain unanswered, such as, "What individual factors affect critical-thinking scores?" "Do critical-thinking skills improve incrementally, or is there a point at which the students 'get it' and their skills improve

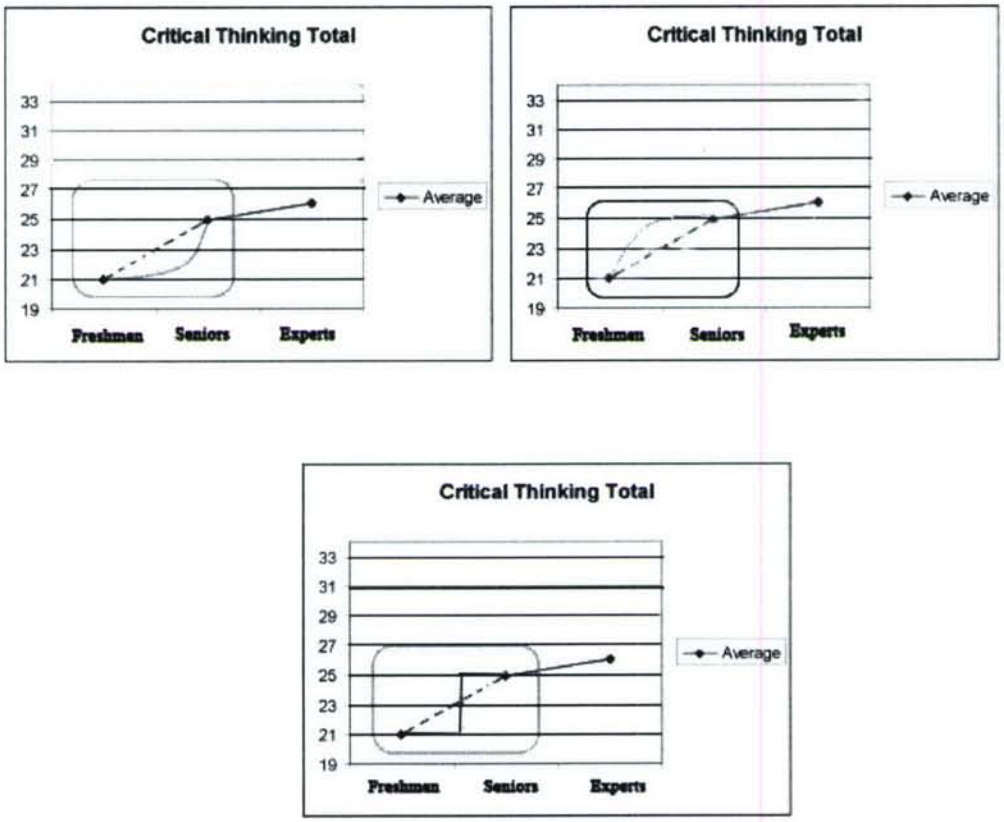


Figure 5.2: Possible shapes of the curve depicting the change in critical-thinking abilities from freshmen to senior computer science students, as measured by the CCTST.

dramatically?" "Do all disciplines see the same types of progression of critical-thinking abilities?" Figure 5.2 shows the possible shapes of the curve depicting the change in critical-thinking abilities from freshmen to senior computer science students as measured by the CCTST. These and other questions remain unanswered and are subjects for future study.

Importantly, the current study shows that critical-thinking skills have little correlation with grade-point average, so it is reasonable to ask if these skills are being sufficiently measured. The importance of developing exceptional critical-thinking skills make their assessment essential for computer science students. Students who rank lower academically and have a lower GPA may still be learning these important critical-thinking skills without their being recognized and nurtured. Measuring academic achievement with content-oriented tests is important and represents the core of computer science knowledge. However, this study has shown that GPA does not accurately reflect critical-thinking abilities and suggests that assessments need to be developed and implemented to assess these skills.

Another interesting issue concerning the student population is that its make-up may have possibly influenced its mean score on the CCTST. Roughly half of the freshmen had declared, or intended to declare, STEM discipline majors, which possibly accounted for the higher critical-thinking scores for those participants. The remaining freshman participants had selected a wide scope of majors; therefore, their scores helped to generalize the freshmen student population. Most of the senior participants came from a compiler construction course, a capstone course designed to challenge the students to use the breadth of their knowledge. The other senior students also came from STEM disciplines. A result is that the freshmen data tended to be more generalized than that of the senior group and suggests that additional work across a broader spectrum of majors could be done to good effect. A university-wide approach could be especially revealing, allowing the researcher an opportunity to consolidate up or down as the data leads.

Surprising results came from the United States Army Signal Corps Officers' scores. Initially, these participants were thought to be a military expert population, similar to the Air Force group. However, they scored relatively low on all phases of critical thinking. In an effort to explain the make-up of the group, the commandant of the school informed the researcher that they are not considered computer experts but are officers who represent a wide breadth of professions and experience. They are not necessarily top-tier performers, and the nature of their mission is quite different from that of the Air Force population. They better represent non-technical professionals and serve as an interesting comparison with the other professional populations.

Interesting results also came from the scores of participants from one particular company. The contact selected a subjective group of participants based on their performance including groups at three performing levels he called "A" or high-level, "B" or middle-level, and "C" or low-level. Although the sample size was too small to make any statistical conclusions, the scores of the "A" level performers were higher than those of the "B" and "C" levels with those of the "C" level scoring the lowest. This suggests that the expert performers, those who were rated highest by the supervisors, had higher critical-thinking abilities, as measured by the CCTST, than did the average or lower level performers within that company. Further research is needed to compare the critical-thinking abilities of the top-tier performers with those of the middle and lower-level performers in various companies.

Limitations of Current Study In assessing the critical-thinking abilities of participants and drawing conclusions, certain limitations must be considered. The assessment used in this study is a one-time test to measure the critical-thinking skills of the participants. Many factors can possibly influence a participant's score on any particular test including, among others, the person's mood at the time of the test, distractions in the testing environment, and the degree of concentration and effort on the part of the participant. These can certainly be limitations, but are uncontrollable with a test such as the CCTST; therefore, critical-thinking skills need to be assessed and observed several times over a 4-year education to ensure that the skills are being learned.

This study was limited to the CCTST that measures certain aspects of critical-thinking by assessing the cognitive abilities of the participants. Other validated critical-thinking tests should be used with their results compared with the results of the CCTST used in this study. Selecting a test with a greater number of questions may improve the spread of the scores; however, a longer test would require greater time commitment on the part of the volunteers and make it more difficult to get participants.

Another potential limitation is the sample size of the populations measured. Although the groups used in this study were large enough from which to draw statistical conclusions and larger than most in previous similar studies, a greater number of participants would produce a broader base of data and would provide the researcher with more flexibility for grouping and consolidating results across additional criteria. Also, this assessment was limited to freshmen and senior students at one major undergraduate institution. Expanding this research across universities, both public and private, and to all class years would provide valuable information.

Previous research has found that critical-thinking, problem-solving, and creativity are all components of the cognitive thinking skills contributing to expert performance. This study focused solely on critical-thinking skills and no attempt was made to investigate the overlap that could exist among the three individual skills. Because problem-solving and creativity skills can possibly influence critical-thinking abilities, future research needs to explore this connection as it relates to computer science.

5.4 Recommendations

5.4.1 Recommendations for Future Study

Research into the cognitive abilities of experts is an emerging field. Future researchers interested in pursuing studies pertaining to the roles of the cognitive abilities of expert computer science performers, to improving the undergraduate curricula and to additional related topics can find a wide array of them from which to choose. For instance,

- An assessment of critical thinking across a wide range of top-tier experts from a variety of computer professions; including software engineers, architects, graphic designers and other specialties; could provide a broad-base benchmark for computer skills.

- An assessment of critical-thinking scores of expert populations outside the computer science profession could serve as an interesting measure for comparison and contrast of cognitive-thinking abilities.

- Conducting a longitudinal study of a particular sample population throughout a 4-year college education could provide insights into the changes in critical-thinking skills, show the progression of these skills, and allow for the measurement of small changes taking place in these cognitive-thinking abilities. Careful selection of an appropriate assessment tool is essential for a long-term research project such as this that has a large test-bank of questions. A longitudinal study could provide insights to the following questions:

  - Is there a common point in the computer science curriculum at which students make the most improvement in critical-thinking abilities?

  - Is there a particular course or course sequence that causes the most gains in critical-thinking abilities?

  - Is there a particular point at which students seem to grasp critical-thinking concepts and make large improvements in a short period of time?

- How do courses designed to promote problem-solving skills, such as those employing problem-based learning models, affect critical-thinking skills?
- How does attrition rate of students leaving the computer science major relate to critical-thinking skills?
- Are those students that survive in computer science the ones with higher initial critical-thinking abilities, or is this a learned skill?
- How do different schools and curricula affect the learning curve of critical-thinking abilities?
- Are there other factors, such as gender, age, geographic region, or ethnicity that affect the learning of critical-thinking skills?

