LEARNING STYLE AS A CORRELATE OF SUCCESS IN INTRODUCTORY COMPUTER SCIENCE EDUCATION

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

James Donald Allert

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE
DEGREE OF
DOCTOR OF EDUCATION

Advisors:

William Ammentorp

Thomas Peacock

Frank Guldbrandsen

Timothy Holst

July, 2005

UNIVERSITY OF MINNESOTA

This is to certify that I have examined this copy of a doctoral dissertation by

James Donald Allert

and have found that it is complete and satisfactory in all respects, and that
any and all revisions required by the final
examining committee have been made

W. Ammentorp

Name of Faculty Adviser(s)

Wm Amp

Signature of Faculty Adviser(s)

6-22-2005

Date

GRADUATE SCHOOL

ACKNOWLEDGMENTS

I am especially grateful to my wife, Debbie, for years of encouragement, love and support. This was a long time coming and would not have happened without her by my side. Thanks Deb! I would also like to acknowledge my parents and thank them for the years of love and patience. This has very much been a family thing. This dissertation presented wonderful opportunities to seek out the wisdom of my work family as well: co-workers, students, fellow-students in the Leadership Academy, teachers, mentors and family. The dissertation provided an opportunity to reflect upon the contributions of all these people and to appreciate their special talents.

I am grateful to all who participated in one way or another, especially the many students in introductory computer science courses who consented to be involved in the study. Thanks to several faculty members of the UMD Department of Computer Science who contributed in a variety of ways, including Donald Crouch, who encouraged and supported my research as Department Head and Steven Holtz who allowed me to carry out this study in his introductory computer science class as well as my own.

There were a host of key mentors to whom I am hugely indebted: Bill Ammentorp, my advisor, and Tom Peacock, co-advisor, for their years of labor and leadership modeling in the EdD vineyard. Frank Guldbrandsen and Tim Holst, committee members, for their guidance, challenging questions and, greatly appreciated, scheduling flexibility. During the course of the research I was continually thankful for the early research methods training in received from William Fleischman and Bob Franz of the UMD Sociology Department and various faculty members of the UMD Department of Mathematics and Statistics. I also look back on the mentorship, for almost 15 years, of Regents Professor Rip Rapp who instilled a love of scientific inquiry.

Thank you all.

ABSTRACT

James Donald Allert

LEARNING STYLE AS CORRELATE OF SUCCESS IN INTRODUCTORY COMPUTER SCIENCE EDUCATION

The Soloman-Felder Inventory of Learning Styles (ILS) is a frequently used instrument for the assessment of learning styles in science and engineering. However, introductory computer science education has rarely been a focus of learning styles research. This study used the ILS, in a test-retest format, in introductory computer science courses at the University of Minnesota Duluth (UMD) as a tool to aid in the understanding of student achievement and retention. Over 300 students in a variety of classes participated in the study during fall semester, 2004. There were important findings in three areas: instrument reliability, learning style characterization, and the relationship of learning style to outcome. Instrument reliability was acceptable along most dimensions of the scale but weak along the sequential-global scale. Specific sources of concern were identified which could lead to improvement of the instrument. Profiles of the learning styles of students in each class were constructed. The visual-verbal scale was skewed to the right in each instance. Other distributions were fairly normally distributed. A significant association with gender was identified (females being less visually oriented than males). This is important because computer science has historically been characterized by low female enrollment. Relationships with outcome identified the active-reflective scale as significantly related in performance in computer programming classes. Active learners were more likely to do poorly. This is important because it may be linked to retention issues. A predictive model of student outcome success identified the active-reflective scale and ACT Composite scores as the key indicators. The study has implications for the ways in which computer science students are selected for enrollment, instructed and assessed and may be linked to larger issues of retention and gender.

TABLE OF CONTENTS

LIST OF TABLES

Tables

FIGURES

Figure

ABBREVIATIONS

AACE. Association for the Advancement of Computing in Education. http://www.aace.org

ACM. Association for Computing Machinery. http://www.acm.org

ACT-REF. Active-reflective learning style continuum (Felder)

ACSC. Australasian Computer Science Conference.

ACT. American College Testing. http://www.act.org

ANOVA. Analysis of variance

ASEE. American Society for Engineering Education. http://www.asee.org

ATPP. Aptitude Test for Programmer Personnel

ATSE. Attitude Toward Software Engineering

CCSC. Consortiuum for Computing in Small Colleges. http://www.ccsc.org

CITC4. Fourth Conference on Information Technology Curricula. Sponsored by SIGITE.

CLT. Center for Learning Technology, Indiana State University. http://www.indstate.edu/ctl/

CRLT. Center for Research on Learning Technology, University of Michigan. http://www.crlt.umich.edu/

CS. Computer Science

CS1. A generic term for the first introductory computer science course for undergraduate computer science majors.

CS-1011. Introduction to Computers and Software. The introductory computer applications course for undergraduate, non-computer science majors at the University of Minnesota Duluth.

CS-1121. Introduction to Programming in Visual Basic.NET. An introductory computer programming course featuring Microsoft® Visual Basic.NET. For undergraduate, non-computer science majors at the University of Minnesota Duluth.

CS-1511. Computer Science I. The introductory computer science course for undergraduate majors at the University of Minnesota Duluth. Also see CS1.

CSEE&T. Conference on Software Engineering Education and Training sponsored by IEEE.

CSRDE. The Consortium for Student Retention Data Exchange. http://www.occe.ou.edu/csrde

DFW. D, Fail, Withdraw. See 'Rate of Withdrawal, F, D' in glossary.

ED-MEDIA. Annual World Conference on Educational Multimedia, Hypermedia and Telcommunications sponsored by AACE. http://www.aace.org/conf/edmedia

GPA. Grade Point Average

HERI. Higher Education Research Institute. http://www.gseis.ucla.edu/heri/darcu_pr.html

IBM. International Business Machines, Inc.

IEEE. Institute of Electrical and Electronics Engineers. http://www.ieee.org

IR. Interquartile Range

IRB. Institutional Review Board, University of Minnesota. http://www.research.umn.edu/irb/

ILS. Index of Learning Styles (Soloman and Felder)

JCSC. Journal of Computing in Small Colleges

LSBE. UMD Labovitz School of Business and Economics

LSI. Learning Style Inventory (Kolb)

MBTI. Myers Briggs Type Indicator

MIS. Management Information Systems

MNSCU. Minnesota State Colleges and Universities system

NCES. National Center for Educational Statistics. http://www.nces.ed.gov

NSF. National Science Foundation. http://www.nsf.gov

NSSE. National Survey of Student Engagement. http://www.indiana.edu/~nsse/

OECD-IMHE. Organization for Economic Cooperation and Development – Institutional Management in Higher Education. http://www.oecd.org

PCA. Principle Component Analysis.

PEO. Postsecondary Education Opportunity. http://www.postsecondary.org/home/default.asp

SAT. Scholastic Aptitude Test.

SEN-INT. Sensing-intuitive learning style continuum (Felder)

SEQ-GLO. Sequential-global learning style continuum (Felder)

SIGCHI. ACM Special Interest Group in Computers and Human Interaction

SIGCPR. ACM Special Interest Group in Computer Personnel Research

SIGCSE. ACM Special Interest Group in Computer Science Education

SIGITE. ACM Special Interest Group in Information Technology Education

SPSS. Statistical Package for the Social Sciences. http://www.spss.com

UML. Unified Modeling Language

UMD. University of Minnesota Duluth. http://www.d.umn.edu

VAK. Visual, Auditory, Kinetic learning style

VIS-VRB. Visual-verbal learning style continuum (Felder)

WFD. Withdraw, fail, D. See 'Rate of Withdrawal, F, D' in glossary.

Chapter 1

INTRODUCTION

1.1 Background

It is a common in college and university science and engineering programs for students to drop out of programs or change majors in their freshmen or sophomore years (Seymour and Hewitt, 1997). For some, leaving science or engineering program for another discipline is the normal result of exposure to new fields of interest. However, it is often the case that science and engineering students feel driven to this decision by poor performance. Doran and Langan (1995) note that introductory computer science courses are often associated with high dropout rates.

Anderson-Rowland (1997) reminds us that it is "easier to retain a student than recruit one" and most colleges and universities are earnestly engaged in attempting to address student retention. Retention is especially important in science and engineering education. Retention rates in these disciplines often fall well below those of other academic fields. A common reaction among science and engineering faculty, and some administrators is that lower retention rates are to be expected given the rigor of these disciplines. Some view them as evidence of high standards. However, the academic profile of students who leave is not significantly different from that of students who stay behind (Tobias, 1990). Based on high-school rank, previous GPA and standardized test scores, students who leave seem to be as well equipped to handle the courses as those who remain. So why do otherwise intelligent and often talented students withdraw from science and engineering programs with such high frequency?

This question appears in the literature as the concern for "second tier" students (Tobias, 1990). The second tier consists of those who are capable of achieving but withdraw from a program for other reasons. An explanation for this phenomenon is that these students are unnecessarily alienated by the learning process. It may be that the reason for high withdrawal rates in traditional science and engineering programs is because they are too traditional. Faculty members often expect that students will learn as they did, and teach the way they were taught. Unfortunately, this formula may be a recipe for an inadequate learning environment. This is especially true for students who are not like the professor in background or interest.

What is at stake here is the extent to which science and engineering instruction is meeting the needs of diverse learners. Students who are female, students with different ethnic and cultural backgrounds, and many others too frequently find science and engineering education geared for someone else (Takahira, Goodings & Byrnes, 1998; Jawitz & Scott, 1997; Reyes & Anderson-Rowland, et al. 1999; Hargrove & Burge, 2002). The inability of the process to engage them can easily lead to alienation, frustration and the search for another program. The failure of science and engineering education to recognize and adapt teaching methods and materials to serve the needs of diverse learners may account for part of the second tier problem.

Learning style matters because it may determine whether students succeed or fail. Students have diverse learning needs, aptitudes and preferences. A one-style-fits-all instructional approach forces them to adapt to a single instructional paradigm. If they are unwilling, uninterested, or unable to do so then a negative outcome may be the result.

This is especially so in science and engineering classes which are often highly technical at all levels. They introduce a myriad of new concepts and terms. This information is then used as a foundation for learning complex, analytical problem-solving techniques and applying them. More often than not, such projects involve the integration of material from other disciplines (especially mathematics). Failure to make continual connections with course material is critical in these disciplines as cumulative knowledge is required to advance from topic to topic. A key topic presented in a manner that is unfriendly or inaccessible to students poses a threat to their performance in the course from that point on. It is therefore critical that instructional methods recognize and address these issues where they can.

Learning theory concerns have become an integral part of teaching theory and practice in the fields of education and the social sciences. They have not effectively penetrated science and engineering education at the tertiary level however.

What has penetrated the curriculum in science and engineering classrooms is technology. There seems to be an implicit assumption that technology-mediated forms of engagement will make courses more engaging and accessible. Much of this involves the use of Internet resources and interactive multimedia to communicate key concepts.

The University of Minnesota Duluth (UMD) Department of Computer Science recently invested considerable resources in developing such tools for those enrolled in introductory courses. Attention was focused on Computer Science I (CS-1511) since virtually all incoming freshmen in engineering disciplines and many of the sciences are required to take it. The results have not been encouraging however. Despite such tools, and positive student reaction to them, the rate of withdrawal, F or D (DFW rate) has not declined.

This suggests that more needs to be done to determine what the learning needs of students in science and engineering courses are and how to address them. This research investigates the learning style profile of computer science students and attempts to determine how they might best be addressed.

1.2 Theoretical Framework

Three bodies of theory inform the current investigation. First, student retention theory focuses on factors associated with both short and long-term success. An important outcome of retention theory has been an appreciation for the value of learning style diversity and the need to address it in the classroom. Learning style theory is based on the broader context of psychological profiling and personality characterization, much of which is beyond the scope of this work. However, it has become increasingly relevant to educators in all disciplines as they struggle to recognize and address the intellectual needs of students. Numerous studies have been conducted to show that learning style awareness is important and to demonstrate that there are certain measures that are effective in addressing multiple learning styles in the classroom.

1.2.1 Student Retention in Science and Engineering

Tertiary science and engineering programs are commonly characterized by low retention rates (Astin, 1993a). Nationwide, annual science and engineering graduation rates have been trending downward since the late 1980's despite cyclical upturns and downturns in the job market. It is common to attribute this to the maintenance of high academic standards and accompanying workloads which separate out students who do not belong in these fields. However, the academic profile of students who leave these majors is not statistically significantly different from those who stay (Besterfield-Sacre, Atman et al. 1997; Hewitt and Seymour, 1991; and Seymour and Hewitt, 1994).

In addition, student expectations of the college experience are changing faster than instructors and college administrators can keep up. Higher education must be responsive to these expectations and strive to mold them (James, 2001) yet few instructors would consider that to be part of their job description. Most present their material in much the same way that it was presented to them. It is little wonder that there is often a lack of connection between teaching and learning.

Other factors often contributing to the sense of frustration may include poor faculty interaction, lack of peer networking, low self confidence and overall attitudes toward courses. Many of these issues can be effectively addressed in the classroom through teaching and learning methods and materials. Some may require a rethinking of the intellectual climate created by the institution and the instructor. Astin (1985) looks at student involvement as the sum total of the physical and psychological energy a student expends on college-related activity and calls for a renewed emphasis on increasing student commitment through involvement with student organizations. Witt and Handal (1984) described the problem as one of "person-environment fit" and attribute student satisfaction and academic achievement more to successful institutional integration than any other factor.

The concern for second tier students in science and engineering education goes beyond the accommodation of learning preferences. It is now widely recognized that women and minority students are disproportionately affected by conventional teaching (Tobias, 1990). Turkle and Papert (1991) solidified the argument by going to its roots. They suggest that no mere revision of tools and techniques can be expected to reform a system that is the result of male privilege and an elitist academic worldview. They point out that there are many methods of problem solving, yet conventional pedagogic techniques use only a few. Very few teachers critically review the assumptions made behind their assignments. This excludes many learners unnecessarily. When this exclusion happens along gender, ethnic, or other lines it effectively amounts to discrimination regardless of the motivation.

For Turkle and Papert what is needed is a new way of thinking about the educational enterprise. They urge educators to engage in a critical examination of the intellectual climate they create in their classrooms and the impact it has on students. Although their research is specifically addressed to the use of computers as educational mediators the implications of their foundational arguments are profound. Teachers have more than technical obligation to present information well; they also have the moral obligation to present learning opportunities that are as inclusive as possible.

1.2.2 Learning Theory

Students can more easily be challenged to learn if they see things that interest them. If the course presents opportunities for learning that match the expectations and style of presentation and problem-solving the student is familiar with higher retention of second tier students may be possible. What is required is that educators know where the students are coming from and have the necessary tools and training to effectively address a diversity of learning styles in the classroom and coursework.

Learning is a process that modifies behavior through a variety of mechanisms. Most often the process is approached as one in which new skills or insights develop through various forms of memory reinforcement. Individuals may have preferences that affect how they internalize information in the learning process. Learning style refers to these factors and learning style theory focuses on delineating which of them are most important and how they affect the process.

Learning theory is informed by a vast body of research coming from personality theory in the field of psychology. The most direct ancestors whose work is relevant today begin with Carl Jung and personality type characterizations. Jung established that there are meaningful categories of personality with differing worldviews (Jung, 1933b). Interaction that takes personality traits like extroversion or introversion into account can be more meaningful and effective. This is especially true in education where interpersonal communication and directed tasking are essential for learning. Most modern personality and learning style assessment tools are related to the Jungian characterization of personality types.

It would interest computer science students to know that personality typing may be related to employment. Warren (1998) describes how personality profiling has been an important part of life in the computer programming industry for many years. IBM developed and used the Aptitude Test for Programmer Personnel (ATPP) in 1955. It was widely adopted across the industry and was administered to hundreds of thousands of programmers over several decades. Ultimately it succumbed to validity issues and other instruments were developed.

Bloom (1964) expanded our perception of the dimensions of education by classifying various types of learning. Bloom's Taxonomy, as it has come to be called, recognizes the complexity of understanding and sees true education as a process of refined engagement. From this perspective, education, like personality, is multifaceted and requires a multifaceted approach to be done effectively.

Bloom's Taxonomy, in combination with Jung's personality theory laid the foundation for the work of Gardner (1993). Gardner describes two "firm foundations" of human learning theory (Gardner, 2001). The first is the finding that humans have different ways in which they learn (multiple intelligences or "frames of mind"). He decries the fact that formal education so often ignores this. The second finding, based on Bloom's Taxonomy, is that learning entails a hierarchical engagement with knowledge going from a state of "What should we know?" to "What does it mean?", "What can we do with it?", and so on. The overall conclusion is that high-level knowledge of a discipline is difficult to achieve. It requires learners to grow through increasingly deeper levels of understanding. This provides all the more reason for appropriate learning styles considerations.

1.2.3 The Felder Learning Styles Model

Identification of learning styles is an issue with a long history, most of it taking place outside of science and engineering education. There are two dominant learning style assessment tools used in science and engineering education, Kolb's Learning Styles Inventory (LSI) (Kolb, 1984; Kolb 1999) and the Felder-Silverman learning styles model (Felder and Silverman, 1988), currently implemented as the Soloman-Felder Index of Learning Styles (ILS) (Soloman and Felder, 2000). Each classifies learning dispositions based on student opinion surveys.

The Felder-Silverman learning styles model recognizes that there are multiple dimensions of learning. They characterize them as Active-reflective, Sensory-Intuitive, Inductive-Deductive, Visual-verbal and Sequential-global. The dimensions form continua such that everyone can place themselves along a line from one pole to its opposite. This allows for almost infinite variation in the configurations. In subsequent years, Felder decided to drop one of the dimensions (Inductive-Deductive) since it proved redundant. The current model is four-dimensional (Sensory-Intuitive, Visual-verbal, Active-Passive and Sequential-global).

The Soloman-Felder ILS assigns the respondent a location coordinate along each of the four continua. This configuration constitutes a learning style profile. Correspondingly, there are dimensions of teaching style. At points of learning and teaching style incongruity both students and teachers are frustrated because learning is not taking place, even though both sides are trying.

1.3 Statement of the Problem

This study provides foundational exploratory research on the relationships of learning styles to student achievement in introductory computer science courses at the University of Minnesota Duluth (UMD). The Soloman-Felder Index of Learning Styles (ILS) was used to identify student learning dispositions. These were correlated with student demographics and outcomes and used to suggest ways in which these courses may be improved. This may provide a precedent for similar research in computer science, and contribute toward development of a more effective learning and teaching model in the discipline.