This longitudinal study could be expanded to follow students after graduation measuring changes in cognitive abilities throughout their professional career, providing answers to the following:

- Do particular career paths promote and enhance critical-thinking abilities more than others?
- Do critical-thinking abilities decline or improve over time in computer professions in general?
- Do critical-thinking abilities predict or correlate to success in a company, as defined by position or responsibility?

- Studies of the critical-thinking abilities of students from a large range of populations such as different disciplines and various age groups can be compared and contrasted with the scores of computer science students.
- Students from different institutions–private colleges, community colleges,

small schools and major universities–could be assessed to measure different factors that may influence critical-thinking abilities.

- An assessment of the critical-thinking abilities of incoming freshmen and how these initial scores affect and predict success at the undergraduate level could be conducted in different disciplines.

- The assessment of the creativity component of expert performance and its correlation to expertise and to critical-thinking abilities could be studied.

In short, a wider study of the impact of critical thinking on the higher education experience as a whole and its relationship, if any, to student success, including when and how these changes are manifested in students, needs to be conducted. The current study is a first step toward recognizing the importance of these cognitive skills beyond subject-matter knowledge.

5.4.2 Curriculum Issues

One of the key issues facing computer science education researchers is that "colleagues regularly convey the attitude that educational research is not real research" [Alstrum et al. 2005]. Rather than being discouraged from accepting, participating in, and benefiting from the results of this type of research, institutions and their faculties must be educated, encouraged and helped to appreciate and understand the process and of its benefits for them and their students. The following recommendations are intended to help institutions and their faculties, and ultimately the students, to get the most benefit from this type of research.

- The importance of critical-thinking skills should be recognized and ways to incorporate the skills into all levels of the undergraduate education should be explored.

- A repository of critical-thinking exercises and details on how to integrate them into existing courses, along with sample lesson plans containing activities and assignments, should be developed to assist computer science educators in promoting and fostering these cognitive skills.

- Critical-thinking skills should be evaluated throughout the educational process with assessments made at key points throughout the curriculum to continually measure progress.

- A variety of critical-thinking assessment tools must be made available to all instructors for integration into key computer science courses.

- Computer science faculty particularly should embrace new educational research and recognize its importance in shaping the scope of educational programs.

- Preparing students to be top-tier performers with the tools and abilities beyond subject-matter expertise must be a goal of all undergraduate institutions.

The lessons learned and the information obtained as a result of this study can be invaluable to future researchers, to institutions with computer science majors and ultimately to the computer science industry as a whole.

APPENDICES

A Assessments of Creativity

See the Indiana University website,

http://www.indiana.edu/bobweb/Handout/cretv_6.html,

for further information on the following creativity assessments.

- Divergent Thinking Tests
  - Guilford's Alternate Use Task 1967
  - Wallas and Kogan 1965
  - Torrance Tests of Creative Thinking 1974
- Convergent Thinking Tests
  - Insight Questions
  - Mednick's Remote Association Task 1962
- Artistic Assessments
  - Barron-Welsh Art Scale
- Self assessments
  - Khatena-Torrance Creative Perception Inventory
  - How Do You Think (Davis)
  - Things Done on Your Own (Torrance, 1962)
  - The Creativity Behavior Inventory
  - Runco Ideation Behavior Scale (RIBS)
  - Creative Attitude Survey (Schaeffer)

- Statement of Past Activities
- NEO-PI-R (Openness to Experience component)
- Gough Personality Scale

- Other Assessments
  - Creativity Assessment Packet
  - Preschool and Kindergarten Interests Descriptors
  - Scales for Rating the Behavioral Characteristics of Superior Students (Renzulli, 1993)

B Assessments of Critical Thinking

The following is a brief list of some of the most popular critical thinking tests.

Project CAT Tennessee Tech

"Project CAT is a cooperative project sponsored by the National Science Foundation and Tennessee Technological University. The project goal is to refine an instrument for assessing critical thinking skills in undergraduate students" [Stein 2006].

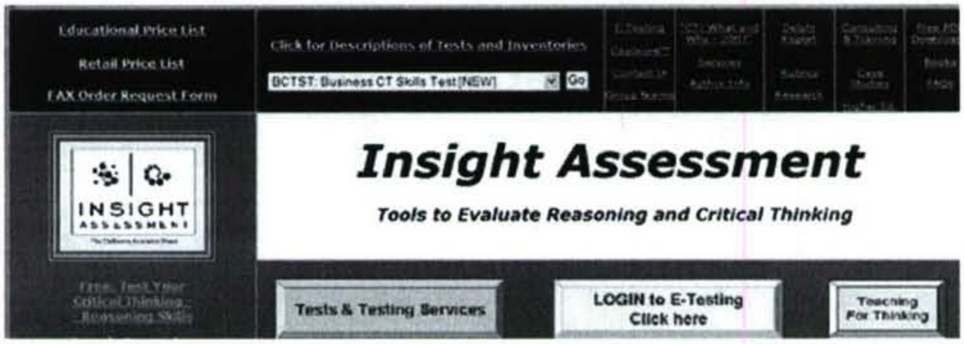
The following abbreviated list of assessments of critical thinking comes from Dr. Ennis at the University of Illinois (http://faculty.ed.uiuc.edu/rhennis/testlistrevised606.htm):

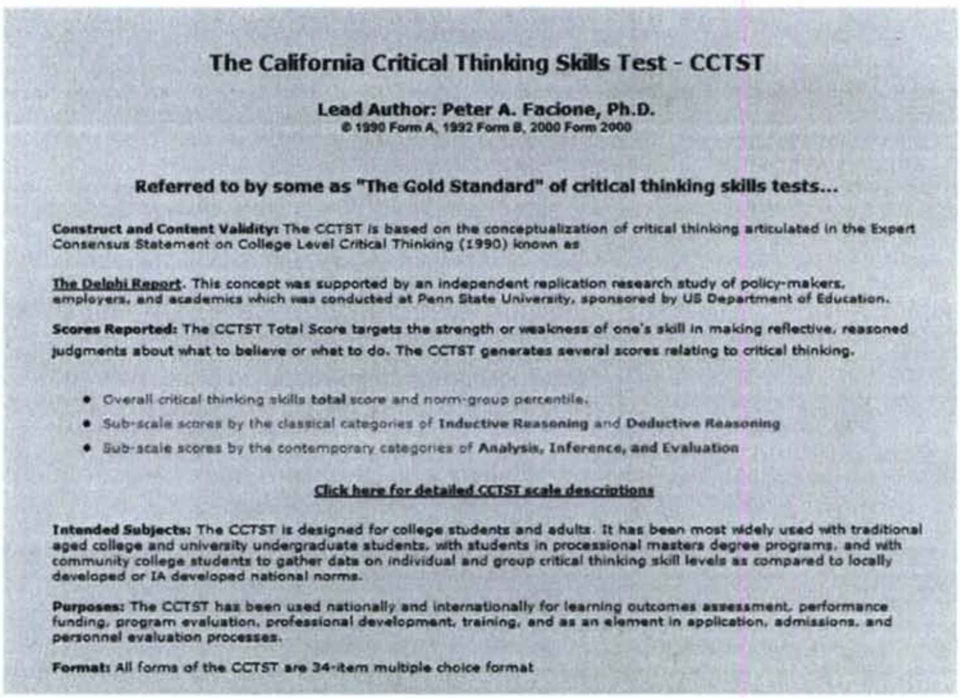
- "California Critical Thinking Dispositions Inventory" (1992) by Peter Facione and N. C. Facione.
- "Cornell Critical Thinking Test - X" (2005) by Robert H. Ennis and Jason Millman.
- "Cornell Critical Thinking Test - Z" (2005) by Robert H. Ennis and Jason Millman.
- "Critical Thinking Interview" (1988) Gail Hughes and Associates.
- "The Collegiate Assessment of Academic Proficiency (CAAP) Critical Thinking Test Distributed by ACT"
- "Ennis-Weir Critical Thinking Essay Test" (1985) by Robert H. Ennis and Eric Weir.
- "International Center for the Assessment of Thinking" (1996).
- "James Madison Test of Critical Thinking"

- "New Jersey Test of Reasoning Skills" (1983) by Virginia Shipman.
- "ETS Tasks in Critical Thinking" (1993).
- "Watson-Glaser Critical Thinking Appraisal" (1980) by Goodwin Watson and Edward Maynard Glaser).

C California Critical Thinking Test

The California Critical Thinking Test (CCTST), developed by Peter Fracione [Facione 1990], is a 34-question, multiple-choice, on-line assessment that measures 5 areas of critical thinking (inductive reasoning, deductive reasoning, analysis, inference, evaluation, and total critical thinking score) and provides the test taker immediate feedback on the results (www.insightassessment.com).





The California Critical Thinking Skills Test - CCTST

Lead Author: Peter A. Facione, Ph.D.
© 1990 Form A, 1992 Form B, 2000 Form 2000

Referred to by some as "The Gold Standard" of critical thinking skills tests...

Construct and Content Validity: The CCTST is based on the conceptualization of critical thinking articulated in the Expert Consensus Statement on College Level Critical Thinking (1990) known as

The Delphi Report. This concept was supported by an independent replication research study of policy-makers, employers, and academics which was conducted at Penn State University, sponsored by US Department of Education.

Scores Reported: The CCTST Total Score targets the strength or weakness of one's skill in making reflective, reasoned judgments about what to believe or what to do. The CCTST generates several scores relating to critical thinking.

- Overall critical thinking skills **total** score and norm-group percentile.
- Sub-scale scores by the classical categories of **Inductive Reasoning** and **Deductive Reasoning**
- Sub-scale scores by the contemporary categories of **Analysis, Inference, and Evaluation**

Click here for detailed CCTST scale descriptions

Intended Subjects: The CCTST is designed for college students and adults. It has been most widely used with traditional aged college and university undergraduate students, with students in processional masters degree programs, and with community college students to gather data on individual and group critical thinking skill levels as compared to locally developed or IA developed national norms.

Purposes: The CCTST has been used nationally and internationally for learning outcomes assessment, performance funding, program evaluation, professional development, training, and as an element in application, admissions, and personnel evaluation processes.

Format: All forms of the CCTST are 34-item multiple choice format

Given the importance of critical thinking to our
democracy, our economy, and our lives in a pluralistic, global community,
we hope that you get most, if not all, of these right.

Click on the link after each item to see an analysis of that item and its various choices.

The items shown here are similar to those found on the **CCTST** and the **TER**

Sample Reasoning Skills Item #1: Using the phone at her desk, Sylvia in Corporate Sales consistently generates a very steady $1500 per hour in gross revenue for her firm. After all of her firm's costs have been subtracted, Sylvia's sales amount to $100 in bottom line (net) profits every 15 minutes. At 10:00 a.m. one day the desk phone Sylvia uses to maker her sales calls breaks. Without the phone Sylvia cannot make any sales. Assume that Sylvia's regular schedule is to begin making sales calls at 8:00 a.m. Assume she works the phone for four hours, takes a one hour lunch exactly at noon, and then returns promptly to her desk for four more hours of afternoon sales. Sylvia loves her work and the broken phone is keeping her from it. If necessary she will try to repair the phone herself. Which of the following options would be in the best interest of Sylvia's firm to remedy the broken phone problem?

A = Use Ed's Phone Repair Shop down the street. Ed can replace Sylvia's phone by 10:30 a.m. Ed will charge the firm $500.
B = Assign Sylvia to a different project until her phone can be replaced with one from the firm's current inventory. Replacing the phone is handled by the night shift.
C = Authorize Sylvia to buy a new phone during her lunch hour for $75 knowing she can plug it in and have it working within a few minutes after she gets back to her desk at 1:00 p.m.
D = Ask Sylvia to try to repair her phone herself. She will probably complete the repair by 2:00 p.m., or maybe later.

Click here for an explanation of Item #1 and its Options

Sample Reasoning Skills Item #2: "I've heard many reasons why our nation should reduce its reliance on petroleum vehicle fuels. One is that relying on imported oil makes our economy dependent on the political whims of foreign rulers. Another is that other energy sources, like the possibility of hydrogen based fuels, are less harmful to the environment. And a third is that petroleum is not a renewable resource so when we've used it all up, it will be gone! But I don't think we're likely to use it all up for at least another fifty years. And by then we'll have invented new and better fuels and more fuel-efficient vehicles too. So that argument doesn't worry me. And I don't really believe the stuff about how foreign leaders can force our nation to change its policies simply by decreasing their oil production. Oil companies like Exxon have made record profits precisely in those times when the supply of foreign oil was reduced. I don't see the big oil companies being very interested in policy change when the money is rolling in. And for another, our nation has demonstrated that it is willing to wage war rather than to permit foreign leaders to push us around. So this whole thing about how we have to reduce our reliance on petroleum based gasoline, diesel, and jet fuel is bogus." The speaker's reasoning is best evaluated as

A = solid. It shows the arguments for reducing petroleum vehicle fuels are weak.
B = solid. The speaker is very clear about what he believes and why he believes it.
C = weak. The speaker probably owns stock in Exxon or some other oil company.
D = weak. The speaker ignored the environmental argument entirely.

Click here for an explanation of Item #2 and its Options

Sample Reasoning Skills Item #3: Consider the claim: "Even the General occasionally uses evasive language," as this claim relates to the following reason: "After all, most politicians strive to please their various constituencies. And the General, although a wise, forthright, articulate, and seasoned leader, like all important people, has to be something of a politician in order to be successful. I find it very hard to imagine always being able to please every constituency without, at least on some occasions, using evasive language." Assuming all the statements made as part of the reason are true, the initial claim about the General using evasive language at times

A = could not be false.
B = is probably true, but may be false.
C = is probably false, but may be true.
D = could not be true.

Click here for an explanation of Item #3 and its Options

The Scales Scores for the CCTST, TER, HSRT, and the BCTST

Scale Inductive Reasoning: Inductive reasoning happens when we decide that the evidence at hand means that a given conclusion is probably true. For example, if we know that the vast majority of people who smoke, as compared to those who do not smoke, suffer serious health problems, we might reasonably conclude by inductive reasoning that smoking is probably hazardous to one's health. Scientific reasoning aims to show that some ideas more likely to be true than others. Scientists use inductive methods, such as experimentation; and they use inductive tools, such as statistics. When we base our predictions about how things will happen in the future on our past experiences we are using inductive reasoning. As long as there is even the most remote and obscure possibility that although all the reasons for a claim could be true and yet the claim itself might still be false, we are in the realm of inductive reasoning.

Scale Deductive Reasoning: Deductive reasoning happens when we decide that, no matter what, it is impossible that the conclusion we are considering is false, given that all the premises of our argument are true. For example, if we know for a fact that San Diego is west of Denver, and we know that Denver is west of Detroit and New York, then we can infer with deductive certainty that San Diego is west of New York. Mathematics uses deductive reasoning. Algebra and geometry are exercises in deductive reasoning. Playing a game can also be an exercise in deductive reasoning, and so can filling out an income tax return. For both games and tax returns are things that require us to apply strict rules and laws. For example, "if the batter swings and misses three pitches, the batter is out, and Johnnie just did that, so Johnnie is out" is a deductive inference. One of the ways that we know that little children can reason deductively is to observe that they can play games that require following rules, even playground rules.

Scale Analysis: We are using our analytical skills when we pull apart arguments and points of view to show why a person thinks what he or she thinks. In effect we are separating the premises and the assumptions a person is using from the claim or the conclusion that the person is reaching. For example, suppose someone proposes that that we should go to war because the enemy is building up weapons of mass destruction to use against us. An analysis of this person's position would reveal that the person is making assumptions about what the enemy is doing ("building up weapons") and about what the enemy is intending ("to use against us").

Scale Inference: We use your inference skills whenever we draw conclusions based on reasons and evidence. We might be using our deductive reasoning inference skills or our inductive reasoning inference skills. We can apply your inference skills to all sorts of things including beliefs, opinions, facts, conjectures, principles, and assumptions. We can even apply our inference skills to mistakes. If we reason to any conclusions based on things that we know are mistaken, then we are most likely going to have reached a faulty conclusion, even if we applied your skills well. For example, we know that Chicago is in Illinois. But suppose we were so confused that we thought that Illinois was in Mexico, and not in the United States. We might then infer that Chicago is in Mexico. Good use of inference skills, but based on mistaken beliefs – the result is, as we would expect, not a true statement. It is important to keep separate what we know to be true and what conclusions we infer based on what we know.

Scale Evaluation: We are using our evaluation skills when we decide how strong or how weak a person's arguments are, or when we determine the believability of a given statement. For example, what do we think about the idea that the sun goes around the earth? Well, if we were standing all day in an open field you might observe that the sun rose in the east and set in the west. This would seem to support the idea that the sun goes around the earth. On the other hand, if we knew that the earth was spinning on its axis and that the solar system includes our planet in

D Previous Studies

In an attempt to find a research project that dealt specifically with the critical-thinking skills of expert performers in top-tier computer science professionals and that compared their assessment scores with the same scores of undergraduate students this researcher reviewed, among others:

- "Knowledge Organization and Skill Difference in Computer Programmers" proposed that "expert computer programmers can recall at a glance far more information relevant to their field than novices can." This is related to the experts' ability to chunk information [McKeithen et al. 1981].

- "Empirical Studies of Programming Knowledge" asserted "expert programmers have and use 2 types of programming knowledge: 1) programming plans which are generic program fragments that represent stereotypic action sequences in programming, and 2) rules of programming discourse, which capture the conventions in programming and govern the composition of the plans into programs" [Soloway and Ehrlich 1984].

- "Some Determinants of Skilled Performance in Programming" proposed that novices are not as able as experts are at "organizing their knowledge around semantics, even when dealing with the simplest code" [Weidenbeck 1984].