1.3.1 Research Questions

The central research question of this study concerns the extent to which learning style is related to outcome in introductory computer science education. The study population for this research was comprised of students enrolled in introductory computer science courses at the University of Minnesota Duluth during fall semester 2004. These course include CS-1011 (Introduction to Computers and Software), CS-1121 (Introduction to Programming in Visual Basic) and CS-1511 (Computer Science I). The primary research questions that are addressed in this study are:

1. Is the Soloman-Felder ILS a reliable learning style assessment tool?
2. What learning style configurations are present?
3. To what extent is learning style associated with course outcome?

1.3.2 Assumptions

This study employs the Soloman-Felder Index of Learning Styles (ILS). It is assumed that this instrument reasonably assesses the learning styles of students. Although this instrument has undergone reliability and construct validity testing in several engineering education contexts no such study has been conducted in a computer science setting. The first part of this analysis addresses instrument reliability and validity.

It is assumed that the Soloman-Felder ILS is equally effective across all learning style categories. This assumption was addressed in the analysis stage by comparing reliability measures across learning style categories.

It should be recognized that use of the Soloman-Felder ILS, or any opinion-survey instrument, necessarily implies the assumption that the results are reasonable surrogates for actual behavior. In other words, expressed student opinions actually match their preferences in real situations.

Learning styles are assumed to be persistent over the course of a single semester. The test-retest method of reliability assessment assumes that the learning style of a student does not alter over the course of a semester. Any variation of results in the second test is assumed to reflect the unreliability of the instrument. To facilitate this, both tests were administered at the same time of day, in the same classroom, by the same administrator, using identical procedures and materials. Tests were administered in the first week and the fourteenth week of the semester.

The analysis phase of this study proceeds under a set of assumptions as well. The assumption of distribution normality is made for each of the variables in the study but was tested for all of them before inclusion in the analysis phase. Similarly the assumption of a representative sample underlies most inferential statistical techniques. The study population consists of all introductory computer science courses at UMD with the intent to describe the nature of such courses now, in the immediate past and immediate future for the purposes of curriculum planning. From this perspective, the courses that were evaluated constitute a sample of all possible courses in this group.

In addition, it was assumed that the Soloman-Felder ILS can be treated as an interval-level scale. Although the Soloman-Felder scale scores are interval-level (they represent the number of questions answered in two groups) the resulting continuum may not accurately represent an actual continuum of learning style preference.

1.3.3 Significance of the Study

Leaders in higher education often need to be able to formulate and direct programs and policies into areas that will enhance teaching and learning while encouraging higher retention. This is a productivity concern at several levels (college, department, instructor, student). Learning style issues have the potential to be key failure points in the teaching and learning process and therefore related to retention issues. This is especially true in science and engineering education and in disciplines like computer science. This study attempts to examine the learning style diversity present in a range of introductory computer science classes. The correlation of learning style to outcome is designed to underscore the importance of learning style in areas where it is clearly related to positive or negative outcomes. This, in turn, serves as a diagnostic tool for instructors, showing them both the strengths and weakness of their approach. Within the broader context of higher education research, such knowledge can be used to seek out or develop better educational methods and materials. This may lay the foundation for an effective increase in the retention rate of science and engineering students.

1.3.4 Limitations

This study focuses on three classes in the Department of Computer Science at the College of Science and Engineering (CSE), University of Minnesota Duluth. Collection of student data is confined to those enrolled in CS-1511 (Computer Science I), CS-1121 (Introduction to Programming in Visual Basic) and CS-1011 (Introduction to Computers and Software) during the fall semester of 2004. It is further restricted in participation to those students 18 or older signing consent authorization forms during the initial survey introduction sessions.

1.4 Purpose of the Study

The purpose of this research is to determine the role learning style plays in introductory computer science courses in determining outcome. The study will also consider the correlation of other key factors (demographics, background preparation and student opinions) and their relative contributions to outcome success and correlations with learning style measures. The primary research question will focus on how learning style may be related to outcome in introductory computer science at UMD. This information should allow instructors to determine which learning styles are being successfully addressed and which are not. In addition, it will seek to identify those factors most likely to lead to success across multiple learning style groups. It is hoped that the results of this study may be applied to reduce the DFW rate in these courses and reach the "second tier" of students, although such assessments require longitudinal data and are beyond the scope of this study.

1.5 Design of the Study

This research focuses on three groups of introductory computer science students. The study population consists of all students, 18 years of age or older, enrolled in CS-1511 (Computer Science I), CS-1121 (Introduction to Programming in Visual Basic) and CS-1011 (Introduction to Computers and Software) at the University of Minnesota Duluth during fall semester of 2004.

Students were asked to participate in this research by filling out two learning-style surveys in the classroom. The first were administered at the start of the semester (during the first week) and the second at the end (during the 14^{th} week). Each survey includes the Soloman-Felder ILS along with a small number of demographic, background and opinion questions. The results are then used to assess the reliability of the survey instrument, learning style profiles of the classes and study population subgroups, and the relationship of learning style to performance.

Chapter 2

LITERATURE REVIEW

This study links two important bodies of theory, student retention and learning styles. At issue is that portion of retention theory that is linked to the academic experience. As students interact with faculty and participate in the learning environments created for them they gain a sense of identity, self-worth, and place in the academic world. The degree to which they are successfully integrated into the academic enterprise is closely linked to retention. Failure to thrive in an academic setting may be due to a number of factors, but teaching and learning styles are critical. Both retention and learning concerns find common ground in the degrees of alienation or integrative satisfaction felt by students as a result of their learning experiences.

2.1 Student Retention in Science and Engineering

Student retention has two dimensions in science and engineering education. The first is the dimension of institutional retention in which the rate of students leaving the university is the key figure. The second sense of the term refers to program retention, or the rate of students leaving a particular program, or program area is monitored. A widely used retention model, developed by Tinto (1993) describes the various factors contributing to the rate of "institutional departure." Figure 1 shows an adaptation of Tinto's model for program retention. Students arrive with a set of expectations, attitudes and aptitudes that they carry with them into their new role as a college student. As they interact with extracurricular, academic and social forces, they evaluate their experiences and seek to adapt to this environment. Ultimately, they reflect upon their success and bring their evaluations forward into the next academic cycle. For some, the conclusions they reach lead them to depart from the interaction cycle. It is common for science and engineering students to switch to non-science and engineering disciplines if they feel unable to complete their program requirements. Rather than drop out of the university they find a new niche in which they have a better chance of success.

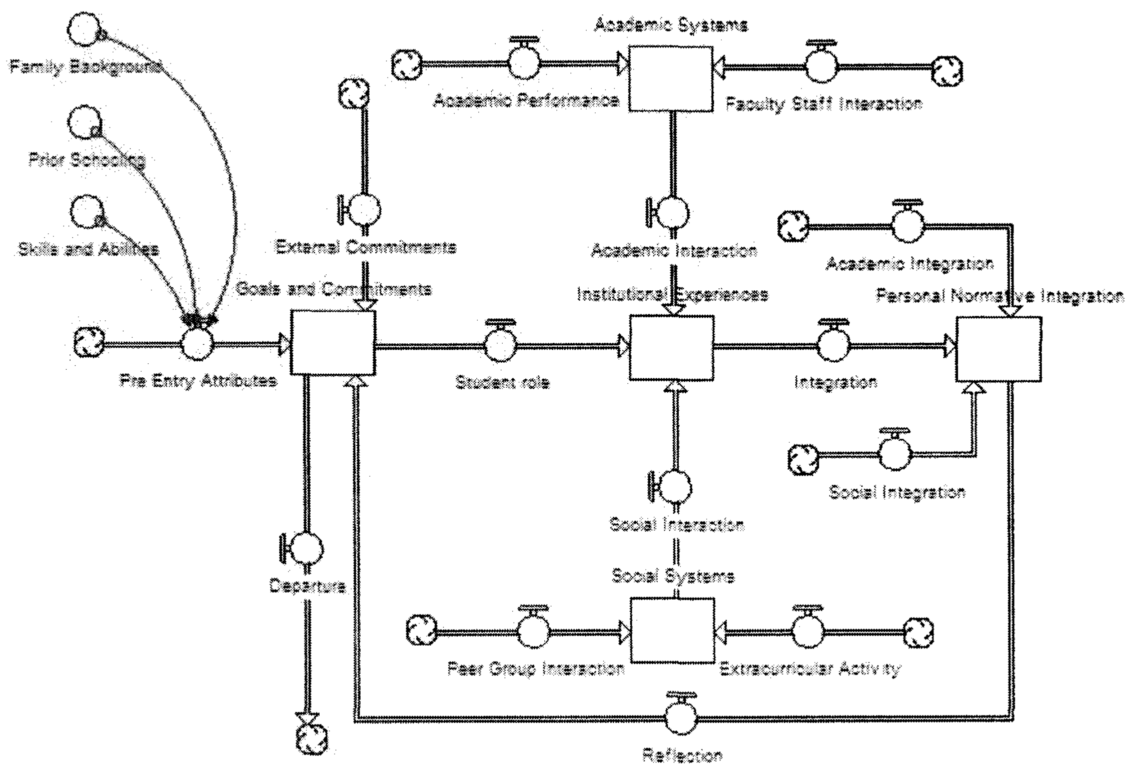

Figure 1. Institutional or program departure model (after Tinto, 1993)

Tobias (1990) was one of the first to call attention to the importance of reaching high aptitude science and engineering students before they make a program departure decision. Those who leave in this manner she called "second tier" students. The second tier consists of students whose college preparatory experience and grades indicate they should be able to perform well in pursuit of an engineering or science career but who under-perform and often drop out during the first two years of college.

This is illustrated well by an ethnographic study of 335 students conducted by Seymour and Hewitt (1997) over the course of three years at seven four-year colleges and universities. All of the respondents had SAT scores of 650 or better on the mathematics section. Presumably all of them should have had the background to pursue and finish a degree in science, math, engineering or technology. Yet, over half of them switched out of these majors into unrelated fields. Across all engineering fields, 40% chose to leave. In physics and biology the rate was 50%. In mathematics it climbed steeper still to 60%. The results pointed to a series of exploratory factors including the loss of interest, newfound interests elsewhere, poor teaching and course workloads. An earlier study by Seymour (1995) found that the major student complaint was the quality of instruction. She also pointed out that women and minority students were disproportionately affected by the trend.

There are many reasons for the failure of students to persist in science and engineering. Anderson-Rowland (1996) discovered that students in the College of Engineering and Applied Sciences at Arizona State often made their initial choice of major based on very cursory understandings of what a career in that field would entail. Similarly, other students chose the major simply because it had been recommended to them by a school counselor, teacher, relative or friend and had never looked at it critically. Johnson (2000) reviewed the advisement files of 309 students who failed to return after their freshman year at the College of Engineering and Applied Science at the University of Wisconsin-Milwaukee. She discovered a number of reasons behind the decisions to leave including employment, financial problems, inability to cope with the demands of college coursework (bad time management and/or study habits), lack of faculty support and poor grades.

Many have called for the development of a science and engineering pre-screening process based on a statistical model that effectively identifies students most likely to succeed (Triplett and Haag, 2004). Such tools are difficult to devise because the predictors of success may vary by gender (Takahira, Goodings and Byrnes, 1998), ethnicity (Jawitz and Scott, 1997; Reyes, Anderson-Rowland, 1999; Hargrove and Burge, 2002) or other factors. First semester GPA and SAT scores have been used as predictors with some success (Besterfield-Sacre, Atman and Shuman, 1997) but no set of standardized indicators has yet emerged that does effective prescreening.

Recruitment of the most likely to succeed is only half of the issue however, retention is the other half. The establishment of material repositories of retention data is an important guide to decision making, but it is currently characterized by uncoordinated proprietary databases (ACT, CSRDE, HERI, NCES, NSSE, PEO, The Chronicle of Higher Education, US News and World Report) often based on voluntary participation or offering only selective or highly aggregated statistics. This makes a comprehensive study of this phenomenon difficult. In addition much campus, program, course and student information critical to developing of an understanding of retention issues will continue to remain unavailable due to its sensitive nature (Bartlett, 2001).

The best source of retention data for institutions is currently the National Survey of Student Engagement (NSSE). Begun in 1999 through the sponsorship of the Pew Charitable Trusts, NSSE is now largely supported by institutional membership fees. NSSE is a central repository of student experience and engagement data. In 2003, approximately 348,000 first-year and senior students from 437 participating members were surveyed (NSSE, 2004). The goal is to establish benchmarks and ongoing monitoring for peer-institution comparison.

Student engagement involves an assessment of factors such as student-faculty involvement, student cooperation, active learning, feedback opportunities, the maintenance of high standards and expectations, respect for diversity, amount of time spent on course-related tasks, communication of performance expectations, an inclusive learning environment, and other similar key engagement indicators identified in the literature (Kuh, 2002). NSSE currently has over 700 institutions actively reporting, including the MNSCU system in Minnesota, but not the University of Minnesota or any of its branch institutions. It has been used to explore and quantify the variation in student engagement that is present by college major (Young, 2003)

Several comprehensive study attempts have been made by academics without affiliation with NSSE. The largest attempt at a coordinated study by private researchers was undertaken by Astin (1993b) who drew together data from more than 300 colleges and universities on more than 25,000 students. The results indicate that only 43% of students who initially enrolled in engineering programs actually finished them. A study at Iowa State University (Moller-Wong and Eide, 1997) of 1,151 engineering majors determined that only 32% had graduated after five years.

There is great interest and there are a wide variety of approaches to the development and implementation of retention-rate intervention plans. Federal initiatives have spurred several effective programs, such as the NSF Model Institutions for Excellence Program funding for the CirCLES project targeted at retention of entering engineering, math and science students at the University of Texas at El Paso (Arenaz et al., 1999). Other approaches borrow from industrial methods of quality control, such as the "Six Sigma" approach advocated by Hargrove and Burge (2002) for retention of minority students in engineering education.

Regardless of the approach taken however, none will succeed unless they can accurately identify both the causes of the problem and the factors most likely to be associated with solving it. One solution that has been the implemented with some success is the establishment of summer bridge programs to expose students to the rigors of college life before their first semester (Reyes, Anderson-Rowland et al. 1999). A side benefit of such programs is the early establishment of student social networks, so that students come to school with friends and a support network already partially in place.

Anderson-Rowland (1997) found that women and minority students could reliably predict whether they would ultimately end up leaving a science and engineering program. Overall, students were also fairly accurate in predicting whether they would fail at least one course. Anderson-Rowland suggests that early intervention programs be designed specifically for women and minority students.

An important example of an intervention strategy designed to address the retention issue was undertaken by Felder, Felder and Dietz (1998). They looked at five chemical engineering courses over five semesters and compared the progress of those in an experimental cohort to those in traditionally taught courses. The experimental group was taught using a variety of learning techniques including active and cooperative learning exercises, open-ended questioning, multidisciplinary problem solving, and other devices targeted at addressing different learning styles. The results indicated that there were significant differences between traditional and experimental treatment groups in grade outcomes by the second semester. The difference carried on outside of the courses involved in the controlled experiment. Students in the experimental cohort received significantly higher grades in upper division chemical engineering courses. Ultimately, the five-year graduation rate for the experimental group was 85% compared to 65% among the traditional group. The authors were able to demonstrate that despite virtually identical starting populations, the groups evolved quite differently. The experimental group developed higher critical skill levels, worked better both individually and within groups, forged closer bonds to the faculty and were more easily able to transfer problem-solving skills to other courses.

There are also studies focusing specifically on retention in computer science education. Most concentrate on rates of withdrawl (W), D or F (DFW rate). Drexel University reported a DFW rate of 25-50% in a variety of computer science courses prior to implementing a Pew Learning and Technology Program grant (Herrmann, Popyack et al. 2004). After this intervention their overall DFW rate dropped to 38% (Jarmon, 2002). Joseph Chase reports that the DFW rate in Computer Science I (CS1) at Radford University averaged 54% prior to an intervention strategy that has reduced it to 32% overall and 15% among female students (Stewart-Gardiner, et al. 2001; Chase and Okie, 2000). Nachiappan and Williams et al (2003) reported that on average, 25% of students in CS1 at North Carolina State University at Raleigh withdraw. Many more received a D or an F. Forte (2003) and Rich, Perry and Guzdial (2004) examined the DFW rate in a number of CS courses at the Georgia Institute of Technology. They found DFW rates varying from 27.8% - 43% in CS1.

Each of the individual CS-related studies mentioned above was characterized by the implementation of one plan or another that successfully reduced DFW rates by introducing non-traditional learning tools appealing to a wide variety of interests. Herrmann and Popyack et al (2004) implemented extensive web-based individualized study modules to allow self-paced learning. Forte (2003) used an approach based on digital media manipulation (examples included assignments to reverse popular songs, create online scrapbooks and alter personal photographs) to teach programming skills. Rich, Perry and Guzdial (2004) designed a similar course around the media manipulation of pictures, sounds and text in a (successful) attempt to appeal to make the course more appealing to women. Nachiappan and Williams et al (2003) and Chase and Okie (2000) found that it was paired-programming that opened up new avenues of student engagement. Giguette (2003) integrated game programming into CS1 and CS2 courses to channel the ubiquitous gaming interests of students in a constructive direction.

What each of the interventions underscores is that new teaching and learning methods are available in computer science education. They succeed because they expand the field of learning resources and draw in a wider group of students, many of whom are turned off by traditional methods. By making new learning tools available they cater to more diverse learning needs.

2.2 Learning Style

Hodgins and Connor (2000) point out that there are three areas of research that have contributed to modern learning theory, perceptual modality, information processing and personality models. Perceptual modality research seeks to understand the way in which biological responses to environmental stimuli allow us to gather information about the world. Often called visual, auditory, kinetic (VAK) learning it focuses on how sensory input is critical to the development of knowledge about the world. Learners most often find that they have a dominant sense from among these three. Teaching should ideally match the mode of presentation to the sensory information strengths of all students.

Information processing research attempts to discover how our brain processes information. Thomas (2000) demonstrated how the teaching of the Unified Modeling Language (UML) in computer science can be an exercise that addresses the each of the VAK learning modalities.

Modern learning theory is an outgrowth of broader personality theory. Carl Jung helped establish this discipline in the early 1900's through the categorization of personality types. Jung began with the postulate that personalities could be profitably viewed as either extroverted or introverted (1933b). As his theory developed he later began to look at personality as a combination of rational functions and experiences. Rational functions involved judgments and were characterized by thinking and feeling. Experiential functions involved intuition and sensation (1933a).

To understand how personality types and learning styles are linked to familiarity with types of learning is crucial. The most well-established model available is Bloom's Taxonomy (Bloom, Mesia and Krathwohl, 1964). The model is predicated on the assumption that there are identifiably different types of learning. These are broadly categorized as cognitive (knowledge-based), affective (attitude-based) and psychomotor (skills-based). Each domain may be further characterized by differing levels of knowledge acquisition and engagement. These form a hierarchy from the simplest type of learning to the most complex.

Cognitive learning, as characterized by Bloom, may take many forms. At its simplest it entails only the memorization of facts. The next level is characterized by a focus on the meaning comprehension. This is followed by application, analysis, synthesis and evaluation stages as one proceeds up the hierarchy. At each stage the learner is progressively challenged to go beyond the limits of the previous one and explore the further significance of what has been learned.