- "The Role of Domain Experience in Software Design" explored "the software designer's underlying constellation of knowledge and skills, and at the way in which this constellation is dependent upon experience in a domain" [Adelson and Soloway 1985].

- "Learning Flow of Control: Iterative and Recursive Procedures" studied the mental models of students and schema used in programming and found that "novices have poor mental models" [Kessler and Anderson 1986].

- "Critical Thinking Ability of Novice and Expert Computer Programmers" examined the critical-thinking skills of college freshmen and seniors using the Cornell Critical Thinking Test and found that "(a) there is a significant difference in the critical-thinking abilities of novice (freshmen) and expert (senior) programmers and (b) computer ability accounted for more variation in critical thinking than mathematical ability" [Hanson 1986].

- "Differences in the Structure of Semantic Knowledge for Computer Programmers of Different Levels of Skill" "investigated differences in the structure of semantic knowledge for computer programmers of different levels of skill at the undergraduate level" [Bateson 1987].

- "Programming in BASIC or LOGO: Effects on Critical Thinking Skills" studied "whether learning to program computers in either the BASIC or LOGO languages affected critical-thinking skills in students... (and) indicated that critical-thinking skills were not affected by age, gender, or which computer language was taught in an introductory course" [Sattler 1987].

- "Problem Decomposition By Computer Programmers" studied the "roles played by knowledge of task, content, and decomposition in the movement from problem definition through solution design to solution implementation in computer programming... (and) that schematic plans ... are inadequate for solving complex design problems and suggested that a combination of breadth-first, depth-first decomposition is used by programmers." The study used a think-aloud research methodology to explore the problem-solving procedures of one expert and thirteen novice programmers [Gong 1988].

- "What Best Predicts Computer Proficiency?" provided a summary of previous research into expert versus novice programming ability from 1970 to 1989 [Evans and Simkin 1989].

- "Cognitive Consequences of Programming Instruction" studied "programming and how precollege programming instruction affected thinking" [Linn and Dalbey 1989].

- "Effect of Computer Programming Instruction on the Problem-solving Ability of College Level Introductory Computer Students" explored the "possible relationship between computer programming instruction and increased general problem-solving ability." This study used a pre-test and post-test of college freshmen using the "Watson-Glaser Critical Thinking Appraisal" and found "no significant difference in general problem-solving ability" after one introductory computer science course [VanLengen 1989].

- "The Effect of Computer Science Instruction on Critical Thinking Skills and Mental Alertness" surveyed the "effect of completion of an introductory level computer programming course on students' critical-thinking and problem-solving skills" [Norris and Jackson 1992].
- "Quantitative and Qualitative Differences Between Experts and Novices in Chunking Computer Software Knowledge" analyzed "quantitative and qualitative differences between experts and novices in knowledge structure and in their chunking of computer software knowledge" [Ye and Salvendy 1994].
- "Computer Programming and Analogical Reasoning: An Exploratory Study" probed the "possibility of designing (an introductory) computer science course... to include more than just 'coverage' of subject matter but also to encompass questions of 'methods and processes'... (of) inquiry (and) abstract logical thinking that are at the heart of the intellectual process" [Schlafmitz 1996].
- "Differences Between Novice and Expert Systems Analysts: What Do We Know and What Do We Do?" identified "specific weaknesses that set novice and expert analysts apart... (and suggested) techniques that may be used to strengthen novice skills. This research supports the current literature on creativity techniques as a strategy for strengthening system analysis skills" [Schenk et al. 1998].
- "Object-Oriented Program Comprehension: Effect of Expertise, Task and Phase" discovered a "four-way interaction of expertise, phase, task

and type of model... (and) show(ed) that novices do not spontaneously construct a strong situation model but are able to do so if the task demands it" [Burkhard et al. 2002].

- "Operationalzing Predictive Factors of Success for Entry Level Students in Computer Science" examined the predictive value of the Clemson math placement examination on the success of students in a first-year computer science course [Weaver 2004].

- "Information Problem Solving By Experts and Novices: Analysis of a Complex Cognitive Skill" determined that "experts spend more time on defining problems and more often activate their prior knowledge, elaborate on the content, and regulate their process" than novices do [Brand-Gruwel et al. 2005].

- "Pair Programming Productivity: Novice vs. Expert" suggested that "novice pairs against novice solos are much more productive in programming performance than expert pairs against expert solos" [Lui and Chan 2006].

- "Using Student Performance Predictions in Computer Science Curriculum" sought to develop a model of success using previous course grades as a predictor of success in future computer science courses [Chamillard 2006].

- "Predictors of Success in a First Programming Course" used several factors, including paper-folding, map sketching, and phone-book searching to predict student success in introductory computer science courses [Simon et al. 2006].

- "What Makes A Good Programmer?" asserted that a person with high theoretical value beliefs, the person who values "order, problem solutions and proofs, and is motivated by the discovery of truth" plays a larger role in determining programming ability at the undergraduate level than does cognitive abilities or personality [Cegielski and Hall 2006].

E Undergraduate Schools of Participants

- Alabama A&M University
- Arizona State University
- Auburn University
- Brown University
- California State University
- Carson-Newman College
- Clemson University
- Coastal Carolina University
- Cornell University
- Dickinson College
- Drexel University
- East Tennessee State University
- Excelsior College
- Florida A&M University
- Florida State University
- George Mason University
- Georgia Institute of Tech
- Harvard
- Hawaii Pacific University

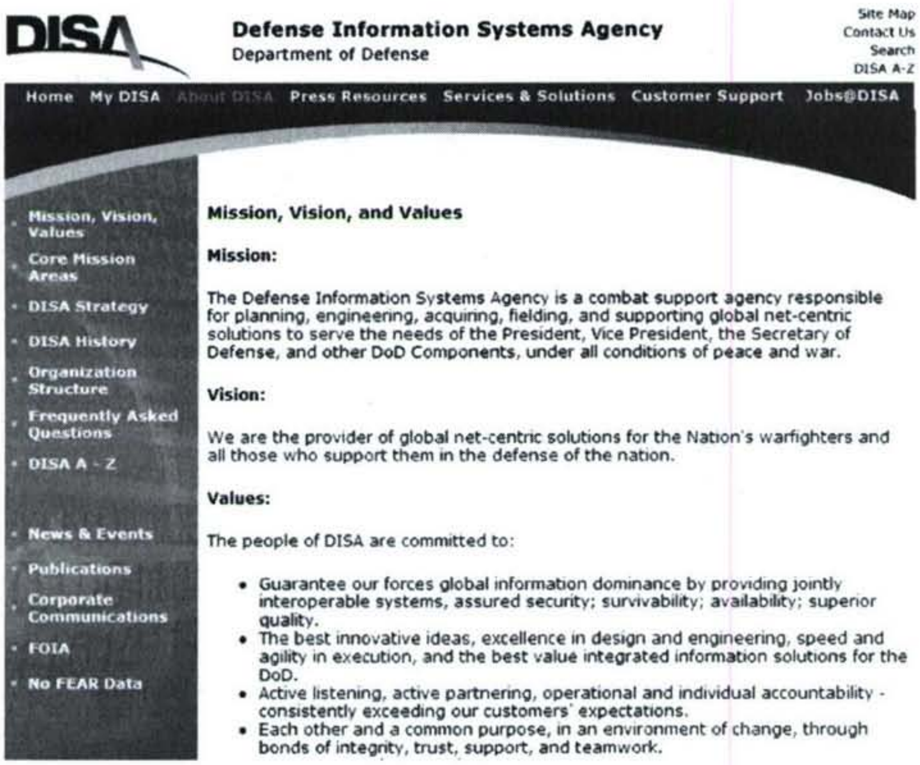
- Indiana University
- Indiana University of Pennslyvania
- Jackson State University
- John Brown University
- Michigan State university
- Middle Tennessee State University
- Mississippi Valley State
- Mumbai University
- North Carolina State University
- Norwich University
- Notre Dame
- Princeton
- Rensselaer Polytechnic Institute
- Siena College
- SUNY Geneseo
- Texas A&M - Kingsville
- The University of Arizona
- Transylvania University
- Troy University
- Tulane University