Early investigations of computer science education concluded that the main issue in learning was the importance of arriving at a high level of abstract reasoning relatively soon in a student's college years (Kurtz, 1980; Barker and Unger, 1983).

The actual learning process, as related to instruction, has been definitively presented by Kolb (1984) developed a cyclical model of learning that is widely used today. Kolb's position is that learning often starts with a physical or mental task. Out of this experience the learner may proceed to higher levels of understanding based on reflection, conceptualization and planning. In the reflection stage the learner reviews their primary learning experience looking for important points, patterns or other ways of describing what it was about. The conceptualization stage follows from reflection. Here the learner goes beyond simple reflection on events to place them in a wider context of meaning. Simple patterns come to be understood as relationships between entities. Both patterns and non-recurring landmark features are explained as the natural outcome of logical processes. In the planning stage this knowledge is expanded further into the realms of prediction and modification. A chief characteristic of the planning stage is the ability to act on knowledge derived from earlier stages and to modify behavior related to the initial learning event. This knowledge is then taken into the next occurrence of an experience. It modifies that experience and then the cycle of reflection, conceptualization and planning continues. Kolb is both an analyst of and advocate for learning through this cyclical process of experience, reflection and action.

The Kolb Learning Cycle has implications for the study of learning styles. It can be seen as a four-quadrant field in which the first quadrant corresponds to the concrete experience and related "Why?" questions. "Why is this important?" Next we proceed to the second quadrant, reflective observation, and the "What?" questions. "What was this experience about?" The third stage involves abstract conceptualization in the form of "How?" questions. "How does what I have learned apply to my situation?" Finally, the learner can ask the "What if?" questions. "What if I change this or that? How will it affect the event?" This allows learners to proceed to active experimentation and reengagement with the original concrete experience.

Others have developed similar models. Dunn, Beaudry and Klavas (1989) identified four dimensions of the learning style process: cognitive, affective, physiological and psychological. The cognitive dimension represents the manner in which individuals typically relate to their surroundings through perception and analytical thought. The affective dimension encompasses emotional personality traits. The physiological dimension includes our physical responses to information stimuli through the body. The psychological dimension relates to the manner in which individuality and the will affect the learning process.

Gardner (1993) adds another piece to the puzzle by proposing that there are numerous types of intelligence, many of which are situational. Learning may take place along one or more of these ways of making sense of the world. His eight basic types of intelligence included verbal/linguistic, logical-mathematical, musical, spatial, kinesthetic, interpersonal, intrapersonal and naturalist. Gardner proposed that different types of learning activities would appeal to each of the types of intelligence, for example kinesthetic learners required physical learning activities while reading materials were more appropriate for verbal/linguistic learners. Gardner believes everyone possesses multiple intelligences but that some are more fully developed than others. Every individual is unique in this respect. Teaching methods should ideally serve multiple learning styles instead of only a few.

Felder and Silverman (1988) developed the first learning model specifically geared at engineering students. Felder (1993) speculated that one of the reasons for the second tier phenomenon in science and engineering education may be that learning styles are not being accommodated. Felder and Soloman developed an Index of Learning Styles (ILS) to assess individual learning style dispositions (Soloman and Felder, 2000). The Soloman-Felder ILS seeks to apply learning theory to engineering education through the assessment of learning styles using a model based loosely on that of Kolb.

Lewandowski and Morehead (1998) first addressed the issue for computer science education. They believe that learning needs are characterized by type of preferred sensory input and approach (active experimentation, concrete experience, reflective observation, and abstract conceptualization). In an effort to insure that no learning need goes unmet they developed materials (Common Learning Experiences) to address all learning styles in several classes. The program was geared to help create active learners and to reduce built-in filtering mechanisms that block learning input. Although not backed with quantitative results their study suggests that learning style is an important factor in determining successful outcomes in computer science education.

The approach of offering multiple content delivery methods and tools to address the unmet needs of diverse learners is rapidly gaining popularity. Howard et al. (1996) shows the extent to which a course may have to be modified to truly integrate learning style considerations into the curriculum. Their approach featured the construction of 40 lessons in circular progressions of approximately 10 lessons each designed to cater to the preferences of various learning style theorists, including Kolb and Felder.

2.3 The Felder Learning Styles Model

Jung's influence on personality assessment tools has been enormous. The Myers Briggs Type Indicator (MBTI), Kolb's Learning Style Inventory (LSI) and the Soloman-Felder Index of Learning Styles (ILS) are all based on Jungian principles. Many other personality and learning style assessment instruments use the extroversion/introversion concept as well as Jung's four functions of thinking, feeling, intuition and sensation.

The MBTI is the most commonly used personality assessment instrument today. It uses four dimension scales and maps the personality of the respondent along each of them. The dimensions include extroversion/introversion, sensing/intuition, thinking/feeling and judging/perceptive. The overall approach is to locate the preferences of individuals in the external world of things or the internal world of ideas.

Felder and Spurlin (2005) recently described the pedigree of the Soloman-Felder ILS and its relationship to both the Kolb model and the MBTI. It is based on a learning style model developed by Richard Felder and Linda Silverman in 1988 specifically targeted at engineering students. The various continua have correlates in other learning style models. This approach is as useful for students as it is for teachers. It places the subject at locations along four learning style dimensions. Howard, Carver and Lane (1996) point out that Felder's classification scheme differs from that of Kolb in that it explicitly acknowledges a visual/verbal learning continuum. Felder and Spurlin acknowledge that the Active-reflective scale is similar to that of Kolb and based on the extroversion/introversion dichotomy of the Meyers Briggs Type Indicator (MBTI). The Sensing-intuitive dimension is very much an MBTI concept and may be similar to Kolb's concrete/abstract dimension. The Visual-verbal dimension is somewhat unique to the Felder-Silverman model although it bears resemblance to aspects of VAK approaches. The Sequential-global scale is more diffuse in its origin although is present in the literature in a variety of forms and is seen by some as the central axis of learning (Schmeck, 1988).

The Felder-Silverman Learning Model (Felder and Silverman, 1988) groups learning styles into various continua. The first, active-reflective, differentiates learners on the basis of their preference for first-hand experimentation often in collaborative settings (active learners). The reflective end of the scale refers to those who prefer to learn by thinking through the process and mentally examining ideas.

The second scale runs from sensing to intuitive learners. The sensing learner prefers empirical facts and practical procedures while the intuitive learner prefers conceptual meanings and theories.

The third continuum goes from the extremes of visual to verbal learning. Visual learners appreciate charts, diagrams, and should be also expected to prefer things like multimedia software and simulations. Verbal learners prefer lecture or textbook learning resources.

The fourth scale differentiates sequential from global learners. Sequential learners prefer learning in a series of steps leading to broader understanding. Global learners prefer to work from larger frameworks and fill in the gaps. They learn by starting with broad trends and patterns and fitting individual pieces of knowledge into the structure.

A fifth scale encompasses the spectrum from inductive learning to deductive learning. Inductive learners learn from specifics to generalities. Deductive learners proceed from generalities to specifics. It should be noted that this scale is not included in the current version of the Felder-Silverman model on the web, known as the Soloman-Felder Index of Learning Styles (ILS). It shares many of the features of the sequential-global dimension and the sensing-intuitive scale.

The Soloman-Felder ILS has been used in many settings to help identify and quantify student learning styles. The instrument is available on the Internet (Soloman and Felder, 2000) and consists of 44 multiple-choice questions designed to separate learning style affinities (Appendix A).

In the field of computer science education several important studies have been undertaken utilizing this tool. Chamillard and Karolick (1999) and Chamillard and Braun (2000) administered a variety of learning style assessment tools to 877 students in introductory computer science classes during 1997-1998. The learning styles instruments used included the Group Embedded Figures Test, Felder Index of Learning Styles, Kolb Learning Styles Inventory II '85, and Keirsey Temperment Sorter. Their goals were to direct students to study material appropriate for their learning style affinities, and to improve instructional approaches. They found, in relation to the Felder instrument, that reflective learners do statistically significantly better than active learners in almost all situations (quizzes, labs, practica, exams) and inferred, from the Kiersey tests that these results were confirmed by indications that introverts do better than extroverts.

Rosati (1999) used the ILS to assess learning styles of engineering students at the University of Western Ontario. In a study of 858 students he determined that definite learning style preferences exist in this population. Active learners comprise 69% of the active-reflective scale. Sensory learners were 59% of the sensory-intuitive scale. Visual learners far exceeded verbal ones (80% to 20%) and sequential learners comprised 69% of the sequential-global continuum. He concluded that this information is vital to decisions on how to approach teaching a course.

Carrizosa and Sheppard (2000) used the Felder-Silverman model as the theoretical basis behind an investigation of how engineering team members teach each other. They discovered that there are often differences between the style one prefers to receive information in and the style one wishes to send it. Visual learning dominated the reception category and they determined that visual communication accounted for over 20% of total engineering design time.

Bernstein et al (2002) have developed a novel approach to the merger of learning style assessment and pedagogy. In software engineering courses at the Stevens Institute of Technology they administer both the Soloman-Felder ILS and their own instrument, the Attitude Toward Software Engineering (ATSE) survey. The later is designed to present students with real-world situations in which their decision may be driven by their learning style preferences. The goal of the study is to show how disciplined software engineering methods must be used to overcome the weaknesses of learning style bias that may flaw program design.

Some researchers have gone beyond learning style characterization to try to develop tools to meet the needs of multiple learning types. Sharp (2003) describes a set of learning modules for freshman introductory engineering courses at Vanderbilt that are targeted at progressing through four modes of learning that characterize the MBTI (sensing, intuiting, thinking and feeling). Students take the Soloman-Felder ILS to become familiar with their own preferences and explicitly deal with both their strengths and weaknesses in the course of working with the learning modules. Yokomoto, et al (1998) developed and advocate instructional methods for electrical and mechanical engineering students that encourage active learning by attaching every task to a semester capstone project.

Thomas and Ratcliffe et al (2002) administered the Soloman-Felder ILS to 107 students. They then compared their students by average overall performance in the course as a whole and in the final examination to each learning style group (active, reflective, etc.). In relation to the exam portion of the course they discovered that reflective learners scored statistically significantly higher than active learners ($p=.015$). Also, verbal learners scored higher than visual learners ($p=.027$). The authors chose to create a variety of materials to appeal to different learning styles.

Computer science has long been in need of teaching and learning tools that are non-traditional and address critical needs (Proulx, Rasala and Fell, 1996). Innovative approaches to curriculum development are taking place in computer science education based on learning style considerations. For example, Hill et al (2003) administered the Soloman-Felder ILS to students in an Operating Systems course. They note the difficulty of meeting diverse student learning needs and give examples of new developments using simulations and custom software to stimulate interest. They also adopt that approach and describe the successful deployment of a "puzzles and games" approach to course material. An approach that stimulates active learning through paired programming has been shown to be effective by Nagappan et al (2003).

2.4 Other Learning Style Assessment Models

2.4.1 The Kolb Learning Styles Inventory (LSI)

The Kolb Learning Styles Model attempts to differentiate learners on the basis of their preference in relation to how information is acquired (concrete or abstract conceptualization) or internalized (through active experimentation or reflective observation). On the basis of their responses subjects are classified into one of four categories: accommodators, assimilators, convergers and divergers. Accomodators tend to be extroverted and intuitive. Divergers are introverted, preferring to observe rather than participate. They are good information gatherers and tend to be imaginative and flexible. Assimilators learn by assembling information into structures they can easily comprehend and act on. Convergers prefer to deal with concrete problems and solutions rather than abstractions.

The Kolb LSI has undergone a series of revisions (1976, 1985, 1993 and 1999). The current version of the LSI is a proprietary, fee-based assessment tool. The Kolb instrument has also been criticized for its use of rankings instead of ratings, potentially jeopardizing the validity of the responses (Hayes and Allison, 1997; Curry, 1990 and Coffield et al. 2004). The Soloman-Felder ILS is available for use without charge over the Internet and has been used in computer science education. For these reasons it was chosen over the Kolb LSI for the current study.

Bostrom and Olfman et al (1988) made extensive use of the Kolb LSI in their study of computer software end-users and believe that learning style is a predictor of performance. This has implications for the way software is designed. They undertook four studies involving students of varying backgrounds in introductory computer courses. In the first (n=63) students were given either an abstract and case-based model of an interactive financial planning system and asked to solve some simple problems. Abstract learners preferred the abstract models and concrete learners preferred to adapt the specific one. In the second study (n=70) the only significant relationship ($p<.05$) was with convergers (who combine both active and abstract learning) shown to be more likely to use a software tool to accompany their research than other learning styles. In their third study incoming graduate business students were enrolled in an introductory computer tools course. Abstract learners scored significantly higher than concrete learners ($p = 0.024$). The fourth study used undergraduate student subjects enrolled in an introductory computer course. Abstract learners were superior in complex tasks ($p = 0.01$). Active learners scored higher than reflective ones in simple tasks ($p = 0.05$). Convergers performed better than the other three styles in complete tasks ($p = 0.04$).

The issue of how to teach abstract concepts best in computer science education has been addressed in relation to learning style by Wu, Dale and Bethel (1998). They investigated the manner in which computer science students learned recursion. Recursion is the, potentially infinite, process of a computer program launching itself again while it is running. Instructors may treat it abstractly through conceptualizations not tied to any specific code implementation, or use very concrete examples derived from the architecture of the computer. Their research discovered that, for novice programmers, concrete models were more effective regardless of learning style preference.

Overall however, abstract learners may have the advantage. Goold and Rimmer (2000) followed the progress of a cohort over the first year (two semesters) of introductory computer science. They note that other studies have shown that learning style and problem solving skills are related to performance. Abstract learners perform better than concrete learners in computer applications (Davidson, Savenye and Orr, 1992). Their study found a direct correlation between abstract reasoning and performance among introductory programmers. This relationship was also found in studies by Kurtz (1980) and Barker and Unger (1983).

Goold and Rimmer quantified learning style using Kolb's indicators. They defined Relative Abstraction as equal to Abstract Conceptualization minus Concrete Experience (RAb = AC – CE). A score greater than three was taken to indicate an abstract learning style. Similarly they defined Relative Activity as equal to Active Experimentation minus Reflective Observation (RAc = AE – RO). A score less than seven was indicative of a relatively active learner. All other learners were classified as Relatively Reflective (RR). They collected demographic profile data (secondary school performance, entrance tests, etc.) on their 36 subjects to accompany the analysis. Multiple regression analysis was used to relate gender, academic ability, learning style, problem-solving ability and individual indicators of personal motivation to the dependent variable – grade. Their overall regression equations account for 42-65% of performance variability depending on the course being assessed. Relative Abstraction (RAb) was a statistically significant factor in only one of the three courses (the introductory one – Information Technology). Gender was also significantly related to outcomes in the first course, with women scoring significantly higher than men.

Karuppan (2001) investigated the role of Kolb learning styles and other variables (gender, GPA, and age) in web-based instruction. She found a statistically significant relationship ($p < 0.05$) between use of web-based materials and gender (males used the materials more than females), GPA (the higher the GPA the more often the web was accessed) and the assimilator learning style. She concluded that learning styles geared toward the synthesis of abstract concepts and ideas were best served by this medium of instruction.

The Kolb LSI was also used by Byrne and Lyons (2001) at the National University of Ireland. They examined the relationship between gender, prior computing experience, learning style and previous academic performance to outcome in an introductory computer science course. Data were gathered from 110 students (67 female, 43 male) using surveys and access to academic records. The study is notable because of its attempt to break down the learning style issue along gender, prior knowledge and other lines.

Lack of prior experience was a disadvantage although the small number of prior-programmers in the study makes it difficult to determine significance. There were no statistically significant relationships between the learning style groups and outcome. Prior academic performance was statistically significant ($p < .01$) in regard to mathematics ($r=.353$) and science ($r=.572$) but not significant for English ($r=.088$) or foreign languages (r-.119).

Online learning has also been addressed by learning style studies. Schipper and Krist (2001) used the Kolb LSI to study freshmen attending universities with less than 5,000 students. In a randomized, pre-test/post-test approach they compared the length of time it took students to complete a tutorial. Various online tutorial modes were studied. They conclude that convergers and assimilators adapted quicker and had better command of content than divergers and accomodators. Similar results had been achieved by Bohlen and Ferratt (1993) in relation to the measurement of end-user efficiency and satisfaction learning computer software and by Abrahamian (2003) with personality-customized user interfaces. Abrahamian used the MBTI to profile personality type.

Grant (2003) also employed the Kolb LSI in her study of the effects of cognitive learning style and gender constructs on critical thinking and problem solving ability in two introductory computer programming courses, one procedural language course taught in C (n=17), the other object-oriented C++ (n=24). Pre and post testing on these measures showed no significant differences. No statistically significant relationship between learning style and performance was detected. Similarly, no relationship between gender and performance was evident. However, there was a statistically significant two-way relationship ($p = 0.017$) between learning style and gender. Females tended to outperform males and convergers outperformed all other learning style groups.

Demetriadis and Triantafillou et al. (2003) administered Kolb LSI questionnaires to 19 students in first year of computer science studies at Aristotle University in Thessaloniki, Greece. The students also filled out pre-study questionnaires including demographic information, a domain knowledge questionnaire (to assess prior knowledge) and questions about media preferences. Student attitudes toward the use of multimedia learning tools were found to differ according to learning style learning styles preferring abstract content preferred printed matter.

The authors also note (similar to Allert, 2004a) that students reported that animation enhanced both their retention and deeper understanding but this did not correlate with better performance. It seems logical that visual media would capture the attention of visual learners and give students the impression they are learning more because of increased engagement with the course, regardless of the results. This has been shown to be the case in computer science classes at UMD (Allert, 2003, Deneen and Allert, 2004).

2.4.2 Other Learning Style Instruments

The Gregorc Style Delineator is built on the work of Dunn and Dunn (1978). Gregorc (1982) devised a self-scored questionnaire focusing on the role of two methods of learning, perception and ordering. Perception addresses how individuals come to be aware of information and ordering refers to the way in which it is organized. Each type of learning mediation is further divided into two subcategories. Perceptual qualities may be center around abstractness (an ability to comprehend what is not perceived directly by the senses) or concreteness (dominated by physical sensation). Ordering qualities are either sequential (linear, focused on one categorization scheme) or random (nonlinear, multidimensional, multitasking). Gregorc characterizes learning styles as "mind styles". The various types are classified as Concrete Sequential, Abstract Sequential, Abstract Random or Concrete Random.

Ross et al. (2001) made use of the Gregorc Style Delineator to correlate learning style with academic performance in two postsecondary computer application courses. They found that Abstract Random learners were the poorest performers in both classes and recommend peer learning approaches for these students.

Houston (1993) used the Gregorc Style Delineator in conjunction with her research on the learning styles, gender and computer science course outcome. She found that gender and learning style were positively associated although course outcomes were not statistically significantly different.

The Dunn and Dunn Learning Styles Model has been used at a number of universities. Larkin, Feldgen and Clua (2002) describe how it has become part of an initiative to improve science and engineering education at American University and at the University of Buenos Aires. They stress that written learning tools are much more important than formerly thought and have developed writing strategies that strengthen learners of all varieties. Hein and Budny (1999) have also been involved in the American University initiative and have expanded it to include the use of the Kolb Learning Style Model in the development of training materials for engineering student counselors. George (2001) has had similar positive experiences with reflective journals in computer programming courses at the University of South Australia. Sikorski (1998) also highlights the verbal learning aspect in relation to computer science courses in Poland.

2.5 Investigative Framework

The institutional departure model of Tinto (1993) identifies many of the key elements needed to understand the complex reality of student engagement and successful integration into the academic community. It would be very difficult to embrace them all in a single study. However, one of the most fundamental determinates of academic integration, closely related to departure decisions, is academic involvement. Academic involvement centers on instruction and learning. This is an area that can be usefully informed by learning style theory. Learning can be tailored to be hostile or helpful depending on the attention given to the match between the performance requirements of a course and the aptitudes and attitudes of students. The current trend toward increased instructional productivity through the use of large introductory classes introduces great potential for student alienation and disengagement if learning style issues are not identified and their consequences known.

Figure 2 is based on portions of the adapted Tinto model (Figure 1) and provides a framework for this research. It presents a linear model in which pre-entry attribute data is gathered, and after exposure to instruction, is related to the course outcome. This is a crucial component of the overall process of student engagement. This linear process is repeated in each course a student takes and forms a persistent feedback loop, as shown by Tinto, in the student's self-evaluation.

Crucial pre-entry attributes related to academic preparation, social, and psychological factors can be assessed to some degree. Some, such as prior computing experience, have previously been determined to be insignificant in relation to course outcome in the settings investigated by this research (Allert, 2004b). Others, including aptitude measures as indicated by ACT scores, high school rank, and high school percentage can be obtained from institutional sources and can be expected to relate to course outcomes.

Learning style is not explicitly identified by Tinto as an important pre-entry factor. This study attempts to demonstrate that it is important, perhaps as important as aptitude measures, in determining student success. Learning styles, as defined by the Silverman-Felder model, can be easily assessed with the Solomon-Felder ILS (2000).

Course performance measures (outcome) constitute the dependent variable. They serve as surrogate indicators of academic involvement and integration. They also presage retention issues.

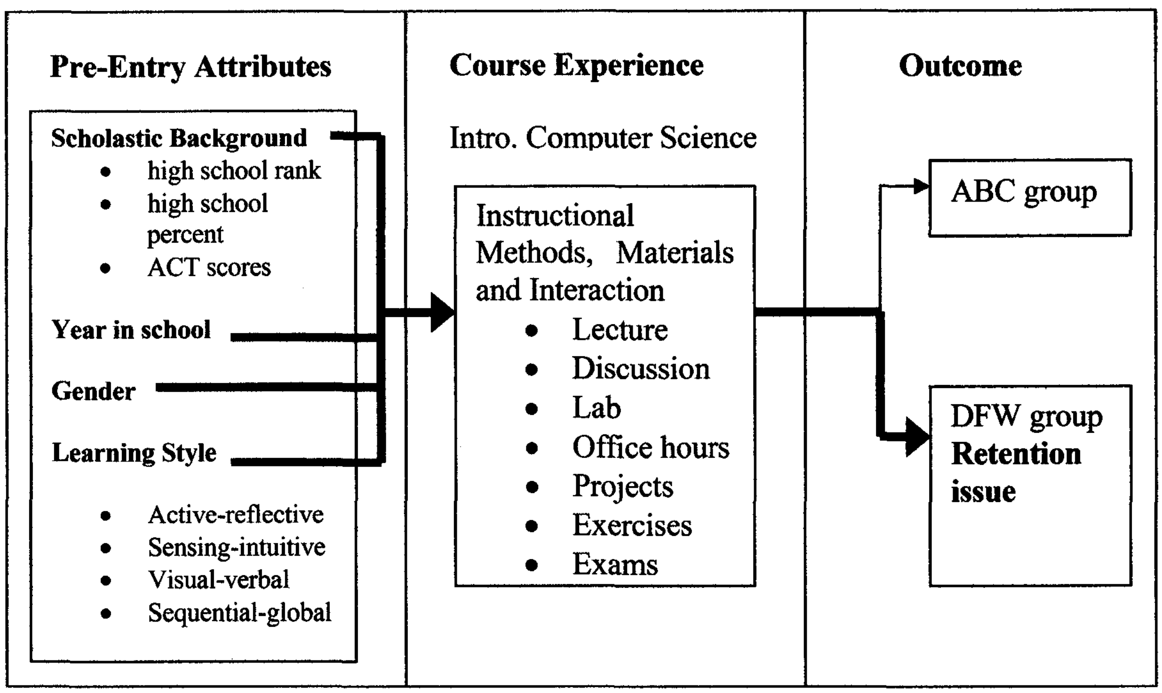

Figure 2. Investigative Framework

This research isolates the role of learning styles as a contributor to success in introductory computer science and compares their importance to other possible causal factors, such as prior scholastic achievement and gender. Although the explanatory power of this group of variables cannot be expected to account for most of the variation in student outcome, it should account for some. The literature suggests that it should have a significant role in explaining the reasons for course and program retention problems.

Chapter 3

METHODOLOGY

3.1 Research Hypotheses

The questions addressed by this research pertain to the assessment of student learning style differences. The study looks first at instrument reliability then at general distributional characteristics, learning styles differences across groups (gender, major, course, year in school, etc.), learning style differences between those who obtained favorable course outcomes and those who did not, and other differences related to performance.

The major hypotheses and sub-hypotheses are developed in the following sections. For each set of hypotheses an explanation is given as to why it is important, what statistical tests are to be used, and rejection values for the test statistic. All are stated as null hypotheses with an implied two-tailed alternative.

The three primary hypotheses are:

H_1: *The Soloman-Felder ILS reliably assesses learning styles.*

H_2: *There are no differences between learning style distributions across sample subpopulations.*

H_3: *Learning styles are unrelated to course outcome.*

3.1.1 Hypothesis 1: Instrument reliability

H_1: *The Soloman-Felder ILS reliably assesses learning styles.*

Instrument reliability is the extent to which it produces the same result each time it is used in the same way on the same population (Gall, Gall and Borg, 2003). The first sub-hypothesis tested was the assumption that the Soloman-Felder ILS produces reliable results from one administration to another on the same population.

$H_{1.1}$: *There are no differences between test/retest results.*

This was achieved by administering the ILS twice (once at the beginning of the semester and once at the end) and comparing the results. The test/retest method of comparison indicates the extent to which students provide similar responses when taking the ILS at different times. Linear regression analysis was used as a primary assessment tool in this research. Pearsons' r was calculated to determine the magnitude and direction of the correlations. It provides a measure of consistency over time. There are not hard and fast rejection limits for Pearsons' r in cases like this. However magnitude does speak to the issue of correlation. Generally in the social sciences correlations of this nature are categorized as very strong if .80 or higher, strong (.60-.79), moderate (.40-.59), weak (.20-.39) and very weak to nonexistent if less than .20 (Ellis, 1994). However, Felder and Spurlin (2005) note that there are two criteria for acceptability of r values. Some measured quantities are based on direct measurement, others on opinions or attitudes. The criteria for meaningful correlation are decided weaker for data derived from the second instance (as is the case with the Soloman-Felder ILS).

This procedure is also predicated on the assumption that learning styles are not changing significantly over the course of a single semester. If so, variation in test/re-test responses might be due to this change rather than deficiency in the instrument. Felder and Spurlin (2005) advocate a short interval (four weeks) as the ideal time differential. Seery et al (2002) achieved Pearson's r correlation values in a four-week test/retest scenario of .804, .787, .870 and .725 for the active-reflective, sensing-intuitive, visual-verbal and sequential-global scales respectively. Livesay et al (2002) achieved test/retest correlations of .73, .78, .68 and .60 after a time differential of seven months. Zywno (2003) found the correlations declining further (.683, .678, .511 and .505) after an eight month interval.

Linear regression analysis and scatter plots were employed as a method of assessing the overall pattern of relationship between responses to the two administrations. Correlations between individual questions were assessed using regression analysis to determine which questions were answered with the most and least consistency. In addition, paired t-tests were used to determine if there are statistically significant differences between the means of the test/retest populations, $p < .05$.

A second aspect of reliability concerns internal consistency:

$H_{1.2}$: Continua components are associated as expected.

The Soloman-Felder ILS consists of 44 questions. The four learning style continua are addressed by eleven questions allocated to each continuum. Scoring consists of a summation of the responses The value -1 was assigned to each response from one end of the scale (active, sensing, visual and sequential) and the value one was assigned to responses on the other end (reflective, intuitive, verbal, global). The internal reliability of this instrument was gauged in several ways, through the calculation of Cronbach's alpha and with factor analysis.

Cronbach's alpha is used to assess the internal consistency of an instrument. It measures the degree to which inter-item correlation occurs within the questions of a given scale. Cronbach's alpha were calculated for each set of eleven questions. An alpha value of .80 or better is often considered an "acceptable" standard for reliability (UCLA, n.d.) although .70 is also commonly used (Santos, 1999). Felder and Spurlin (2005) point out that a Cronbach's alpha value of .75 for data derived from direct measurement, which is considered a strong correlation, is analogous to an alpha value of .50 for attitudinal data (Tuckman, 1999). Cronbach's alpha has been used to assess the reliability of the Soloman-Felder ILS by a number of researchers (Livesay et al. 2002; Spurlin, 2002; Van Zwanenberg et al. 2000; Zwyno, 2003). Sample size for these studies ranged from 242-584. The weighted averages for the alpha values obtained are .586, .715, .635 and .518 for the active-reflective, sensing-intuitive, visual-verbal and sequential-global scales respectively.

Factor analysis looks at answers given to each of the questions and determines the extent to which they correlate with those of other questions. Ideally, four factors should emerge with each of the four continua in tact. The purpose of the factor analysis is to discover the extent to which questions that should group together really do. Ideally there should be factor groupings similar to the ILS scale categorizations. Questions statistically assigned to the wrong factor may need to be excluded from later inferential statistical analysis. If too many questions are assigned to other scale factors the reliability of the entire scale may be called into question.

3.1.2 Hypothesis 2: Learning Style Distribution

The second major hypothesis relates to the distribution of learning styles. The null hypothesis states that learning styles are distributed in the same way within themselves and across groups.

H_2: There are no differences between learning style distributions across sample subpopulations.

T-tests were used to determine whether there are statistically significant differences in learning style categorization across variables such as class, major, gender and year in school. Null hypotheses were rejected at a p-value $< .05$. Each of the independent variables were examined separately constituting four distinct sub hypotheses:

$H_{2.1}$: Learning styles are the same across CS classes.

$H_{2.2}$: Learning styles are the same across gender subgroups.

$H_{2.3}$: Learning styles are the same across college majors.

$H_{2.4}$: Learning styles are the same across college year.

Each of these subgroup categories may be important controls. They are used to isolate the effects of learning style within the sample population.

3.1.3 Hypothesis 3: Correlations with Outcome

There are two basic outcome indicators in this study. The first looks at the breakdown of learning styles across the entire grading spectrum, treating each grade as a separate category. The second compares students in the DFW category to those who completed the course with a grades of C- or higher. A third sub-hypothesis relates to the ability to construct an explanatory model for the relationship between outcome (as percentage of total points) and relevant independent predictor variables. The primary null hypothesis states that there is no difference between the learning styles of students across each of the subgroups in relation to performance.

H_3: Learning styles are unrelated to course outcome subgroups.

The percentage of total points served as the most important indicator of student outcome in the courses under study. Each course used percentages to determine final grade and used the same percentage cutoffs (90/80/70/60) for these grades.

$H_{3.1}$: Learning styles are unrelated to total point percentages.

Each learning style continuum was assessed separately in relation to this variable. T-tests were employed, with a p-value of .05 as the rejection limit, to determine the significance of differences between outcome groups in relation to variables with the highest correlations.

For the purpose of investigating retention issues, the most important distinctions are between the DFW group and those achieving a C- or higher. The first consists of students who dropped out after the second week (W) or achieved a grade of D or F. The sum of these students divided by total second-week enrollment constitutes the DFW rate. Students finishing the course with a grade of A, B or C were assigned the ABC group. The sub hypothesis for this category is:

$H_{3.2}$: Learning styles are unrelated to (DFW, ABC) completion groups.

A second measure of learning style was applied in relation to course outcome as measured by total points. Total points were used to determine final grades for each of the courses in the study using a percentage-based cutoff scheme (90/80/70/60 for A-, B-, C-, D respectively). The general sub hypothesis assumes that final grades and learning style are not related:

A third area of interest in regard to student grade is the construction of a model of student outcome. This was done using stepwise multiple regression analysis. The dependent variable was total points. Learning style scores, student opinion data and other information were used as dependent variables. The general hypothesis is:

$H_{3.3}$: Learning styles do not account for total point variability.

Models were constructed for each of the courses involved in the study. The resulting models indicate the amount of variation in total point outcome explained by each learning style factor, as well as other independent variables. This yields a comparative look at the importance of learning style in relation to other possible determinates of course outcome. A secondary data source (university admissions data) was used at this stage to provide information pertaining to students classified as incoming freshmen in the College of Science and Engineering. The data were gathered for CS-1121 and CS-1511.

3.2 Study Design

3.2.1 Selection of Subjects

The Soloman-Felder ILS was administered during the first and 14th weeks of fall semester 2004 in CS-1511 (Computer Science I), CS-1121 (Introduction to Programming in Visual Basic) and CS-1011 (Introduction to Computers and Software). These courses were chosen because they address a large number of students from varying disciplines.

CS-1511 is taught as a required course to science and engineering majors. It is valued at five semester credits. Students in this course major primarily in Computer Science, Information Systems and Technology, Electrical and Computer Engineering, Industrial Engineering, Mechanical Engineering, Chemical Engineering and Pre-Aerospace Engineering although it is also a liberal education course. The content of the course centers on the development of basic program analysis and design skills as well as familiarity with core computer science concepts in the context of programming assignments. The C++ language is used for the programming portion of the course. The class meets five times each week. Three large lecture sessions focus on overviews of course concepts. Graduate teaching assistance conduct two one-hour class sessions each week. One of these is dedicated to discussion of course materials, assignments and topics. Formal exercises and quizzes are often held in this setting. Students also meet in the computer lab for one hour each week to work on shorter "in-lab" programming assignments. In addition, students work on longer (one to three week) projects outside of class. There are three midterm exams and one final examination. Final grades are percentage-based. In fall 2004 there were 116 students enrolled in this course. A high number, 113, gave consent to be involved in this study (response rate = 97.41%). Seventy percent of the respondents (79/113) were majoring in computer science, mathematics or an engineering profession.

CS-1211 is primarily composed of Mechanical and Industrial Engineering majors and Management Information Systems majors from the Labovitz School of Business and Economics (LSBE). It also serves as a liberal education course and is generally considered the place to start if you have no prior programming experience. It is a three semester credit course and meets three hours each week. Two of these are held in large lecture format. The third is conducted by a graduate teaching assistant in the computer lab. Course content revolves around a textbook that provides a series of tutorials. Students learn essential programming skill in the context of the Visual Basic.NET programming language. Each week in lab they demonstrate the programming assignment assigned the previous week. There are three midterm examinations and a final examination to go along with the projects. Final grades are percentage-based. In fall 2004 there were 134 students enrolled in this course. A high number, 129, gave consent to be involved in this study (response rate = 96.41%). Sixty-two percent (80/129) were engineering majors. Of these 53 were from mechanical engineering.

CS-1011 students are from an assortment of majors. This is a liberal education service course. It serves as an entry-level, applications course appealing to students from the social sciences, liberal arts, and other fields. The course is worth four semester credits and meets for four hours each week. Three of these are held in a lecture setting and the fourth in lab. The course content centers on learning to use programs common to college and business environments (databases, spreadsheets, presentation software, web design). Students work on projects each week in a tutorial fashion and present their finished projects to the teaching assistant during lab time. No computer programming is involved. There are three midterm examinations and a final exam. Final grades are percentage-based. In fall of 2004 there were 107 students enrolled in this course. A high number, 99, gave consent to be involved in this study (response rate = 92.52%). These students came from a wide variety of disciplines. Over thirty different majors were represented in this class.

The variety of learners addressed in this study provides a cross-section of the student body that should be good for comparative purposes.

All students in these courses were asked to complete the Soloman-Felder ILS as a required, for credit assignment. Students were given the option of allowing the instructor to use this information for study purposes.

3.2.2 Subject Risk and Informed Consent

The IRB-approved consent form was distributed by the investigator in class, discussed in the context of a presentation on learning styles and collected. Students were informed of the background of the project, procedures to be used, risks and benefits and how data were to be kept confidential. Students were informed that their participation was strictly voluntary and that they may withdraw at any time without it affecting their relationship with the investigator. A copy of their signed consent form was returned to them. In addition, information on how to contact the investigator was included on the consent form (phone number and email). A copy of this consent form is included in Appendix B.

University of Minnesota student identification numbers were used to match the learning styles database with information in the course grade book. Once the match was made they were no longer needed and were dropped from the study data base. This measure ensured anonymity in the final data base. No information that could be used to identify an individual student is present. Given this anonymity the risks in this study are minimal.

In addition, all data were stored in password protected files on computers that are in compliance with the current University of Minnesota Office of Information Technology standard for securing private data (University of Minnesota, 2005).

There were important benefits for participants. Respondents received their learning style profile and were instructed as to how this knowledge can aid in developing study strategies. This knowledge also has implications for studying strategies in other courses. The results of the research may also be used to help strengthen teaching methodology in introductory computer science courses at UMD and elsewhere.

3.2.3 The Survey Instrument

This research made use of an established survey instrument (the Soloman-Felder ILS) supplemented by a short list of additional questions. Questions accompanying the initial use of this instrument were already built in to the Pearson NCR scoring sheet (student identification number, birth date, sex and year in college).

Student identification numbers were used to link the surveys to the instructors' grade book. This was essential since correlation with outcome was a primary focus of this study.

Birth date was crucial information since students younger than 18 years of age are ineligible to provide informed consent and participate in this study. Their surveys were removed from consideration. Gender was a fundamental demographic parameter linked to numerous learning style studies. Females are proportionately under-represented in science and engineering, especially computer science, and constitute a key retention group. Year in school was used to identify freshmen and separate them from other undergraduates and upper-division students.