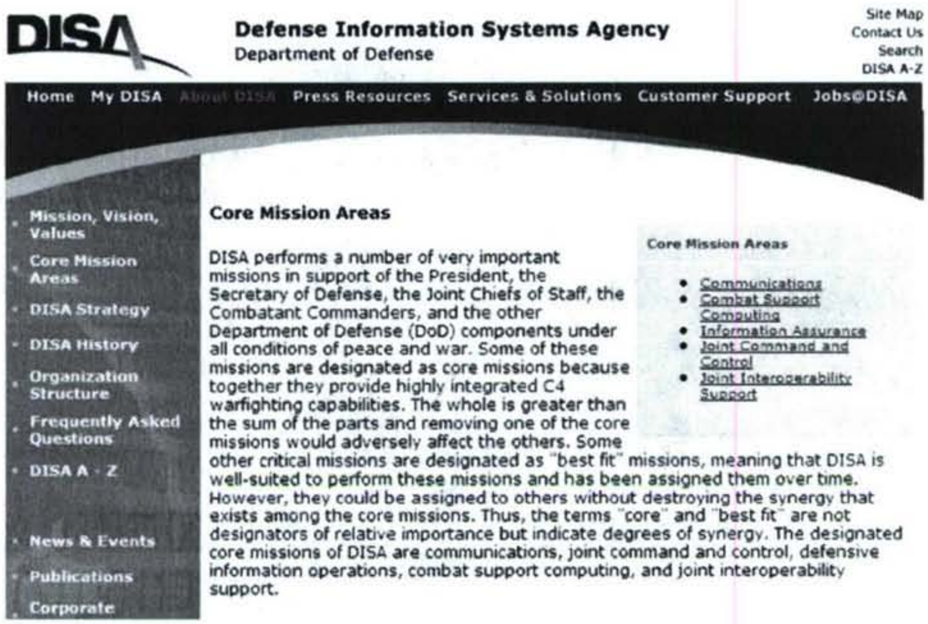
- United States Military Academy
- Univ of Southern Mississippi
- University of Puerto Rico
- University of Akron
- University of Alabama
- University of Delaware
- University of Florida
- University of Iowa
- University of Nebraska
- University of Northern Colorado
- University of Southern California
- University of Texas-Arlington
- University of Texas-San Antonio
- University of Virginia
- University of Wisconsin-Green Bay
- United States Air Force Academy
- VJTI, Mumbai
- Weber State University
- Western Oregon University

F Military Participants

F.1 DISA

For more information on DISA see, www.disa.mil.





F.2 Signal Corps

For more information see the School of Information Technology website, http://www.gordon.army.mil/sit/.

School of Information Technology

"Leading the way in Todays Technology"

Site Information | Component Websites | AKO & Other Links | General Information

OUR MISSION

To provide trained Information Technology (IT) soldiers and civilians to the Army and the joint community. The resident training is done through classroom instruction, hands-on practical exercises, and interaction with simulation equipment for critical IT skills associated with networking concepts and configurations, network management, systems administration and security, and information dissemination. SIT conducts both resident and non-resident functional courses in support of Information Assurance (IA), Communications Security (COMSEC), Defense Message Systems (DMS), and Joint Networks. The SIT trains all IT officers in the grades warrant officer one through lieutenant colonel in officer Areas of Concentration (AOC) within the Signal Regiment's spectrum at the basic and advanced levels. These AOCs include Functional Area (FA) Officers 53A and 24A; AOC 25A; and, 250N, 251A, and 254A Signal Corps Officers. All Signal Corps noncommissioned officers (NCOs) attend portions of IT courses at both the basic and advanced levels. Many of the IT students are DoD Civilians as well as Allied Students who attend under the International Military Student Program conducted by the Department of State.

For comments or questions CONCERNING THE WEBSITE contact: Web Administrator.

G Assessment Procedures

G.1 Faculty Recruitment Letter

I am a graduate student working under the direction of Dr. Steve Stevenson and am conducting research on traits of creativity and critical-thinking skills of computer science experts and computer science students.

I am seeking volunteers to take a 45-minute, computerized assessment of critical-thinking abilities, "The California Critical Thinking Skills Assessment, "produced by Insight Assessments. It is a standardized validated assessment that will provide you with immediate results.

I will use the faculty scores as my "control" expert group and as a comparison with student scores. No identifying information will be collected from faculty members with their scores. I will collect educational data, including GPA, HS GPA, and SAT scores from the students who take these same assessments to see if there is any correlation between test results.

Please respond to this email (deanb@clemson.edu) to schedule a time to take the test. Thank you in advance for your help!

Respectfully,
Dean Bushey

G.2 Assessment Instructions

Volunteers received the following survey instruction letter:

Thank you for volunteering to help me in my research by taking the California Critical Thinking Skills Test. Allow 40 to 45 minutes for the test.

Steps to follow:

1. Go to: http://www.insightassessment.com/ia/login.asp

2. Login id: xxxxxxxx

   Password: xxxxxxxx

   If you have problems with this username/password, let me know and I will give you an alternate

3. Click the tab at the top (4th from left) entitled "Start Test/Survey."

4. You will see the on-line Testing/Survey Tool Page.

5. Click the "START ONLINE TESTING/SURVEY" in the top paragraph. You may need to install a Java web application. It should go smoothly, but email me if you have questions.

   The preceding steps should launch the test. You will have to re-login with the same user id and password as above.

6. Try it out - If you have any problems, please call or email me.

Thank you again for your participation.

H Institutional Board Review Approval

CLEMSON
UNIVERSITY

January 22, 2007

Dr. Steve Stevenson
Computer Science
315 McAdams Hall
Clemson University
Clemson, SC 29634

SUBJECT: Human Subjects Proposal # **06-IRB-226 entitled "Creativity and Critical Thinking Skills of Computer Science Students".**

Dear Dr. Stevenson:

The Institutional Review Board (IRB) of Clemson University reviewed the above-mentioned study using Expedited review procedures and has recommended approval. **Approval for this study has been granted as of January 22, 2007.**

Your approval period is **January 22, 2007 to January 21, 2008**. Your next continuing review is scheduled for November 2007. Please refer to the IRB number and title in communication regarding this study. Attached is handout regarding the Principal and Co-Investigators' responsibilities in the conduct of human research. The Co-Investigator responsibility handout should be distributed to all members of the research team.

No change in this approved research protocol can be initiated without the IRB's approval. This includes any proposed revisions or amendments to the protocol or consent form. Any unanticipated problems involving risk to subjects, any complications, and/or any adverse events must be reported to the Office of Research Compliance immediately. Please contact the office if your study has terminated or been completed before the identified review date.

We appreciate your assistance in complying with federal regulations and institutional policies. You may contact the Office of Research Compliance at 656-6460 if you have any questions.

Sincerely,

Laura A. Moll

Laura A. Moll, M.A., CIP
IRB Coordinator
Institutional Review Board

OFFICE OF RESEARCH COMPLIANCE

223A Brackett Hall Box 345704 Clemson, SC 29634-5704 864.656.1525 FAX 864.656.4475 www.clemson.edu/research
Institutional Review Board: 864.656.6460 Institutional Biosafety Committee: 864.656.0118 Animal Research Committee: 864.656.4538

I Supplemental Data

Raw data collected for this research is listed in Table I. Individual identifying information has been removed as directed by the Clemson IRB.

Table 1: Raw Data

ID	Race	Gender	Age	Ed level	Maj	V SAT	M SAT	CUM HRS	GPR	Ind	Ded	Ana	Inf	Eval	TOT
31787	Caucasian	Male	41	PhD	Computer Science	0	0	0	0	14	12	7	11	8	26
31942	Caucasian	Male	23	Senior	Computer Science	610	650	137	1.97	12	16	5	14	9	28
31943	Caucasian	Male	19	Freshman	Computer Engineering	530	630	16	3.23	13	14	7	13	7	27
31945	Caucasian	Male	22	Junior	Electrical Engineering	0	0	58	3	11	6	5	6	6	17
31947	Black	Female	20	Junior	CIS	600	610	93	3.78	14	6	6	8	6	20
31952	Caucasian	Male	18	Sophomore	Mechanical Engineering	560	700	35	3.29	9	10	5	9	5	19
31957	Caucasian	Male	25	Senior	Computer Science	640	660	154	2.19	13	11	5	11	8	24
31963	Caucasian	Male	18	Freshman	Biology	0	0	0	0	10	6	6	5	5	16
31965	Caucasian	Male	21	Senior	Computer Science	680	600	122	3.34	13	12	6	11	8	25
31967	Caucasian	Male	20	Junior	Computer Science	710	710	89	3.95	16	17	7	16	10	33
31968	Asian	Male	19	Freshman	Mathematical Sciences	480	640	20	2.62	13	9	5	11	6	22
31969	Caucasian	Male	25	Senior	Computer Science	700	700	99	2.57	14	16	6	15	9	30
31975	Caucasian	Male	23	Senior	Computer Science	560	620	155	2.34	10	9	4	11	4	19
31976	Caucasian	Male	21	Senior	Computer Science	800	620	134	2.82	14	11	7	11	7	25
31977	Caucasian	Female	25	Masters	Mathematical Sciences	0	0	0	0	14	12	6	13	7	26
31978	Caucasian	Male	25	Senior	Computer Science	700	630	50	3.61	12	14	4	14	8	26
31979	Caucasian	Female	21	Senior	Computer Science	700	630	108	2.85	15	10	7	9	9	25
31980	Black	Male	18	Freshman	History	0	0	0	0	10	9	6	9	4	19
31983	Caucasian	Male	64	PhD	Computer Science	0	0	0	0	11	6	4	9	4	17
31985	Caucasian	Male	62	PhD	Poli Sci	0	0	0	0	12	8	6	9	5	20
31987	Caucasian	Male	18	Freshman	Computer Engineering	0	0	0	0	12	11	6	10	7	23
31988	Caucasian	Female	19	Freshman	Undeclared	0	0	0	0	12	10	6	9	7	22
31992	Other	Female	19	Freshman	Political Science	0	0	0	0	8	10	5	10	3	18
31993	Asian	Female	18	Freshman	None	0	0	0	0	8	6	4	5	5	14
31997	Caucasian	Female	18	Freshman	Undecided	0	0	0	0	12	13	4	14	7	25
32000	Black	Female	57	Masters	Mathematics	0	0	0	0	15	15	7	14	9	30
32001	Caucasian	Male	51	PhD	Physics	0	0	0	0	15	15	6	15	9	30
32955	Caucasian	Male	40	PhD	Computer Science	0	0	0	0	14	16	6	15	9	30
32956	Caucasian	Male	37	PhD	Computer Science	0	0	0	0	12	12	5	14	5	24
32957	Caucasian	Male	52	PhD	Computer Science	0	0	0	0	13	11	6	12	6	24
32958	Caucasian	Male	28	Masters	Computer Engineering	0	0	0	0	15	17	7	15	10	32
32959	Caucasian	Male	35	PhD	Computer Science	0	0	0	0	16	13	7	11	11	29
32962	No Data	Male	46	PhD	Computer Science	0	0	0	0	13	17	7	15	8	30
32964	Caucasian	Male	47	PhD	Math	0	0	0	0	13	13	7	12	7	26
32967	Caucasian	Male	28	Masters	Computer Science	0	0	0	0	14	16	5	14	11	30
32968	Caucasian	Male	63	PhD	Industrial Engineering	0	0	0	0	16	12	6	13	9	28
32969	Caucasian	Male	30	Masters	Computer Science	0	0	0	0	12	11	6	11	6	23
32970	Caucasian	Male	28	Masters	Computer Science	0	0	0	0	15	13	7	14	7	28