3.2.4 Pilot Study

The Soloman-Felder ILS (Appendix A) was pre-tested in the fall of 2003 in CS-1511. The results of the initial testing phase serve as a guideline for the proposed methodology. During fall semester of 2003, 211 students in CS1 (CS-1511) at the University of Minnesota Duluth were asked to complete the online version of the Soloman-Felder ILS during the first and last week of the semester. Most students completed the questionnaire on the Internet without difficulty. The response rate was over 95%, n=207. The results were approximately normally distributed with the exception of the visual-verbal scale which was highly skewed to the right. There were many more visual than verbal learners (a fact which alone should help determine learning style approach).

The two sets of results were correlated in a test/re-test comparison of the reliability of the Soloman-Felder ILS survey instrument. 117 students completed the ILS surveys and both questionnaires. The test/re-test method used Pearson's *r* to determine the degree of association between two interval-level variables. Table 1 compares the results achieved in that study to those of Zywno (2003). The correlations were slightly higher than those achieved by Zwyno.

The results of reliability testing on the Soloman-Felder ILS indicate that each of them has moderate to strong reliability in the measured population. This legitimates its use as an assessment tool in the proposed study. The pre-test also highlights specific trends for later consideration, such as the dispersion of global learners and volume of visual learners.

Table 1. Test/re-test correlations Compared with Zywno (2003)

ILS Continua	CS1 results*	Zywno (2003)**
Active-reflective	0.743	0.683
Sensing-intuitive	0.814	0.678
Visual-verbal	0.686	0.511
Sequential-global	0.570	0.507

* n=117, ** n=124, Significance level 0.01, 2-tailed test

3.2.5 Data Collection

Both administrations of the Soloman-Felder ILS were collected in the form of standard NCS Pearson Answer Sheets (form 4521). Responses were marked on the sheets using a #2 pencil by filling in the correct oval for each question. Students completed the sheets in class during the first week and they were collected by the instructor and sent to UMD Information Technology Systems and Services (ITSS) for compilation. All answer sheets were numbered for later reference. Survey numbers were recorded in the database along with responses.

The results were returned to the student during the second week along with a printed interpretation of what they meant. Classroom discussion was held on how to benefit from the information.

A similar administration of the Soloman-Felder ILS took place during the 14th week of the semester. Results were compiled after the semester ended using the same procedures as the first administration and combined with data from other sources. The learning style results were combined in a Microsoft® Excel™ spreadsheet separate from the course grade book. When the construction of these files was complete grade information was added from the course grade book. Data from students who did not give consent to participate in the study were then removed. Once this procedure was finished student id number, name, and any other individual identifiers were deleted from the data set to preserve anonymity.

3.3 Data analysis

Data analysis was conducted using the statistical and graphical capabilities of Microsoft® Excel™ as well as those of the Statistical Package for the Social Sciences™ (SPSS 13.0). The SPSS procedures used were those related to the testing of each hypothesis and sub hypothesis. Hypothesis 1 issues were addressed through the use of SPSS reliability analysis (Cronbach's alpha), factor analysis, and regression (Pearson r, scatter plot) procedures. Hypothesis 2 was addressed with the use of SPSS Frequencies and Descriptive packages and SPSS independent sample t-tests of group means. Hypothesis 3 employed t-tests, bivariate correlation analysis of ordinal variables and stepwise multiple regression analysis.

3.3.1 Descriptive Statistics

SPSS Frequencies was used to check for coding errors and identify invalid values. Questionable values that could not be reconciled with the original data on the survey sheets were recoded as missing. Values that were miscoded were corrected. Very little data was hand-entered, so invalid items were rare. There was only one instance of a miscoded survey response. Each field was examined for missing values, out-of-range values or typographical errors. SPSS descriptive statistics procedures were used to examine the distributions of all variables by computer science course. Measures of central tendency, range, and frequency distributions were produced and were used to summarize student responses.

3.3.2 T-tests

T-tests of two independent samples were used to compare interval-level data (such as percentage of total points and learning style scores) across two groups (indicated by a nominal, binary variable). Groups used for comparison purposes in this study include gender (1=male, 2=female) and learning style (recoded to represent extremes, as in 1=Active, 2=Reflective, etc.).

The t value is calculated as the number of standard deviations from the mean of the sampling distribution of the difference between group means generated from samples of size n under H_0 assumptions of no difference. The sample sizes in this study were large enough (> 30) that the sampling distributions were normal. For group sample sizes less than 30 this statistic reverts to the calculation of t based on the appropriate Student's t distribution. In either case, the distribution represents the probability of occurrence of all possible outcomes as areas under the curve; t is used to locate the result in question on this curve as a position measured in standard deviations. The area of the curve beyond the t-value location represents the probability used to assess significance. Two-tailed tests of significance were used as H_0 was always non-directional.

3.3.3 Factor analysis

Factor analysis was conducted to verify the internal consistency of the Soloman-Felder learning style scales. Four factor dimensions were called for, to correspond with the four learning style scales. The assignment of each learning style variable to a particular factor was based on the inter-correlation of the variables. A correlation matrix was calculated for all 44 variables and a covariance matrix as well. From the covariance matrix eigenvectors and eigenvalues are computed. The eigenvectors characterize the data as a "line of best fit" for each dimension from the standpoint of data covariance.

The extraction of factors from the covariance matrix was carried out using principle component analysis. The eigenvector with the largest eigenvalue is the principle component (it accounts for the most variance). The components are then ranked, in descending order by eigenvalue. The larger an eigenvalue the more variation is explained by the component, so this list was also sorted in descending order by the percent of variance explained (varimax rotation). The top four components were then chosen (extracted). The list of eigenvalues associated with each variable in relation to the four principle components (eigenvectors) is then sorted in descending order by component and eigenvector to allow for the identification of variables assigned to each component.

Ideally, if the learning style indicators were 100 percent internally consistent, each component would consist only of related indicators. For example, all active-reflective indicators would be strongly intercorrelated and therefore all assigned together to a single component. Similarly, no indicators other than active-reflective ones would be assigned to that component. In practice this is difficult to achieve but it is an important guarantee of the reliability of the instrument.

3.3.4 Cronbach's alpha

The internal consistency of the Soloman-Felder ILS was assessed using Cronbach's alpha. This value is a measure of the reliability of a single dimension scale. In this study there are four dimensions that can be assessed (active-reflective, sensing-intuitive, visual-verbal, sequential-global). Each of these scales consists of eleven questions (indicators). When each indicator in a single scale is correlated with the others in that scale an 11x11 correlation matrix is produced. The matrix is symmetric around the diagonal (upper left to lower right). Averaging the correlation values in half of the matrix (above or below the diagonal) produces the average inter-item correlation. Cronbach's alpha (α) extends the expression of the average inter-item correlation ($\bar{r}$) by expressing it as a ratio (alpha value). The alpha value (α) runs from 0 to 1 where 0 is indicative of no internal consistency and 1 indicates 100% internal consistency.

The formula for Cronbach's alpha is represented as:

$$\alpha = (n\bar{r})/(1+(n-1)\bar{r})$$

where n is the number of indicators in the scale (11 in this case) and $\bar{r}$ is the average item-intercorrelation. The larger $\bar{r}$ becomes, the larger α will be. The lower the $\bar{r}$, the lower α will be.

3.3.5 Bivariate Ordinal Association Analysis

The analysis of bivariate ordinal relationships was conducted in this study using chi-square (χ^2) analysis and gamma (γ). Ordinal variables included recoded learning style inventories (i.e. the active-reflective scale recoded as 1=Active, 2=Mixed, 3=Reflective) and student outcome (recoding the percentage of total points as 1=90%-100%, 2=80%-89%, 3=70%-79%, 4=60%-69%, 5=<60%).

Chi-square analysis was used to determine the probability that a bivariate, ordinal relationship could have come about by chance. It is a measure of variable independence, but not association. For association estimate the gamma statistic was chosen because it gives a measure of both the magnitude and direction of the relationship.

Chi-square analysis proceeds by calculating the expected frequencies (f_e) in each cell of a bivariate correlation table based on the corresponding row and column totals for that cell (multiplied and divided by the total sample size (*n*)).

$$(f_e) = ((row\ total)(column\ total)) / n$$

These are then used to determine the difference between expected frequency (f_e) and observed frequency (f_o) values for each cell. It assumes that the expected frequency for each cell is at least five. Analyses in which 25% or more of the cells do not have expected frequencies of at least five are considered suspect and were not used in this research.

The χ^2 value is determined by the summation of the squared difference of the observed and expected frequency for each cell:

$$\chi^2 = \sum \frac{(fo - fe)^2}{fe}$$

Chi-square values are positive and are used to locate position along a chi-square probability distribution. This distribution represents, through the area under its curve, the probability of occurrence of particular χ^2 values. Distributions assume differing shapes relative to the number of degrees of freedom in the relationship. The degrees of freedom are calculated as the number of rows in the bivariate frequency table minus one multiplied by the number of columns in the table minus one.

$$df = (rows - 1)\ (columns - 1)$$

The probability under the chi-square distribution curve beyond that of the χ^2 value is tested against an established rejection limit for the hypothesis. In most cases, this study focused on relationships in which a probability value less than .05 was obtained from this procedure.

The χ^2 value describes the degree of independence of two variables. If it was unlikely ($p < .05$) those two ordinal variables were independent then gamma was used to determine the strength and direction of the relationship. It is possible that strong evidence against independence exists but that the actual association is weak.

Gamma takes on a value from -1 to 1 such that the absolute value of the magnitude indicates association strength (0 is weak, -1 and 1 are strong) while the sign indicates direction (negative or positive). Gamma was first introduced by Goodman and Kruskal (1954) and is calculated as the ratio of the difference between concordant and discordant pairs divided by the sum of those pairs. This formula can be better expressed as the difference between the proportion of concordant pairs to all pairs and the proportion of discordant pairs to all pairs:

$$\gamma = \frac{C-D}{C+D} = \frac{C}{C+D} - \frac{D}{C+D}$$

Concordant pairs are those in which the values for each variable have similar or identical ranks (high,high), (low,low). Discordant pairs are those in which the values for each variable have dissimilar ranks (high, low), (low, high). The stronger an association the more concordance is expected and the higher the proportion of concordance will be. The weaker an association the higher the proportion of discordance will be. Subtracting proportional discordance from concordance yields the gamma measure of association.

3.3.6 Regression Analysis

Linear regression analysis is used to explore the relationship between two interval-level variables. It was used twice in this study. First, to investigate the relationship between learning style profiles derived from two administrations of the Soloman-Felder ILS. This test-retest comparison was used in an assessment of the reliability of the ILS by checking consistency of responses over time.

The primary correlation statistic in regression analysis is Pearson's r. This measure summarizes the degree of correspondence in interval-level test values using difference between the observed dependent variable results and the predicted one along the least squares regression line. This line is expressed as $\hat{y} = a + bx$ where estimated y values are calculated for each x value based upon a (the intercept coefficient) and b (the slope). Once the mean x value ($\bar{x}$) and mean y value ($\bar{y}$) are computed, the slope (b) and intercept (a) are determined as follows:

$$b = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}, a = \bar{y} - b\bar{x}$$

Pearson's r is based upon the standard deviations of the residual values of x ($\hat{\sigma}_x$) and y($\hat{\sigma}_y$):

$$\hat{\sigma}_x = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}} \quad \text{and} \quad \hat{\sigma}_y = \sqrt{\frac{\sum (y_i - \bar{y})^2}{n-1}}$$

Pearson's correlation coefficient r may be interpreted as a standardized slope since it is the ratio of the two standard deviations multiplied by the actual slope of the least squares regression line.

$$r = \left(\frac{\hat{\sigma}_x}{\hat{\sigma}_y}\right) b$$

Pearson's r ranges from -1 to 1 and is a measure of correlation such that the absolute value of the magnitude is an indicator of the strength of the relationship (0 is weak, -1 and 1 are strong) and the sign indicates the direction.

Multiple regression analysis was used in the later portions of this study to formulate a predictive model for course achievement. The advantage of multiple regression is that it allows for the consideration of more than one independent variable and calculates an r^2 value that approximates the total amount of variability in the dependent variable explained by the independent variable(s) in the regression model.

Stepwise regression was used in this study with one independent variable added at a time until entry criteria were no longer satisfied. Then entry criterion in this case was an F

value less than .05. Independent variables could also be removed if the probability of *F* exceeded .10. F values are always positive and the F-distribution is usually skewed to the right. One variable, with a significant *F* value ($p < .05$) is allowed to enter the model at each step. Doing so increases the amount of variation explained by the model, however, it may also reduce the likelihood of inclusion of other variables. At any step, if the probability represented by the *F* value of a variable in the model is no longer significant ($p > .1$) it is removed. Eventually, no variables outside the model can be found with *F* probability < .05. Similarly, none inside the model have an F probability > .01. At that point the stepwise process ends and the model is complete.

Chapter 4

RESULTS

4.1 Instrument Reliability

The reliability of the Soloman-Felder ILS should be verified first before proceeding to further analyses. This process was conducted in several stages. First, the results of test/retest correlations were assessed for a reasonable level of correlation. Second, specific questions were analyzed to identify and quantify those that were most and least reliable. Third, the reliability of the ILS internally and across subgroups (class, gender, etc.) is examined to determine if the ILS is reliable only in limited circumstances.

4.1.1 Test/Re-test Correlations

The test/retest procedure was carried out in such a way that both overall student scale scores and the responses to individual questions were able to be compared. This allows reliability testing at both the individual question and composite levels.

Linear regression analysis conducted on the test/retest data yielded varying results. Table 2 compares the results of correlations for all learning style scales for both the overall group and for each class within it.

Table 2. ILS Test/Retest Pearson Correlation Overall and by Group.

ILS Scale	Overall (n=341)	CS-1511 (n=113)	CS-1121 (n=129)	CS-1011 (n=99)
Active-reflective	0.686	0.638	0.714	0.702
Sensing-intuitive	0.663	0.563	0.724	0.690
Visual-verbal	0.764	0.806	0.692	0.790
Sequential-global	0.497	0.504	0.426	0.610

Correlations are significant at the 0.01 level (2-tailed). The overall and group correlations are similar to those for the pretest group and for the study by Zywno (2003). They are also similar among themselves and in comparison to the overall group. Of concern is the sequential-global scale due to its lower r values, although a similar result characterized the pretest group and the Zywno (2003) study as well.

The results of this analysis indicate that the Soloman-Felder ILS has good, but not great test/retest correlation reliability. A major source of concern is the sequential-global scale, which is low across the board.

Comparative response charts (Figures 3-6) show the extent to which respondents were able to duplicate their original score for each learning style scale on the second administration of the ILS. A strong diagonal trend is evidence of higher correlation.

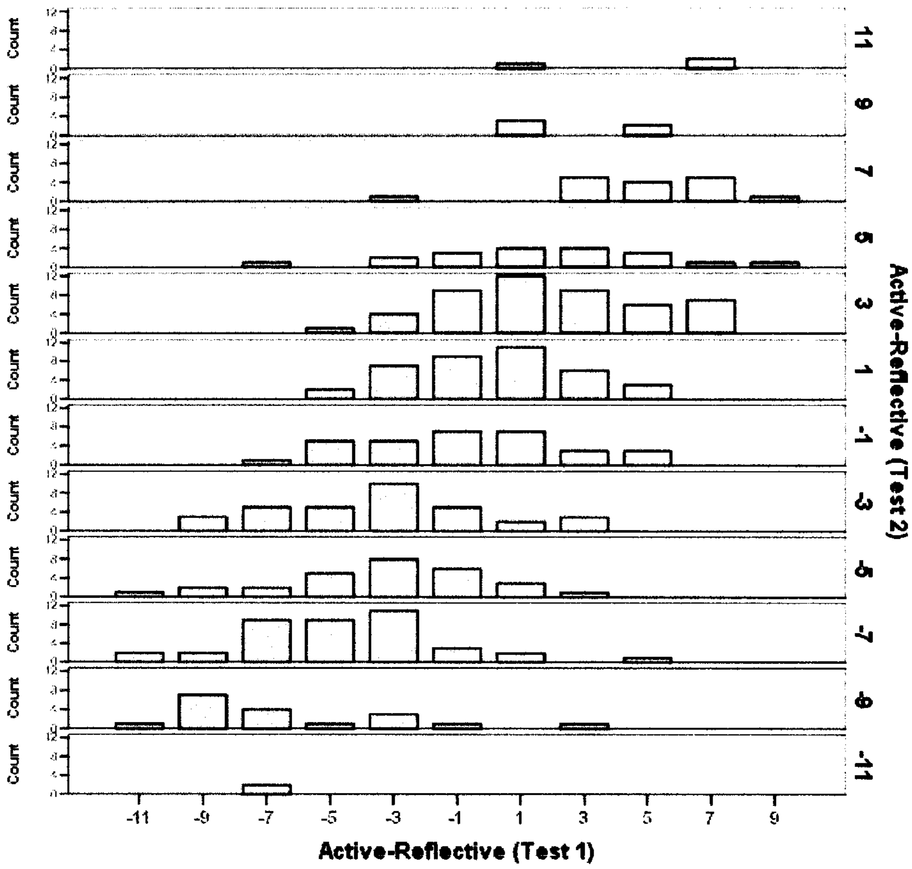

Figure 3. Comparative responses: the active-reflective scale (horizontal axis: first test, vertical axis: retest)

The relationship between responses to the first administration of the ILS and the second are shown in Figure 3. The positive relationship indicated by the diagonal trend and the strong Pearson's r (.686) are indicative of a high level of response reliability for this variable.

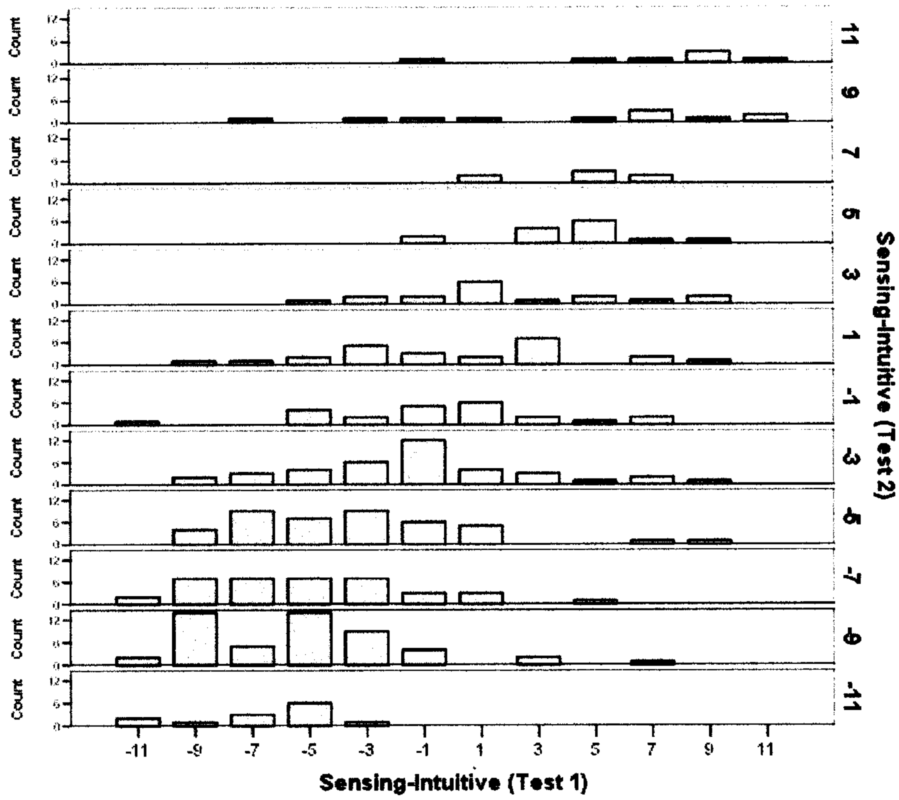

Figure 4. Comparative responses: the sensing-intuitive scale (horizontal axis: first test, vertical axis: retest)

The sensing-intuitive scale was somewhat skewed to the right on both administrations of the ILS, with a preponderance of learners classifying themselves in the sensing realm. The diagonality of the correlation distribution indicates a strong trend of reliable responses. Pearson's r for this relationship was .663.

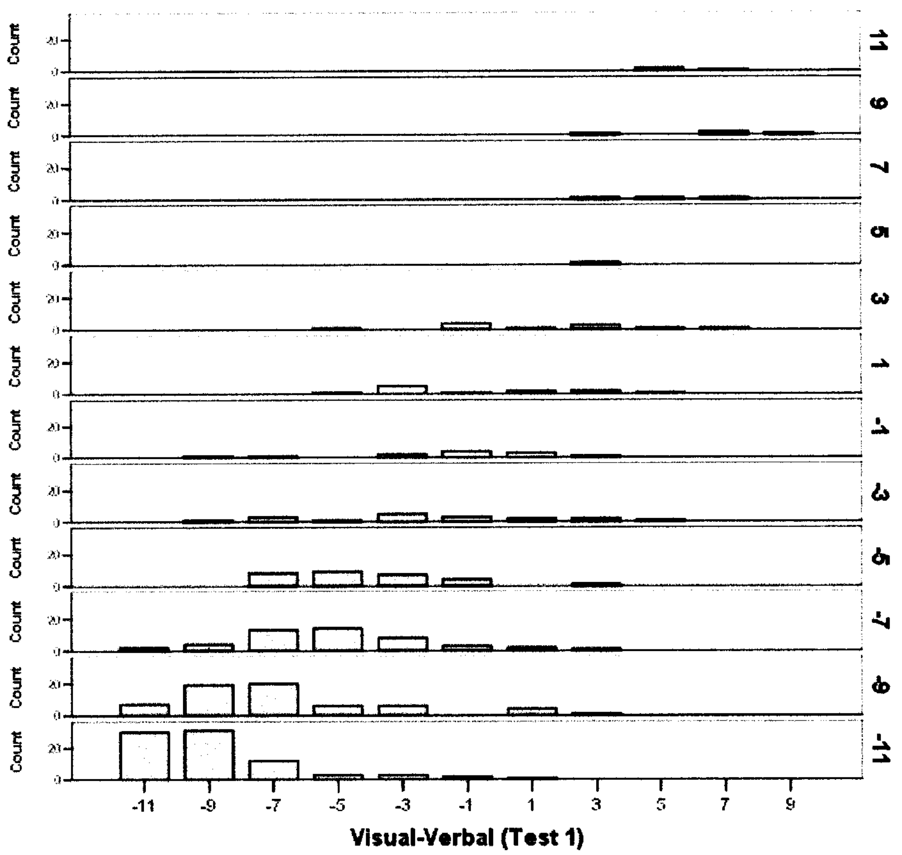

Figure 5. Comparative responses: the visual-verbal scale (horizontal axis: first test, vertical axis: retest)

Most students characterized themselves as visual learners on both administrations of the ILS. This accounts for the large concentration of responses in the extreme categories (-9 and -11). The trend is strongly diagonal with a Pearson's r of .686 indicative of reliable response correspondence.

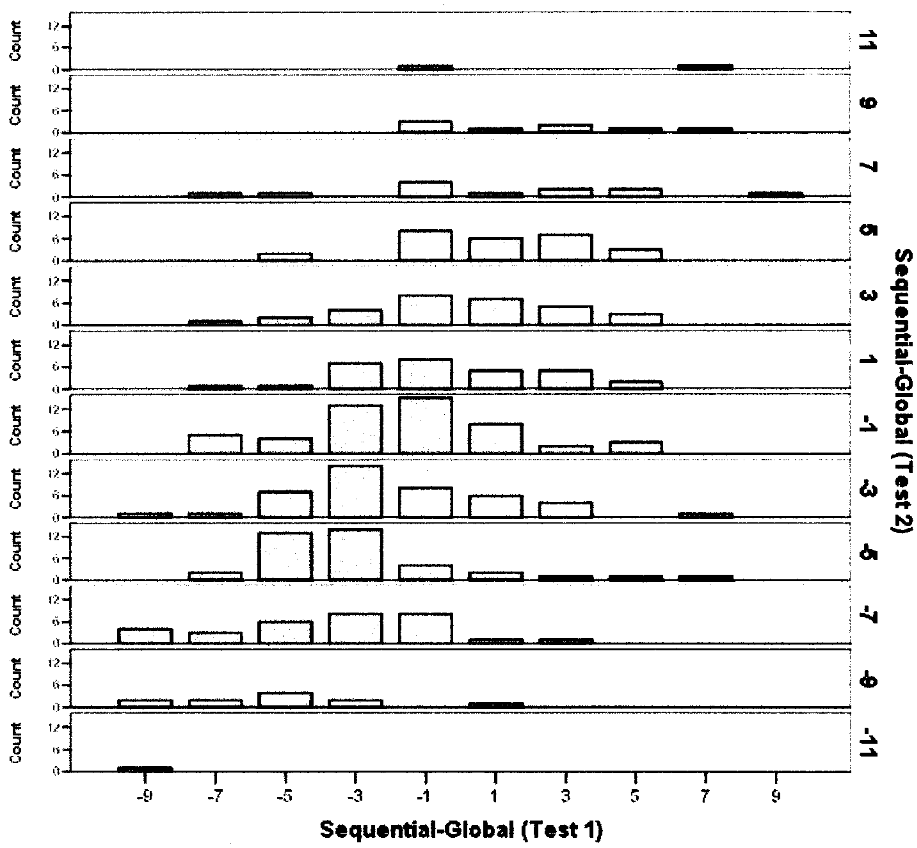

Figure 6. Comparative responses: the sequential-global scale (horizontal axis: first test, vertical axis: retest)

The sequential-global scale was the least consistent of all four ILS continua. The moderate Pearson's r characterizing this correlation distribution (.497) indicates some ambiguity. This distribution was normal around the central values but with considerable variation of first and second administration responses. This is seen most clearly in the horizontal spread of bars across each of the rows of this chart. Although the trend is still roughly diagonal the spread is much greater than that seen for any of the other ILS categories.

4.1.2 Internal Question Correlation

The Soloman-Felder ILS is comprised of 44 questions (11 from each of the four learning style scales). Table 3 shows the scale each question is designed to indicate.

Table 3. Soloman-Felder ILS Learning Style Indicators by Question

Learning Style Scale	ILS questions
Active-reflective	q1, q5, q9, q13, q17, q21, q25, q29, q33, q37, q41
Sensing-intuitive	q2, q6, q10, q14, q18, q22, q26, q30, q34, q38, q42
Visual-verbal	q3, q7, q11, q15, q19, q23, q27, q31, q35, q39, q43
Sequential-global	q4, q8, q12, q16, q20, q24, q28, q32, q36, q40, q44

4.1.2.1 Cronbach's Alpha

The reliability of this instrument can be further determined by examining the internal consistency of its questions. This analysis was carried out using Cronbach's alpha as the benchmark for reliability.

The eleven questions comprising the active-reflective scale were compared overall in a covariance matrix (Table 4) as part of the process for calculating Cronbach's alpha. Correlation strengths for different questions ranged from -.08 to .33. There were no strong negative correlations. The Cronbach's alpha for this group of questions was .526. The Cronbach's alpha for each of the classes individually was as follows: CS-1511 (.515), CS-1121 (.540), CS-1011 (.517).

Table 4. Active-reflective Inter-Item Correlation Matrix (all classes, n=341)

	Q1	Q5	Q9	Q13	Q17	Q21	Q25	Q29	Q33	Q37	Q41
Q1	1.00										
Q5	.23	1.00									
Q9	.02	.12	1.00								
Q13	-.02	.10	.23	1.00							
Q17	.13	-.04	-.01	-.03	1.00						
Q21	.08	.29	.10	.16	.03	1.00					
Q25	.24	.13	.04	-.01	.17	.09	1.00				
Q29	.22	.12	-.08	.06	.02	.02	.13	1.00			
Q33	.04	.13	.08	.03	-.06	.16	.05	-.04	1.00		
Q37	.12	.12	.31	.33	.06	.16	.11	.04	.06	1.00	
Q41	.10	.21	-.06	-.01	.00	.33	.04	-.05	.18	.08	1.00

Similar inter-question correlations were investigated for the sensing-intuitive scale. These results are shown in Table 5. Correlation strengths for different questions ranged from -.09 to .54. There were only three negative correlations, all of then small and all of them tied to one question. The Cronbach's alpha for this group was .717. The alpha for each of the classes individually was: CS-1511 (.661), CS-1121 (.699), CS-1011 (.782).

Table 5. Sensing-intuitive Inter-Item Correlation Matrix (all classes, n=341)

	Q1	Q5	Q9	Q13	Q17	Q21	Q25	Q29	Q33	Q37	Q41
Q1	1.00										
Q5	.15	1.00									
Q9	.13	.32	1.00								
Q13	.09	.28	.22	1.00							
Q17	.21	.48	.35	.34	1.00						
Q21	.26	.16	.14	.20	.25	1.00					
Q25	.13	.27	.13	.14	.21	.10	1.00				
Q29	.25	.21	.17	.08	.18	.20	.21	1.00			
Q33	.28	.17	.12	.22	.19	.24	.26	.16	1.00		
Q37	.20	.54	.41	.31	.62	.19	.25	.21	.19	1.00	
Q41	.05	.05	.02	.06	.01	.11	-.01	-.09	-.03	.01	1.00

Table 6 lists the inter-question correlation for the visual-verbal scale. Correlation strengths for different questions ranged from -.07 to .47. There were no strong negative correlations. The Cronbach's alpha for this group of questions was .696. The Cronbach's alpha for each of the classes individually was: CS-1511 (.688), CS-1121 (.648), CS-1011 (.748).

Table 6. Visual-verbal Inter-Item Correlation Matrix (all classes, n=341)

	Q1	Q5	Q9	Q13	Q17	Q21	Q25	Q29	Q33	Q37	Q41
Q1	1.00										
Q5	.18	1.00									
Q9	.21	.47	1.00								
Q13	.15	.26	.23	1.00							
Q17	.21	.37	.32	17	1.00						
Q21	.10	.28	.18	.19	.18	1.00					
Q25	.18	.28	.28	.17	.37	.15	1.00				
Q29	.22	.42	.41	.22	.33	.26	.24	1.00			
Q33	.10	.10	.20	.13	.15	-.03	.12	.16	1.00		
Q37	.10	.15	.15	.08	-.02	.10	.13	.08	.10	1.00	
Q41	.07	.05	.01	.09	.03	.07	.03	.07	-.07	.03	1.00

Sequential-global scale inter-question correlation is shown in Table 7. Correlation strengths for different questions ranged from -.19 to .28. There more negative correlations than any of the other ILS scales and several stronger that -.10. The Cronbach's alpha for this group of questions was .293. The Cronbach's alpha for each of the classes individually was: CS-1511 (.197), CS-1121 (.307), CS-1011 (.373).

Table 7. Sequential-global Inter-Item Correlation Matrix (all classes, n=341)

	Q1	Q5	Q9	Q13	Q17	Q21	Q25	Q29	Q33	Q37	Q41
Q1	1.00										
Q5	.10	1.00									
Q9	.02	.09	1.00								
Q13	.03	.01	.05	1.00							
Q17	.00	.11	.08	.06	1.00						
Q21	-.03	.06	.19	.07	-.10	1.00					
Q25	.26	.12	.01	.15	.11	-.05	1.00				
Q29	.01	-.01	.04	-.01	.12	.03	-.02	1.00			
Q33	-.02	.08	.07	.03	.28	.15	.07	.10	1.00		
Q37	-.03	-.11	-.04	-.13	-.19	-.12	.04	.03	-.16	1.00	
Q41	-.01	.02	.22	.11	.17	.04	-.03	.04	.12	-.12	1.00

4.1.2.2 Factor Analysis

Factor analysis was used to further explore the relationship between questions in the Soloman-Felder ILS. Principle component analysis with an extraction of four components produced a set of component matrices from which the factor classifications could be examined. Tables 7, 19, 11 and 13. display the complete rotated component matrix for this analysis for each set of factor variables. Boldface type is used to indicate the component assignments for that factor. Secondary assignments (those with magnitudes > one third of their primary assignment) are shown in italics.

Component 1 (Table 8) is comprised mainly of variables from the sensing-intuitive scale. Of the fifteen variables in this grouping ten were sensing-intuitive indicators, including the top nine assignments. Four sequential-global variables (questions 20, 36, 44 and 32) were also assigned to this group, however these were among the lowest correlations with the group. Unlike the sensing-intuitive scale indicators, most sequential-global variables had viable secondary assignments (shown in italics). This indication of ambiguity may indicate a weakness in the operationalization integrity of this category.

Table 8. Rotated Component Matrix for Factor 1 Variables

	Component			
	1 ↓	2	3	4
Q38	**.710**	-.014	-.135	.062
Q18	**.698**	-.027	-.138	.086
Q6	**.656**	.117	.091	.057
Q10	**.522**	-.073	.143	.102
Q14	**.498**	-.048	-.016	.022
Q30	**.467**	-.006	.074	-.131
Q34	**.466**	-.072	.027	-.131
Q22	**.444**	-.131	-.071	.151
Q26	**.443**	*.172*	.003	-.104
Q2	**.415**	-.052	.026	-.081
Q20	**.392**	-.021	.069	*.211*
Q36	**.370**	-.003	-.028	*.178*
Q39	**.291**	*.255*	.141	-.109
Q44	**.289**	.022	*.201*	*.262*
Q32	**.136**	.023	.038	*-.090*

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 5 iterations.

Table 9 shows the assignment of learning style category questions to Factor 1. This can fairly be called the "sensing-intuitive" factor based on these assignments and the facts that virtually all of the sensing-intuitive indicators were included here and that they accounted for nine of the ten strongest constituents of this factor.

Table 9. Assignment of ILS Questions to Factor 1

Active-reflective	Sensing-intuitive	Visual-verbal	Sequential-global
	q38, q18, q6, q10, q14, q22, q30, q34, q26, q2	q39	q20, q36, q44, q32

Factor 2 (Table 10) is comprised almost exclusively by visual-verbal indicators. Of the ten variables in this grouping the top nine were from the visual-verbal scale. The weakest association was question 29, which derives from the active-reflective scale and whose strong secondary assignment would place it in Factor 3 (primarily an active-reflective group).

Table 10. Rotated Component Matrix for Factor 2 Variables

	Component			
	1	**2** ↓	3	4
Q7	-.098	**.701**	.061	.129
Q11	-.017	**.682**	.087	.063
Q31	.014	**.676**	-.107	.106
Q19	.005	**.614**	.043	.102
Q27	.114	**.556**	.109	-.020
Q15	-.150	**.475**	-.059	*-.236*
Q23	-.046	**.441**	-.117	-.167
Q3	-.101	**.423**	-.040	.081
Q35	.059	**.296**	*.184*	-.059
Q29	.128	**.221**	*.208*	.080

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a Rotation converged in 5 iterations.

Table 11 shows the assignment of learning style category questions to Factor 2. This was strongly visual-verbal.

Table 11. Assignment of ILS Questions to Factor 2

Active-reflective	Sensing-intuitive	Visual-verbal	Sequential-global
q29		q7, q11, q31, q19, q27, q15, q3, q23, q35, q43	

Factor 3 (Table 12) is comprised mainly of variables from the active-reflective scale. Of the nine variables in this grouping six were active-reflective indicators, including the top five assignments. Three sequential-global variables (questions 8, 16 and 28) were also assigned to this group toward the bottom of the association list.

Table 12. Rotated Component Matrix for Factor 3 Variables

	Component			
	1	2	3 ↓	4
Q5	.069	-.026	**.583**	.159
Q21	-.052	.056	**.573**	.014
Q41	.045	.132	**.516**	-.209
Q1	.073	.088	**.447**	.081
Q25	-.051	.091	**.444**	-.050
Q28	.098	-.072	**.301**	-.035
Q33	-.092	-.008	**.288**	.063
Q16	*.156*	.028	**.219**	*.177*
Q4	-.005	*-.143*	**.186**	.003

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a Rotation converged in 5 iterations.

Table 13 shows the assignment of learning style category questions to Factor 3. This was predominantly active-reflective as indicated both by the number of indicators from this scale and their strength (the top five indicators were all active-reflective).

Table 13. Assignment of ILS Questions to Factor 3

Active-reflective	Sensing-intuitive	Visual-verbal	Sequential-global
q5, q21, q41, q1, q25, q33,			q28, q16, q4

Factor 4 (Table 14) is comprised largely of variables from the sequential-global and active-reflective scales. Of the ten variables in this grouping four were from each. One Sensing-intuitive indicator (question 42) and one visual-verbal indicator (question 43) were also assigned to this group. The distribution effect resembles an alternation between sequential-global and active-reflective indicators.

Table 14. Rotated Component Matrix for Factor 4 Variables

	Component			
	1	2	3	4 ↓
Q12	.144	-.033	-.059	**.489**
Q9	-.216	-.117	.174	**.472**
Q42	.035	.052	-.046	**.438**
Q37	-.260	-.023	.364	**.415**
Q24	.039	-.026	-.236	**.402**
Q40	-.182	-.131	.013	**-.396**
Q13	-.100	.053	.167	**.391**
Q8	.056	-.035	.165	**.312**
Q17	.101	-.021	.237	**-.279**
Q43	-.119	.108	.028	**.140**

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 5 iterations.

Table 15 shows the assignment of learning style category questions to factor 4. This was largely sequential-global with some active-reflective indicators mixed in. It should be noted that of the seven sequential-global variables assigned to other factors four had reasonably large secondary assignment values linking them to this group. Similarly, all of the active-reflective variables assigned to this group had strong secondary assignments to Factor 3 (which was strongly active-reflective).