Continued on next page

ID	Race	Gender	Age	Ed level	Major	V SAT	M SAT	CUM HRS	GPR	Ind	Ded	Ana	Inf	Eval	TOT
32973	Caucasian	Male	50	PhD	Computer Science	0	0	0	0	14	14	6	15	7	28
32976	Caucasian	Male	42	Masters	Engineering Physics	0	0	0	0	17	13	7	12	11	30
32977	Black	Male	32	Masters	Industrial Engineering	0	0	0	0	15	15	7	14	9	30
32978	Caucasian	Female	36	PhD	Electrical Engineering	0	0	0	0	12	15	5	12	10	27
32979	No Data	Male	40	Masters	Computer Engineering	0	0	0	0	16	14	7	14	9	30
32980	Caucasian	Male	34	Masters	Mathematics	0	0	0	0	15	12	6	12	9	27
32981	Caucasian	Male	38	Masters	Electrical Engineering	0	0	0	0	16	15	7	14	10	31
32982	Caucasian	Male	30	Masters	Electrical Engineering	0	0	0	0	16	14	6	14	10	30
32983	Caucasian	Female	33	Masters	Applied Math	0	0	0	0	12	11	6	12	5	23
32984	Caucasian	Male	49	PhD	Mathematics	0	0	0	0	15	11	6	12	8	26
32985	Caucasian	Male	36	PhD	Computer Engineering	0	0	0	0	13	12	6	14	5	25
32987	Caucasian	Female	34	PhD	Math/physics	0	0	0	0	14	13	7	13	7	27
32988	Caucasian	Male	44	PhD	Electrical Engineering	0	0	0	0	15	14	7	14	8	29
33132	Caucasian	Male	18	Freshman	Operations Research	0	0	0	0	12	12	6	14	4	24
33133	Caucasian	Male	18	Freshman	Behavioral Science	0	0	0	0	11	10	6	11	4	21
33135	Caucasian	Female	18	Freshman	Behavioral Science	0	0	0	0	10	7	3	8	6	17
33136	Caucasian	Male	18	Freshman	Undeclared	0	0	0	0	6	7	2	7	4	13
33137	Other	Male	20	Freshman	Astronautical Engineering	0	0	0	0	10	9	4	10	5	19
33138	Caucasian	Male	18	Freshman	None	0	0	0	0	14	12	6	11	9	26
33139	Other	Male	17	Freshman	Undeclared	0	0	0	0	9	11	5	10	5	20
33140	Caucasian	Male	18	Freshman	Astro Engineering	0	0	0	0	13	14	7	13	7	27
33147	Asian	Female	19	Freshman	FAS/GIS	0	0	0	0	9	5	4	6	4	14
33148	Caucasian	Male	19	Freshman	Aero or Astro	0	0	0	0	13	14	6	14	7	27
33149	Asian	Male	19	Freshman	Undeclared	0	0	0	0	8	9	6	6	5	17
33151	Caucasian	Male	19	Freshman	Biology	0	0	0	0	11	9	6	9	5	20
33153	Caucasian	Male	18	Freshman	Foreign Area Studies	0	0	0	0	9	6	4	5	6	15
33154	Caucasian	Male	19	Freshman	Behavioral Sciences	0	0	0	0	4	2	1	3	2	6
33155	Caucasian	Male	18	Freshman	Undecided	0	0	0	0	14	14	5	13	10	28
33156	Other	Male	20	Freshman	Civil Engineering	0	0	0	0	12	3	5	5	5	15
33158	Caucasian	Male	18	Freshman	Undeclared	0	0	0	0	12	9	4	11	6	21
33159	Caucasian	Male	19	Freshman	Undecided	0	0	0	0	12	11	4	13	6	23
33160	Caucasian	Male	18	Freshman	Physics	0	0	0	0	11	12	5	11	7	23
33161	Caucasian	Female	19	Freshman	Materials Science	0	0	0	0	10	14	6	14	4	24
33162	Caucasian	Male	19	Freshman	Computer Science	0	0	0	0	8	11	4	11	4	19
33163	Caucasian	Male	19	Freshman	Chemistry	0	0	0	0	14	9	5	11	7	23
33164	Caucasian	Male	18	Freshman	Biology	0	0	0	0	12	11	5	11	7	23
33165	Caucasian	Male	19	Freshman	Civil Engineering	0	0	0	0	11	12	7	13	3	23
33166	Caucasian	Male	18	Freshman	systems engineering	0	0	0	0	14	10	7	11	6	24
33167	Caucasian	Female	18	Freshman	Undecided	0	0	0	0	10	8	3	8	7	18
33168	Black	Male	19	Freshman	Foreign Area Studies	0	0	0	0	10	4	3	7	4	14

Continued on next page

ID	Race	Gender	Age	Ed level	Major	V SAT	M SAT	CUM HRS	GPR	Ind	Ded	Ana	Inf	Eval	TOT
33169	Caucasian	Male	18	Freshman	Undeclared	0	0	0	0	12	9	5	10	6	21
33170	Caucasian	Male	21	Freshman	Behavioral Science	0	0	0	0	15	15	6	13	11	30
33171	Caucasian	Male	22	Freshman	Undeclared	0	0	0	0	12	4	3	8	5	16
33172	Caucasian	Male	18	Freshman	None	0	0	0	0	12	10	5	10	7	22
33173	Caucasian	Male	18	Freshman	Chemistry	0	0	0	0	10	11	5	12	4	21
33174	No Data	Female	19	Freshman	Physics	0	0	0	0	8	10	5	9	4	18
33510	Caucasian	Male	20	Sophomore	Electrical Engineering	520	640	42	2	13	15	7	15	6	28
34509	Caucasian	Female	43	Masters	Computer Science	0	0	0	0	14	15	5	13	11	29
34510	Caucasian	Male	37	Masters	Computer Science	0	0	0	0	14	10	5	10	9	24
34512	Caucasian	Male	40	Masters	CIS	0	0	0	0	12	16	6	14	8	28
34513	Caucasian	Male	42	Masters	Construction Management	0	0	0	0	11	7	5	9	4	18
34519	No Data	Male	40	Masters	ENGINEERING	0	0	0	0	11	13	8	12	9	26
34520	Caucasian	Male	27	Masters	Computer Science	0	0	0	0	15	13	5	15	8	28
34521	Caucasian	Male	35	Masters	Computer Science	0	0	0	0	14	11	5	13	7	25
34524	No Data	Male	28	Bachelors	BBA Marketing	0	0	0	0	13	13	7	10	9	26
34525	Black	Female	41	Masters	Information Technology	0	0	0	0	5	7	4	7	1	12
34527	Caucasian	Male	45	Masters	CIS	0	0	0	0	13	11	4	10	10	24
34530	Caucasian	Male	45	Masters	Computer Science	0	0	0	0	15	14	6	13	10	29
35391	Caucasian	Male	22	Senior	Computer Science	610	640	120	3.76	13	8	5	10	6	21
35392	Caucasian	Male	23	Senior	Computer Science	660	710	125	2.99	13	12	5	11	9	25
35396	Caucasian	Male	22	Senior	Computer Science	590	680	129	2.26	15	12	6	13	8	27
35398	Caucasian	Male	22	Senior	Computer Science	610	700	147	2.95	14	13	7	14	6	27
35402	Caucasian	Male	26	Senior	Computer Science	0	0	0	0	15	14	5	14	10	29
35404	Caucasian	Male	20	Senior	Computer Science	640	700	94	3.21	13	15	7	13	8	28
35405	Black	Male	45	Masters	Computer science	0	0	0	0	10	9	6	10	3	19
35409	Caucasian	Male	21	Senior	Computer Science	620	740	120	3.8	14	12	6	11	9	26
35410	Caucasian	Female	22	PhD	Computer Science	0	0	0	0	14	10	6	10	8	24
35412	Asian	Male	25	Senior	Computer Science	430	440	123	2.04	9	5	1	6	7	14
35894	Asian	Male	27	Bachelors	Systems Engineering	0	0	0	0	7	12	4	12	3	19
35898	Asian	Male	41	Bachelors	Physical Geography	0	0	0	0	4	6	2	8	0	10
35901	Caucasian	Male	23	Masters	Marketing Managment	0	0	0	0	7	6	5	5	3	13
35902	Hispanic	Male	29	Masters	Criminal Justice	0	0	0	0	4	3	1	4	2	7
35904	Asian	Male	26	Masters	Engineering Management	0	0	0	0	7	6	3	6	4	13
35905	No Data	Male	30	HSGrad	Law enforcement	0	0	0	0	9	4	4	6	3	13
35906	Caucasian	Male	36	Bachelors	Theatre	0	0	0	0	13	6	4	8	7	19
35914	Black	Male	36	Masters	BUS MGMT	0	0	0	0	10	5	5	5	5	15
35915	Caucasian	Male	35	Masters	Economics	0	0	0	0	14	8	4	10	8	22
35918	Black	Female	33	Bachelors	CIS	0	0	0	0	6	5	4	3	4	11
35919	Caucasian	Male	35	Senior	Criminal Justice	0	0	0	0	10	6	4	8	4	16
35921	Black	Male	39	Bachelors	Political Science	0	0	0	0	9	2	4	2	5	11

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ID	Race	Gender	Age	Ed level	Major	V SAT	M SAT	CUM HRS	GPR	Ind	Ded	Ana	Inf	Eval	TOT
35923	Black	Male	38	Senior	Criminal Justice	0	0	0	0	11	6	5	6	6	17
35924	No Data	Male	30	Senior	General Studies	0	0	0	0	9	4	3	5	5	13
35925	Caucasian	Male	32	Bachelors	sociology	0	0	0	0	8	9	6	7	4	17
35926	Black	Male	45	Masters	Public Administration	0	0	0	0	7	5	4	5	3	12
35927	Black	Male	32	Masters	molecular biology	0	0	0	0	3	4	2	3	2	7
35956	Caucasian	Male	22	Senior	CIS	490	600	104	2.49	15	7	4	10	8	22
35957	Caucasian	Female	18	Freshman	Computer Engineering	0	0	32	3.56	12	11	5	10	8	23
35958	Caucasian	Male	19	Freshman	Engineering	710	770	49	4	14	13	6	11	10	27
35960	Caucasian	Male	19	Freshman	Business Management	500	550	10	2.08	10	6	3	9	4	16
35961	No Data	Female	19	Freshman	Computer Science	510	540	22	3	7	6	5	5	3	13
35962	Caucasian	Male	19	Sophomore	Mechanical Engineering	480	620	33	2.13	10	9	5	8	6	19
35966	Caucasian	Female	18	Freshman	Political Science	640	640	14	2.5	16	10	7	10	9	26
35967	Caucasian	Male	21	Senior	CIS	700	740	140	3.68	13	14	7	13	7	27
35970	Caucasian	Male	22	Senior	CIS	670	570	118	2.41	12	12	4	11	9	24
35972	Caucasian	Female	43	Sophomore	CIS	0	0	68	3.45	11	14	6	13	6	25
35973	Caucasian	Male	22	Senior	Computer Science	750	610	110	3.07	15	15	7	15	8	30
35974	Caucasian	Male	21	Senior	Computer Science	800	730	125	3.01	16	16	6	15	11	32
35976	Caucasian	Male	20	Junior	Computer Science	620	690	60	3.13	13	15	6	14	8	28
35979	Caucasian	Male	36	Sophomore	Computer Science	0	0	0	0	14	15	6	14	9	29
35982	Caucasian	Male	18	Freshman	Pre-Business	510	640	9	3.11	10	10	2	12	6	20
35983	Black	Female	17	Junior	Computer Science	0	0	0	0	10	12	5	11	6	22
35984	Caucasian	Male	20	Sophomore	Computer Science	700	800	59	3.74	16	14	7	14	9	30
35988	Black	Female	21	Senior	CIS	0	0	0	0	6	7	4	8	1	13
36334	Black	Male	32	Bachelors	Finance	0	0	0	0	8	5	4	4	5	13
36335	No Data	Male	32	Bachelors	History	0	0	0	0	4	6	3	5	2	10
36336	Caucasian	Male	50	Bachelors	Geomatics	0	0	0	0	5	5	2	5	3	10
36337	Caucasian	Male	28	Bachelors	Computer Science	0	0	0	0	13	12	7	10	8	25
36339	Asian	Male	25	Bachelors	Engineering	0	0	0	0	7	5	3	6	3	12
36340	Caucasian	Male	41	Bachelors	Organizational Management	0	0	0	0	13	6	5	7	7	19
36344	Black	Male	29	Bachelors	kinesiology	0	0	0	0	4	5	1	6	2	9
36346	Hispanic	Female	33	Bachelors	Behavioral Science	0	0	0	0	6	5	2	5	4	11
36348	Hispanic	Male	28	Bachelors	Communications	0	0	0	0	13	8	5	11	5	21
36356	Caucasian	Male	32	Masters	Engineering Management	0	0	0	0	15	13	6	14	8	28
36358	Caucasian	Male	29	Bachelors	CIS	0	0	0	0	17	11	6	13	9	28
36360	Hispanic	Male	29	Bachelors	Athletic Training	0	0	0	0	8	5	2	7	4	13
36364	Caucasian	Male	26	Bachelors	Computer Science	0	0	0	0	14	10	5	9	10	24
36594	Hispanic	Male	42	Bachelors	CIS	0	0	0	0	12	8	7	8	5	20
36611	Caucasian	Male	37	Masters	Management	0	0	0	0	11	10	5	9	7	21
36614	Caucasian	Female	45	Bachelors	CSC	0	0	0	0	13	13	6	15	5	26
36615	Caucasian	Male	41	Bachelors	Electrical Engineering	0	0	0	0	11	17	5	16	7	28

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ID	Race	Gender	Age	Ed level	Major	V SAT	M SAT	CUM HRS	GPR	Ind	Ded	Ana	Inf	Eval	TOT
36686	Caucasian	Female	33	PhD	Systems Engineering	0	0	0	0	15	16	7	15	9	31
36795	Caucasian	Female	51	Masters	Chemistry	0	0	0	0	14	12	7	11	8	26
36797	Caucasian	Female	21	Senior	Mathematical Sciences	630	800	172	3.88	15	13	7	12	9	28
36799	Caucasian	Male	38	Masters	Computer Science	0	0	0	0	14	12	6	12	8	26
37414	Caucasian	Male	67	PhD	Physics	0	0	0	0	16	10	7	10	9	26
37680	Caucasian	Male	55	Masters	Physics	0	0	0	0	14	13	7	13	7	27
37802	Caucasian	Male	28	Bachelors	Computer Science	0	0	0	0	15	12	6	13	8	27
37803	Caucasian	Male	28	Masters	Computer Science	0	0	0	0	14	14	6	15	7	28
37804	Caucasian	Male	24	Bachelors	CIS	0	0	0	0	14	15	6	14	9	29
37805	Caucasian	Male	24	Masters	Computer Science	0	0	0	0	12	14	6	11	9	26
37806	Other	Male	24	Bachelors	Computer Engineering	0	0	0	0	11	12	7	12	4	23
37808	Hispanic	Male	32	Masters	Finance	0	0	0	0	13	12	5	11	9	25
37810	Asian	Male	24	Bachelors	Computer Engineering	0	0	0	0	16	15	7	15	9	31
37812	Caucasian	Male	29	Bachelors	Computer Science	0	0	0	0	11	11	5	9	8	22
37815	Black	Male	31	Masters	Statistics	0	0	0	0	10	10	5	10	5	20
37817	Asian	Male	24	Masters	Computer Science	0	0	0	0	11	10	6	11	4	21
37818	Other	Male	25	Masters	Computer Science	0	0	0	0	13	8	3	12	6	21
38005	Caucasian	Female	22	Senior	Mathematical Sciences	590	740	122	3.46	16	12	6	12	10	28
39245	Caucasian	Male	47	Masters	english	0	0	0	0	12	13	6	13	6	25
40324	Caucasian	Male	62	PhD	Engineering Physics	0	0	0	0	15	13	6	12	10	28
40713	Caucasian	Male	39	Bachelors	Computer Science	0	0	0	0	12	17	5	16	8	29

J CCTST 2000 Interpretation

INSIGHT ASSESSMENT

This document provides score interpretation information for the CCTST. Your Capscore™ results will include test-takers scores and corresponding percentile scores that are based on the data provided in this document.