Table 15. Assignment of ILS Questions to Factor 4

Active-reflective	Sensing-intuitive	Visual-verbal	Sequential-global
q9, q37, q13, q17	q42	q43	q12, q24, q40, q8

Only a small number of indicators were assigned to a group that did not include the bulk of their ILS companion variables and could also not be correctly reassigned based on secondary values. These were questions 4, 28 and 32. All were sequential-global indicators. Although it is premature to suggest modification or removal of these questions based on this one study, these questions should be monitored by researchers using this instrument. It does suggest a reason for the weakness in Cronbach's alpha reliability scores for this learning style category.

4.1.2.3 Chi-square Analysis

Ideally each learning style scale should measure different aspects of the learning experience. No two scales should overlap. If they did, this would show up as correlations between scales. To test this, the scales were recoded into ordinal values. The negative extreme of each scale was collapsed into a single value (1) for all values in the range -11 through -5. The middle portion of each scale was treated similarly with each value in the range -3 through 3 being categorized as a 2. Finally, values 5 through 11 were all reclassified as 3. The result allowed each scale three states, for example, the active-reflective scale now consisted of values 1, 2 or 3 standing for Active, Mixed, Reflective. This procedure was applied to all ILS scale variables to prepare them for ordinal comparison. The Chi-square statistic (χ^2) was used to determine the significance of the distribution as a deviation from expected random assignment. The gamma statistic (γ) was used to determine the magnitude and direction of significant χ^2 relationships. The cross tabulation results are shown in Table 16 for each of the classes as well as the combined group for the active-reflective/sequential-global relationship for CS-1511.

Table 16. Chi-square Ordinal Relationships by Class

Class	χ^2	χ^2 **sig**	γ	γ **sig**
All	8.043	.090	.251	.009
CS-1011	1.242	.871	-.064	.723
CS-1121	5.945	.203	.366	.02
CS-1511	8.897	.064	.401	.01

At the .05 level of there are no significant relationships in this group. This is expected if the scales are truly independent. However, the confusion of active-reflective and sequential-global indicators found earlier in the factor analysis shows up in the low Chi-square probability values for CS-1511 and for the combined groups overall. This provides further support, although weak, for the relationship between these variables. Further details regarding CS-1511 are shown in Table 17. The positive diagonal trend indicated by the gamma value in Table 16 (.401) is evident here. Both sequential and active learning scores were the lowest recoded values whereas reflective and global scores were the highest. The relationship is roughly diagonal from upper left to lower right, although it is not significant at $p<.05$.

Table 17. CS-1511 Active-reflective by Sequential-global Crosstabulation Table

		Sequential Global			Total
		Sequential	Mixed	Global	
Active Reflective	Active	7	20	0	27
	Mixed	17	45	6	68
	Reflective	1	13	4	18
Total		25	78	10	113

4.2 Learning Style Distribution

4.2.1 Overall Distribution of Learning Styles

The pretest results indicated that roughly normal distributions were present in all scales with the exception of the visual-verbal, which was skewed to the right and roughly normal about the median for students in CS-1511. These results were confirmed for all three classes investigated in this research.

Figures 7-10 show the overall distribution of student ILS scores on the initial test across all classes for each of the ILS scales. These results closely follow those of the pretest. The distribution of active and reflective learning styles (Figure 7) is centered on the scale midpoint with few students at the extremes. The sensing-intuitive scale (Figure 8) is approximately normal but weighted toward the sensing side somewhat. The visual verbal scale is highly skewed toward the right (Figure 9). This suggests that there is a strong bias in favor of visual learning situations both overall and within each class. The sequential-global scale (Figure 10) resembles the active-reflective scale. In both cases the distribution is indicative of mixed approaches to learning.

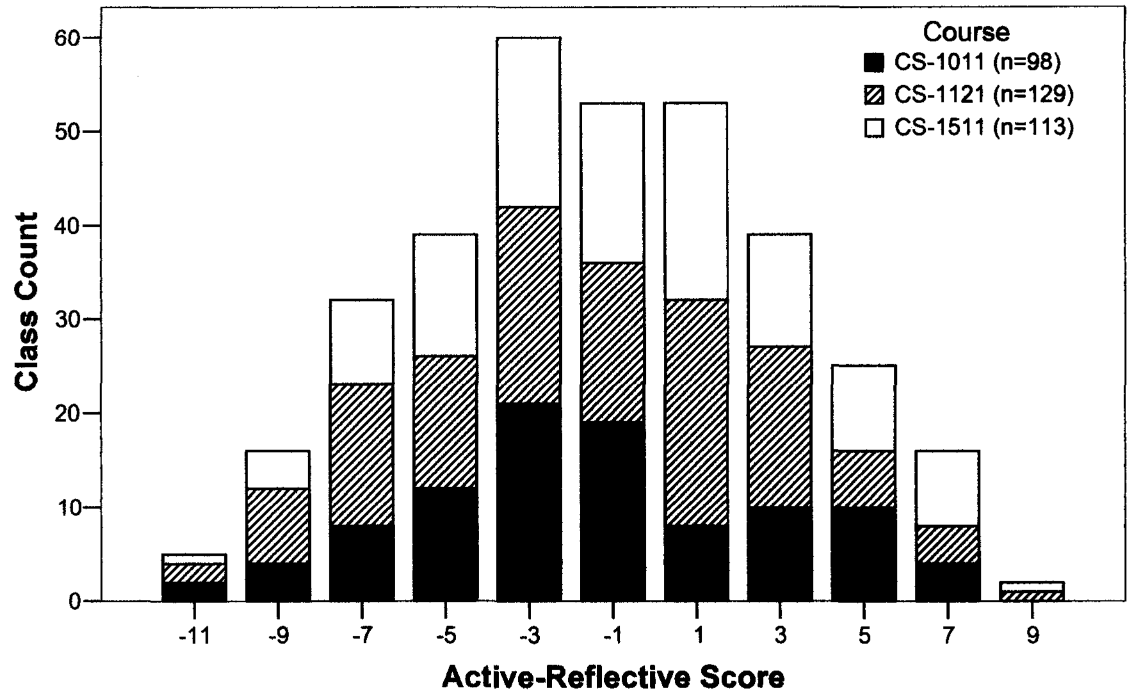

Figure 7. Distribution of active-reflective scores overall and by class.

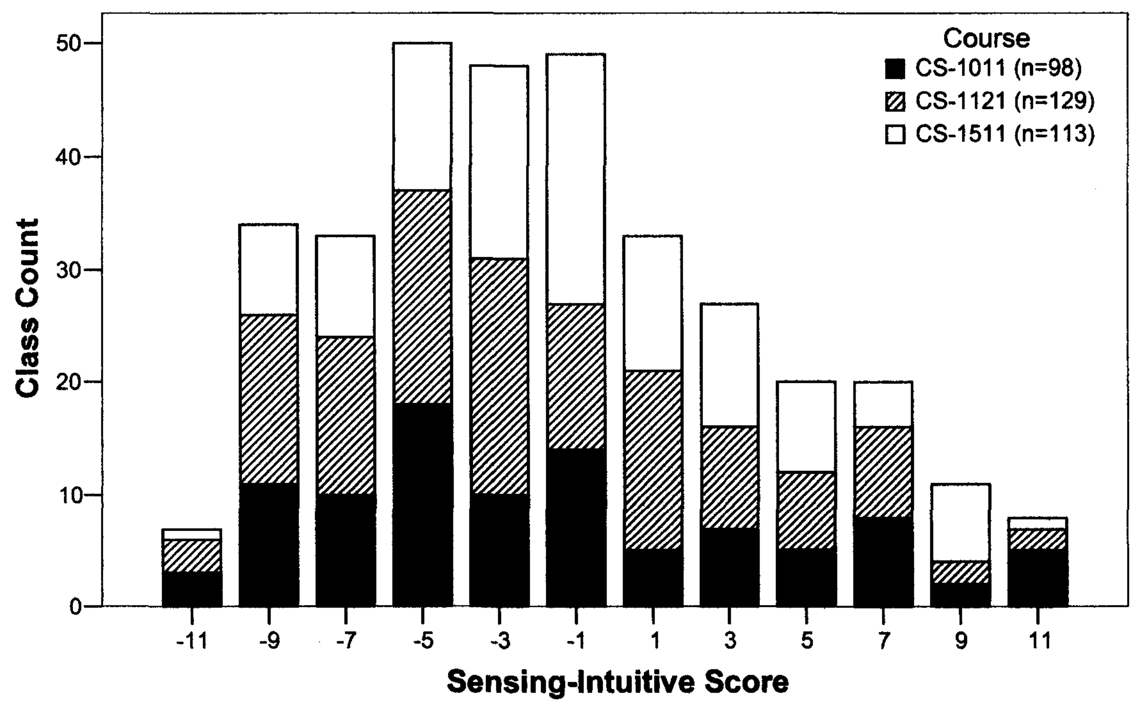

Figure 8. Distribution of sensing-intuitive scores overall and by class.

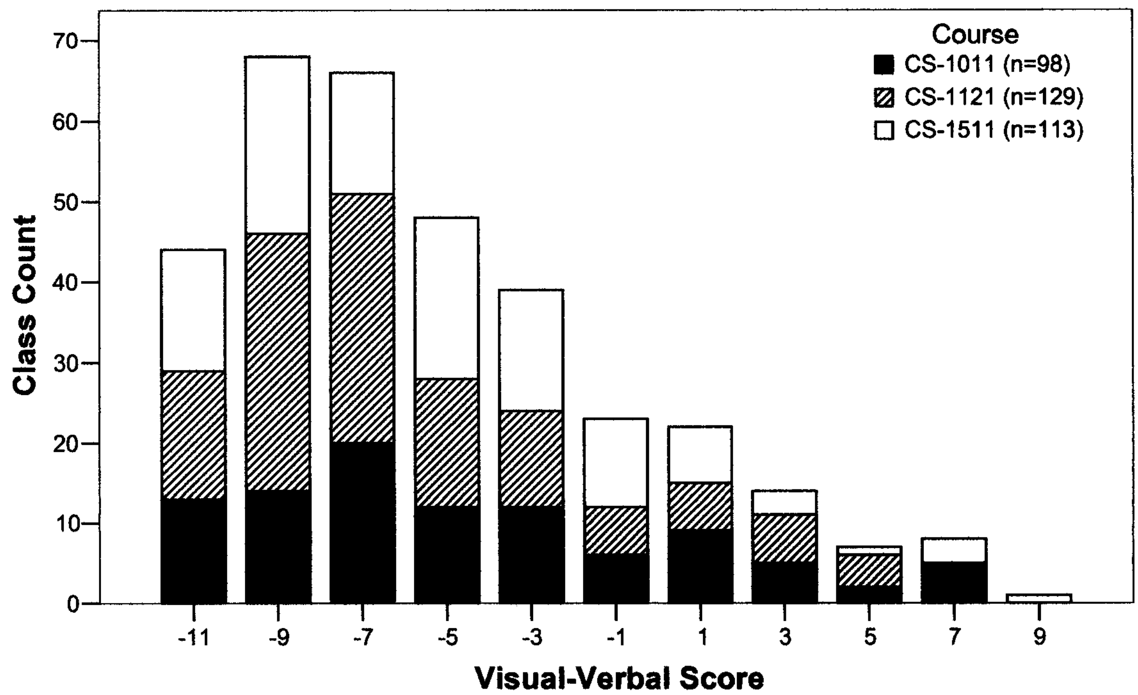

Figure 9. Distribution of visual-verbal scores overall and by class.

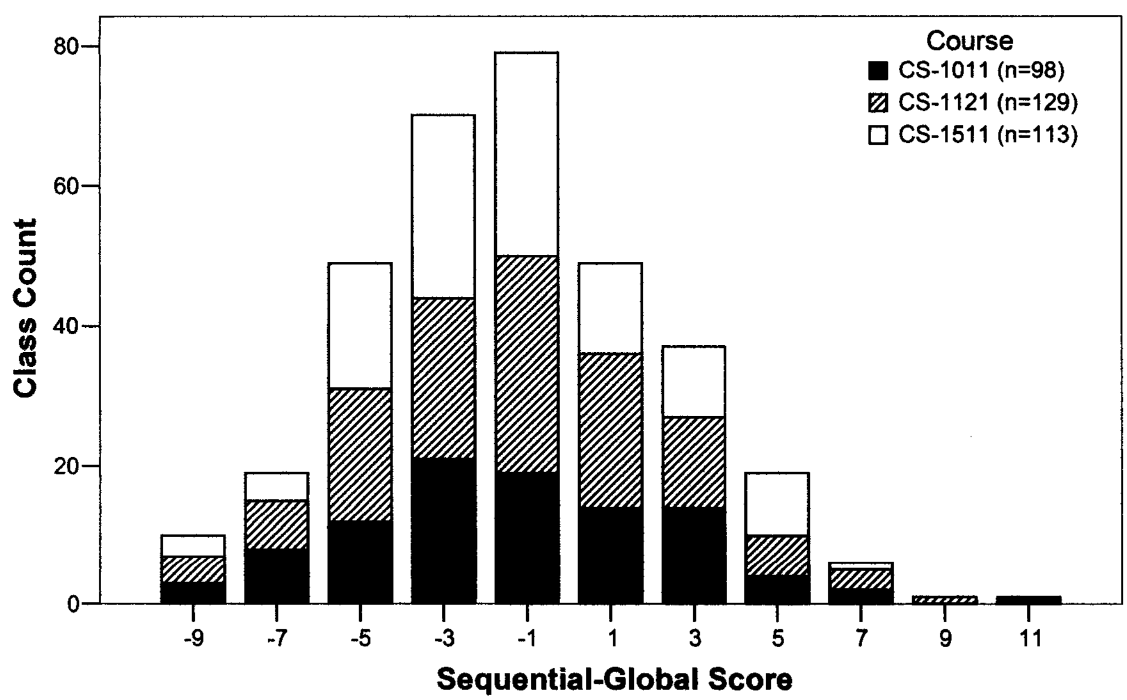

Figure 10. Distribution of sequential-global scores overall and by course.

4.2.2 Differences by Class

This section addresses the distribution of learning styles across the student population as a whole and within each class. T-tests were used to assess the differences between group means. Each set of classes was compared for differences using two-tailed t-tests of independent group means. Table 18 shows the results of comparisons between CS-1511 (Computer Science I) and CS-1121 (Visual Basic). Two sets of analyses were conducted, the first under the assumption of equal variance and the second assuming unequal variance. Differences between the two sets of results were minimal. The conservative assumption (unequal variances) is shown in Tables 18, 19 and 20.

Table 18. T-test Comparison of Group Means: CS-1511 and CS-1121

Scale	**Mean CS-1511**	**Mean CS-1121**	**t**	**Sig. (2-tailed)**
Active-reflective	-.70	-1.60	-1.602	.110
Sensing-intuitive	-.86	-2.04	-1.793	.074
Visual-verbal	-5.07	-5.88	-1.430	.154
Sequential-global	-1.39	-1.23	.345	.730

Results from Table 18 show that there is a statistically significant difference between the group means of these two classes at the $p < .10$ level in regard to the sensing-intuitive scale. The mean value for CS-1121 for this variable was -2.04 (n=129) as compared to the mean for CS-1511 of -.86 (n=113). A comparative histogram (Figure 11) is used to show the difference. The distribution for CS-1121 is skewed to the right while CS-1511 is roughly normal around the value -1.0. CS-1121 (Visual Basic) students scored significantly higher on the "Sensing" end of the spectrum, although this must be regarded as a weak relationship due to the p value > .05 (.074).

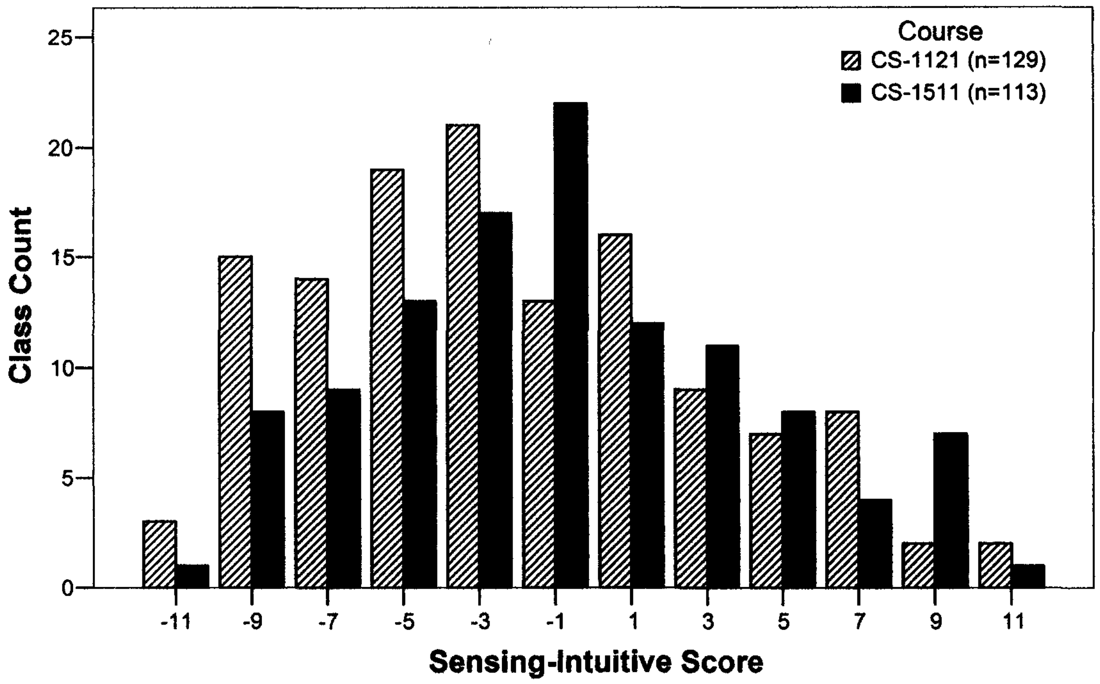

Figure 11. Comparison of CS-1211 and CS-1511 sensing-intuitive scores.

Table 19 shows the results of comparisons between CS-1011 (Intro to Computers) and CS-1121 (Visual Basic) using t-tests of independent sample means (assuming unequal variance).

Table 19. T-test Comparison of Group Means: CS-1011 and CS-1121

Scale	**Mean CS-1011**	**Mean CS-1121**	**t**	**Sig. (2-tailed)**
Active-reflective	-1.48	-1.60	.206	.837
Sensing-intuitive	-1.57	-2.04	.631	.529
Visual-verbal	-4.47	-5.88	2.253	.025
Sequential-global	-1.26	-1.23	-.060	.952

Results from Table 19 show that is a statistically significant difference between the group means of these two classes at the $p < .05$ cutoff. This causes us to reject the null hypothesis with regard to the visual-verbal scale for these classes. The mean value on this scale for CS-1011 was -4.47 (n=99) and for CS-1121 it was -5.88 (n=129). The indication is that CS-1121 (Visual Basic) learners are significantly more likely to be visual learners than students in CS-1011 (Intro to Computers). This relationship is evident in the histogram shown in Figure 12. The CS-1121 distribution shows a substantial peak in the high range of the visual scale while the CS-1011 distribution has a peak that is much less pronounced and an overall flatter distribution.