The aspects of critical thinking measured by the CCTST are defined below. Comparison norms follow.

CRITICAL THINKING DEFINED

The CCTST is based on the APA Delphi consensus conceptualization of Critical Thinking[1] described in the following section of this manual. This conceptualization of CT is an historically important benchmark. It is an expression of expert consensus articulated without the constraints of accreditation or legislation, and based on the participation of 46 leading theorists, teachers, and CT assessment specialists from several disciplines. This conceptualization of CT was reaffirmed in the 1993/1994 national survey and replication study conducted by the National Center for Higher Education Teaching, Learning and Assessment at The Pennsylvania State University.[2]

These experts characterize critical thinking as the process of purposeful, self-regulatory judgment.[3] Critical thinking, so defined, is the cognitive engine which drives problem-solving and decision-making. This robust concept of CT supplied the conceptual architecture used to address the US Department of Education's Education Goals: 2000 mandate.[4] In that context it became the framework of a national replication study of the definition and valuation of CT which yielded a broad consensus among hundreds of educators, employers, and policy makers.[5]

The skills of **Analysis, Evaluation, and Inference** are specifically targeted by the CCTST. These are described below.

Analysis as used on the CCTST has a dual meaning. First it means "to comprehend and express the meaning or significance of a wide variety of experiences, situations, data, events, judgments, conventions, beliefs, rules, procedures or criteria," which includes the sub-skills of categorization, decoding significance, and clarifying meaning. Analysis on the CCTST also means "to identify the intended and actual inferential relationships among statements, questions, concepts, descriptions or other forms of representation intended to express beliefs, judgments, experiences, reasons, information or opinions," which includes the sub-skills of examining ideas, detecting arguments, and analyzing arguments into their component elements.

Evaluation as used on the CCTST has a dual meaning. First it means "to assess the credibility of statements or other representations which are accounts or descriptions of a person's perception, experience, situation, judgment, belief or opinion; and to assess the logical strength of the actual or intended inferential relationships among statements, descriptions, questions, or other forms of representations," which includes the sub-skills of assessing claims and assessing arguments. Evaluation on the CCTST also means "to state the results of one's reasoning; to justify that reasoning in terms of the evidential, conceptual, methodological, criteriological and contextual considerations upon which one's results were based; and to present one's reasoning in the form of cogent arguments" which includes the sub-skills of stating results, justifying procedures, and presenting arguments.

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[1] The American Philosophical Association. (1990) Critical Thinking: A Statement of Expert Consensus for Purposes of Educational Assessment and Instruction, ("The Delphi Report"). ERIC Doc. No. ED 315-423, pp. 80. An executive summary including tables and recommendations (pp. 22) also available through The California Academic Press.

[2] Jones EA, Hoffman S, Moore LM, Ratcliff G, Tibbetts S, Click BL. *National Assessment of College Student Learning: Identifying the College Graduate' Essential Skills in Writing, Speech and Listening, and Critical Thinking*. Washington DC: National Center for Eduational Statistics. US Department of Education, Office of Educational Research and Improvement; 1995. OERI publication NCES 93-001.

[3] The American Philosophical Association. (1990) Critical Thinking: A Statement of Expert Consensus for Purposes of Educational Assessment and Instruction, ("The Delphi Report"). ERIC Doc. No. ED 315-423, pp. 80. [Executive summary including tables and recommendations (pp. 22) also available through The California Academic Press, 217 La Cruz Ave., Millbrae CA, 94030.]

[4] National Center for Educational Statistics, Commissioned papers for November 1991 National Conference. Office of Educational Research and Improvement, US Department of Education, ERIC Document Numbers: 340753 through 340768, 1992.

[5] Jones E., Corrallo S., Facione, P., & Ratcliff G., Developing consensus for critical thinking. Paper presented at the annual meetings of the American Association of Higher Education, Washington DC, June 1994. (This work was also presented at the Sixth International Conference on Thinking, MIT, Boston, MA, July 1994 and at The Fourteenth International Conference on Critical Thinking, Sonoma, CA, August 1994.) This survey research was based on the "Critical Thinking Goals Inventory," developed by Beth Jones and Gary Ratcliff (US Department of Education, Office of Educational Research and Improvement Grant R11760037, CFDA No: 84.117G). For additional information contact the National Center for Higher Education Teaching, Learning & Assessment, The Pennsylvania State University, 403 South Allen Street, Suite 104, University Park, PA 16801.

Inference as used on the CCTST means "to identify and secure elements needed to draw reasonable conclusions; to form conjectures and hypotheses, to consider relevant information and to educe the consequences flowing from data, statements, principles, evidence, judgments, beliefs, opinions, concepts, descriptions, questions, or other forms of representation," which includes the sub-skills of querying evidence, conjecturing alternatives, and drawing conclusions.

The following traditional scores are also provided

Deductive Reasoning as used in the CCTST sub-scale means the assumed truth of the premises purportedly necessitates the truth of conclusion.
Inductive Reasoning as used in the CCTST sub-scale means an argument's conclusion is purportedly warranted, but not necessitated, by the assumed truth of its premises. Scientific confirmation and experimental disconfirmation are examples of inductive reasoning.

The Inductive and deductive scales overlap with the analysis, inference, and evaluation scales. analysis, inference, and evaluation add up to the CCTST total score. Induction and deduction also add up to the CCTST total score.

Norm Sample

This is an aggregated sample of 4-year college students.

Descriptive Statistics:

Variable	N	Mean	Median	TrMean	StDev	SE Mean
Total	2677	16.801	16.000	16.729	5.062	0.098
Analysis	2677	4.4378	5.0000	4.4645	1.4080	0.0272
Inference	2677	7.8450	8.0000	7.8144	2.6848	0.0519
Evaluation	2677	4.5185	4.0000	4.4612	2.1431	0.0414
induction	2677	9.5293	10.0000	9.5509	2.8217	0.0545
deduction	2677	7.2719	7.0000	7.1876	2.8897	0.0559

Variable	Minimum	Maximum	Q1	Q3
Total	1.0000	32.0000	13.0000	20.0000
Analysis	0.0000	7.0000	4.0000	5.0000
Inference	0.0000	15.0000	6.0000	10.0000
Evaluation	0.0000	11.0000	3.0000	6.0000
induction	0.0000	17.0000	8.0000	11.0000
deduction	0.0000	16.0000	5.0000	9.0000

Total	Totpct
0	0
1	0.000187
2	0.00056
3	0.001121
4	0.002428
5	0.004109
6	0.008218
7	0.018491
8	0.033433
9	0.052858
10	0.080874
11	0.120844
12	0.175196
13	0.237393
14	0.305379
15	0.382144
16	0.461898
17	0.541091
18	0.613934
19	0.676317
20	0.737206
21	0.793052
22	0.839746
23	0.879716
24	0.910534
25	0.934442
26	0.954053
27	0.969742
28	0.980388
29	0.98898
30	0.995704
31	0.998879
32	0.999813
33	1
34	1

Analysis	anapct
0	0.002241
1	0.015129
2	0.058461
3	0.166604
4	0.365708
5	0.628129
6	0.854688
7	0.971236

Inference	infpct
0	0.000187
1	0.002615
2	0.010086
3	0.029697
4	0.071722
5	0.146806
6	0.257191
7	0.397833
8	0.544453
9	0.675196
10	0.781285
11	0.864774
12	0.92585
13	0.963205
14	0.986739
15	0.997385
16	1

Evaluation	evalpct
0	0.005977
1	0.036048
2	0.119724
3	0.263915
4	0.439484
5	0.609451
6	0.754763
7	0.864027
8	0.931453
9	0.969369
10	0.989354
11	0.997945

Induction	indpct
0	0.00056
1	0.001307
2	0.002988
3	0.01102
4	0.029511
5	0.061076
6	0.110758
7	0.190325
8	0.299589
9	0.422488
10	0.555286
11	0.690325
12	0.801457
13	0.883638
14	0.941726
15	0.975906
16	0.993463
17	0.999253

Deduction	dedpct
0	0.000747
1	0.003736
2	0.016063
3	0.055286
4	0.127195
5	0.228614
6	0.361972
7	0.502055
8	0.628315
9	0.73814
10	0.819201
11	0.879903
12	0.928838
13	0.962832
14	0.983377
15	0.993463
16	0.998319
17	1

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