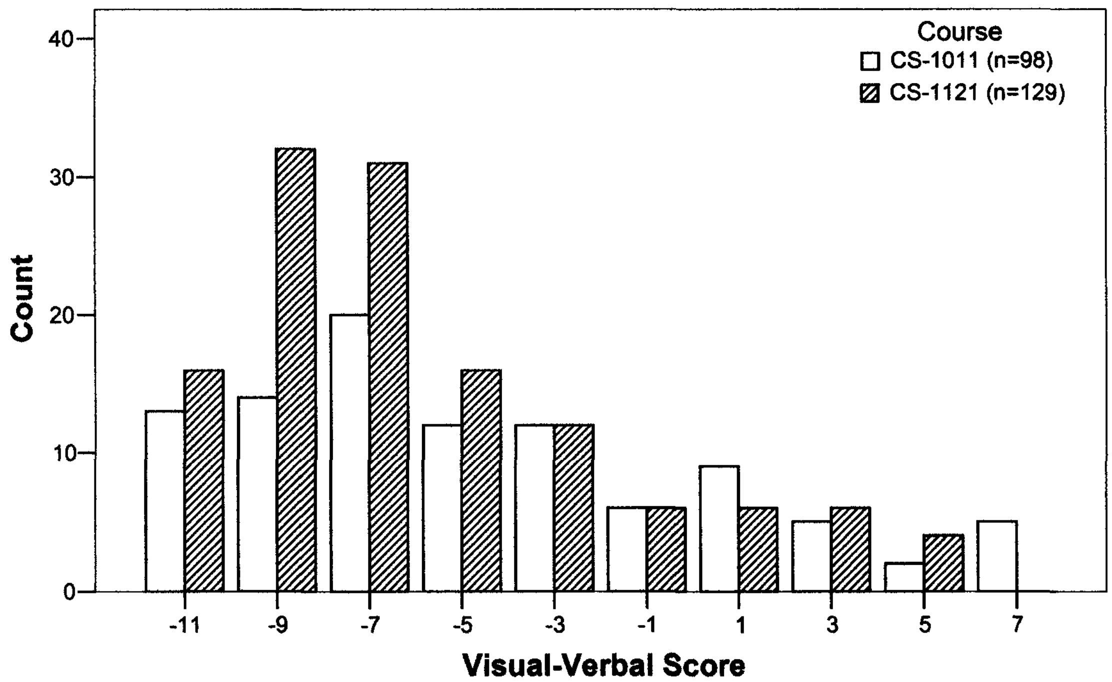

Figure 12. Comparison of CS-1011 and CS-1121 visual-verbal scores.

Table 20 shows the results of comparisons between the two remaining classes: CS-1011 (Intro to Computers) and CS-1511 (Computer Science I) using the same procedure of t-tests of independent sample means (assuming unequal variance). No statistically significant differences were found between these classes.

Table 20. T-test Comparison of Group Means: CS-1011 and CS-1511

Scale	Mean CS-1011	Mean CS-1511	t	Sig. (2-tailed)
Active-reflective	-1.48	-.70	-1.309	.192
Sensing-intuitive	-1.57	-.86	-.933	.352
Visual-verbal	-4.47	-5.07	.898	.370
Sequential-global	-1.26	-1.39	.252	.801

The retest results were also investigated using independent sample t-tests. The difference in the visual-verbal scores of CS-1011 and CS-1121 students was again significant at $p < .05$. In addition, a statistically significant difference ($P < .05$) between CS-1121 and CS-1511 was also noted on the visual-verbal variable.

4.2.3 Differences by Gender

Computer science is not a discipline that attracts a large proportion of women. This is true at UMD, at colleges and universities nationwide, and in the profession as a whole. Table 21 shows this situation as it exists in the courses under study. Female students made up only 11.3% of CS-1211 and 11.7% of CS-1511 while they accounted for 37.8% of the enrollment in CS-1011. The larger number in CS-1011 is explained by the fact that it is a service course and involves no programming. As such, it is taken by students in a variety of disciplines as a basic introduction to computer applications.

Table 21. Gender by Class

Gender * Course Crosstabulation

Count

		Course			Total
		CS-1011	CS-1121	CS-1511	
Gender	Male	61	110	98	269
	Female	37	14	13	64
Total		98	124	111	333

The distribution of males and females can be further understood if broken down by year in college (Table 22). Of the 33 women attending CS-1011 who reported their year in school, 19 (57.6%) were at the sophomore level while most of the women in the other classes were freshmen. This makes sense in relation to college major requirements. Women in science and engineering fields would be expected to take CS-1511 or CS-1121 early in their freshman year while women in other majors would not be required to have a computer science course as early.

Table 22. Gender by Class by Year

Gender * Year in College * Course Crosstabulation

Count

Course			Year in College				Total
			Freshman	Sophomore	Junior	Senior	
CS-1011	Gender	Male	12	27	13	4	56
		Female	7	19	7	0	33
	Total		19	46	20	4	89
CS-1121	Gender	Male	70	23	8	9	110
		Female	7	4	2	1	14
	Total		77	27	10	10	124
CS-1511	Gender	Male	73	13	6	3	95
		Female	7	3	3	0	13
	Total		80	16	9	3	108

Potential differences between the learning styles of men and women across these classes were assessed using independent sample t-tests. These are reported in Table 23. There were 269 male and 64 female respondents in each learning style category.

Table 23. Independent t-tests of Gender Differences and Learning Style

Scale	**Mean (Males)**	**Mean (Females)**	**t**	**Sig. (2-tailed)**
Active-reflective	-1.06	-2.03	1.624	.108
Sensing-intuitive	-1.38	-1.97	.748	.456
Visual-verbal	-5.54	-3.72	-2.757	.007
Sequential-global	-1.09	-2.03	1.818	.072

The difference between males and females is strongly significant $p < .007$ in the realm of the visual-verbal. Males were significantly more visually oriented than females, although it should be noted that the score among the females was still centered in the visual domain. In addition, the p-value for both the means of the sequential-global and active-reflective scales hovered close to $p = .10$. Only the sensing-intuitive scale could be said to be strongly unrelated to gender.

The difference between male and female means on the visual-verbal scale is shown in Figure 13. Differences between the female subpopulations (by class, year, etc.) were not examined with inferential statistics because of the small n in each category.

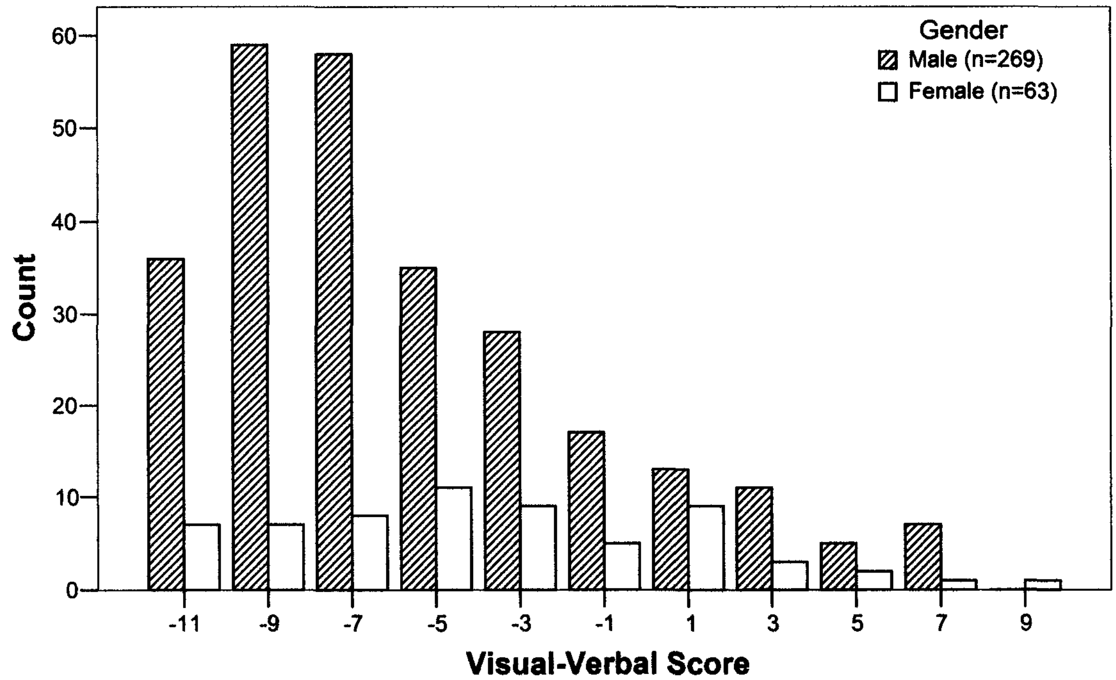

Figure 13. Comparison of the Visual-verbal Learning Styles Scale by Gender.

4.2.4 Differences by Major and College

Between the programming classes (CS-1121 and CS-1511) 28 declared fields of study were represented (27 plus "Undecided"). Of these, the largest groups were Mechanical Engineering (62), Computer Science/IS&T (33), Electrical and Computer Engineering (33) and Undecided (31). No other group major for more than 12 students. Subgroup comparisons were made focusing on the groups with the largest representation.

No statistically significant differences were detected between any of these majors using a $p < .05$ significance level cutoff for independent t-tests.

When the mean scores on each of the learning style scales were compared using the same method several statistically significant differences were found. These were covered in a previous section (Differences by Class).

Colleges were quite homogenous among CS-1511 and CS-1121, as would be expected from a required UMD College of Science and Engineering (CSE) course. CSE students in those two classes accounted for 210 of the 242 respondents (86.8%). In addition, there were 17 students from the Labovitz School of Business and Economics (LSBE), most enrolled in CS-1121. They accounted for another 7 percent of the total.

The lack of diversity in students by major in CS-1121 and CS-1511 is contrasted by the wide variety of students enrolled in CS-1011. That course had 99 students from 30 majors but apart from Undecided (28) and Pre-Business (14) no major had more than 6 students. Unfortunately, comparisons of students by collegiate unit was not possible since CSE students accounted for most of the freshmen and non-CSE students for most of the sophomores, confounding these two variables. The breakdown by college among CS-1011 students is shown in Table 24.

Table 24. Frequency Table of CS-1011 College Enrollment

UMD College	Frequency	Percent	Valid Percent	Cumulative Percent
CE	4	4.0	4.0	5.1
CEHSP	19	19.2	19.2	24.2
CLA	31	31.3	31.3	55.6
CSE	27	27.3	27.3	82.8
SBE	14	14.1	14.1	97.0
SFA	3	3.0	3.0	100.0
Total	99	100.0	100.0	

4.2.5 Differences by Year

The year of students in these courses varied. Table 25 reports the frequency of occurrence of each year over the study group as a whole and by course.

Table 25. Frequency Table of CS Class by Year in College

Count

		Year in College				Total
		Freshman	Sophomore	Junior	Senior	
Course	CS-1011	19	46	20	4	89
	CS-1121	79	28	11	11	129
	CS-1511	81	17	9	3	110
Total		179	91	40	18	328

The table underscores the nature of CS-1121 and CS-1511 as freshman-level courses. CS-1011 however had more than half of its students coming from sophomore ranks.

Independent t-tests of the differences between freshmen and sophomores disclosed a statistically significant difference ($p < .05$) in relation to the active-reflective scale (Table 26). Sophomores were decidedly more inclined to higher scores in the active learning domain than freshmen. Since most of the sophomores (50.5%) were from CS-1011 this relationship may be an artifact of differences between courses themselves and not students on the basis of their year in college.

Table 26. Independent t-tests of Learning Style Differences by Year in College.

Scale	Mean (Fresh)	Mean (Soph)	t	Sig. (2-tailed)
Active-reflective	-.98	-2.21	2.181	.031
Sensing-intuitive	-1.69	-1.29	-.585	.559
Visual-verbal	-5.38	-5.13	-.424	.672
Sequential-global	-1.22	-1.86	1.265	.208

4.3 Correlates with Outcome

4.3.1 Learning Styles and Total Point Percentages

Learning style correlations with student outcome (total points) were assessed using several methods. T-tests of group means were used after recoding learning styles into binary variables. For example, values -1 through -11 on the active-reflective scale were all categorized active. Similarly 1 through 11 on the active-reflective scale were all categorized reflective. Further subtlety in the relationship between learning style and outcome was captured in subsequent analyses by recoding the ILS scales in ordinal fashion. In that configuration each student's ILS scale value was assigned one of three values based on whether it was in the range (-5 through -11, 3 through -3 or 5 through 11). This yielded an ordinal ranking (i.e. Active-Mixed-Reflective) which could be used in conjunction with ordinal inferential statistics such as Chi-square. Both the nominal and ordinal data groupings were evaluated to determine whether relationships could be detected and what they might be.

The recoded nominal variables were first investigated using t-tests of independent group means. Results are shown in Table 27 for each learning style in each class and when combined.

Several statistically significant relationships ($p < .05$) may be seen in Table 27 including the active-reflective scale variables (reflective students did better than active learners) for all classes combined and within CS-1511 and the sequential-global scale (Sequential learners did better than global learners in CS-1121 and worse in CS-1511).

Table 27. Independent t-tests of Outcome Differences by Class.

All classes combined	**Mean**	**n**	**t**	**T Sig. (2-tailed)**
Active Reflective	72.41 77.75	201 133	-3.464	.001
Sensing Intuitive	74.94 73.76	219 115	.733	.464
Visual Verbal	74.49 74.80	286 48	-.141	.888
Sequential Global	74.46 74.69	224 110	-.144	.885
CS-1011	**Mean**	**n**	**t**	**T Sig. (2-tailed)**
Active Reflective	76.08 77.93	62 30	-.818	.415
Sensing Intuitive	76.55 77.00	64 28	-.196	.845
Visual Verbal	76.65 76.85	75 17	-.076	.940
Sequential Global	76.73 76.59	60 32	.065	.948
CS-1121	**Mean**	**n**	**t**	**T Sig. (2-tailed)**
Active Reflective	70.57 75.10	77 52	-1.823	.071
Sensing Intuitive	73.48 70.31	85 44	1.232	.224
Visual Verbal	72.18 73.97	113 16	-.481	.631
Sequential Global	74.19 69.11	85 45	1.980	.050
CS-1511	**Mean**	**n**	**t**	**T Sig. (2-tailed)**
Active Reflective	71.01 80.35	62 51	-3.126	.002
Sensing Intuitive	75.26 75.17	70 43	.026	.979
Visual Verbal	75.51 73.35	98 15	.473	.637
Sequential Global	73.06 80.47	80 33	-2.219	.029

Ordinal data categorizations were constructed for both the outcome scores (percentages) and the ILS variables. Student outcomes were grouped by percentiles (90-100%, 80-89%, 70-79%, 60-69% and below 60%). Learning style categories were also grouped into a negative extreme (-11 through -5), middle range (-3 through 3), and a positive extreme (5 through 11). Scales were characterized as Active-Mixed-Reflective, Sensing-Mixed-Intuitive, Visual-Mixed-Verbal, and Sequential-Mixed-Global. Crosstabulation tables of grade categories by learning style categories (5 rows by 3 columns) were computed and appropriate bivariate ordinal statistics computed. Chi-square (χ^2) was calculated for each table to determine the probability that the relationship could have come about by chance if the two variables were independent. Gamma (γ) was used to assess the magnitude and direction of these relationships.

Several significant relationships were detected which were unable to be assigned a magnitude or direction because of an overabundance of expected cell counts below five. In regard to the combined class data, the significant χ^2 value associated with the visual-verbal scale ($p = .035$) can be discounted because the distribution was so heavily visual that the combined n for all verbal categories was only 12, leaving expected cell counts less than five for 33% of the cells in the matrix and invalidating further analysis. Similarly, a relationship between the sequential-global scale and outcome was shown to exist for CS-1121. The trend was not significant however largely due to expected cell counts less than five for 53.3% of the matrix. In both cases further research could be pursued by aggregating the outcome data from five categories down to three or four.

The importance of Table 28 lies in the identification of statistically significant ordinal relationships ($p < .05$) between learning style and outcome. By reclassifying the learning style continua in a way that does not force middle values to identify with either extreme the approach accommodates the fact that many students have mixed learning aptitudes. This gives a better picture of the relationship based on a separate accounting of these mixed strategies.

Table 28. Ordinal Relationships (Chi-square (χ^2)and gamma (γ)values

All Groups	χ^2 **value**	**df**	χ^2 **sig.**	γ	γ **sig.**
Active-reflective	28.11	8	.000	-.380	.000
Sensing-intuitive	11.77	8	.162	-.064	.345
Visual-verbal	16.60	8	.035	-.136	.113
Sequential-global	13.75	8	.089	-.120	.162
CS-1011	χ^2 **value**	**df**	χ^2 **sig.**	γ	γ **sig.**
Active-reflective	10.15	8	.254	-.245	.075
Sensing-intuitive	3.99	8	.870	.018	.883
Visual-verbal	7.22	8	.513	.012	.941
Sequential-global	6.34	8	.609	-.024	.878
CS-1121	χ^2 **value**	**df**	χ^2 **sig.**	γ	γ **sig.**
Active-reflective	14.86	8	.062	-.376	.001
Sensing-intuitive	5.89	8	.659	-.080	.473
Visual-verbal	13.49	8	.096	-.208	.182
Sequential-global	16.43	8	.037	.002	.988
CS-1511	χ^2 **value**	**df**	χ^2 **sig.**	γ	γ **sig.**
Active-reflective	25.69	8	.001	-.473	.000
Sensing-intuitive	5.44	8	.709	-.076	.497
Visual-verbal	5.60	8	.691	-.102	.463
Sequential-global	13.73	8	.089	-.279	.046

From this perspective, the picture changes somewhat in relation to previous discussion based only on binary categorizations. Statistically significant relationships ($p < .05$ for both χ^2 and γ) are shown to exist overall between outcome active-reflective learning. The trend is in a negative direction indicating that students with reflective classifications performed better than those with active classifications. Much of the strength of this relationship may derive from the CS-1511 component. This class was strongly significant ($p = .001$) in the χ^2 analysis and had a strong, negatively trending gamma value (-.473, $p = .000$) indicative of the correspondence between reflective learning and performance.

These relationships are shown in Figures 14 and 15. Both figures display the distribution of outcome scores within each of the raw value ILS score categories on the active-reflective scale. The trend is seen most easily in Figure 14 (CS-1511) where scores can be seen fanning out across the upper left diagonal. The narrowest region (upper right) corresponds to high reflective ILS scores and strong course outcomes.

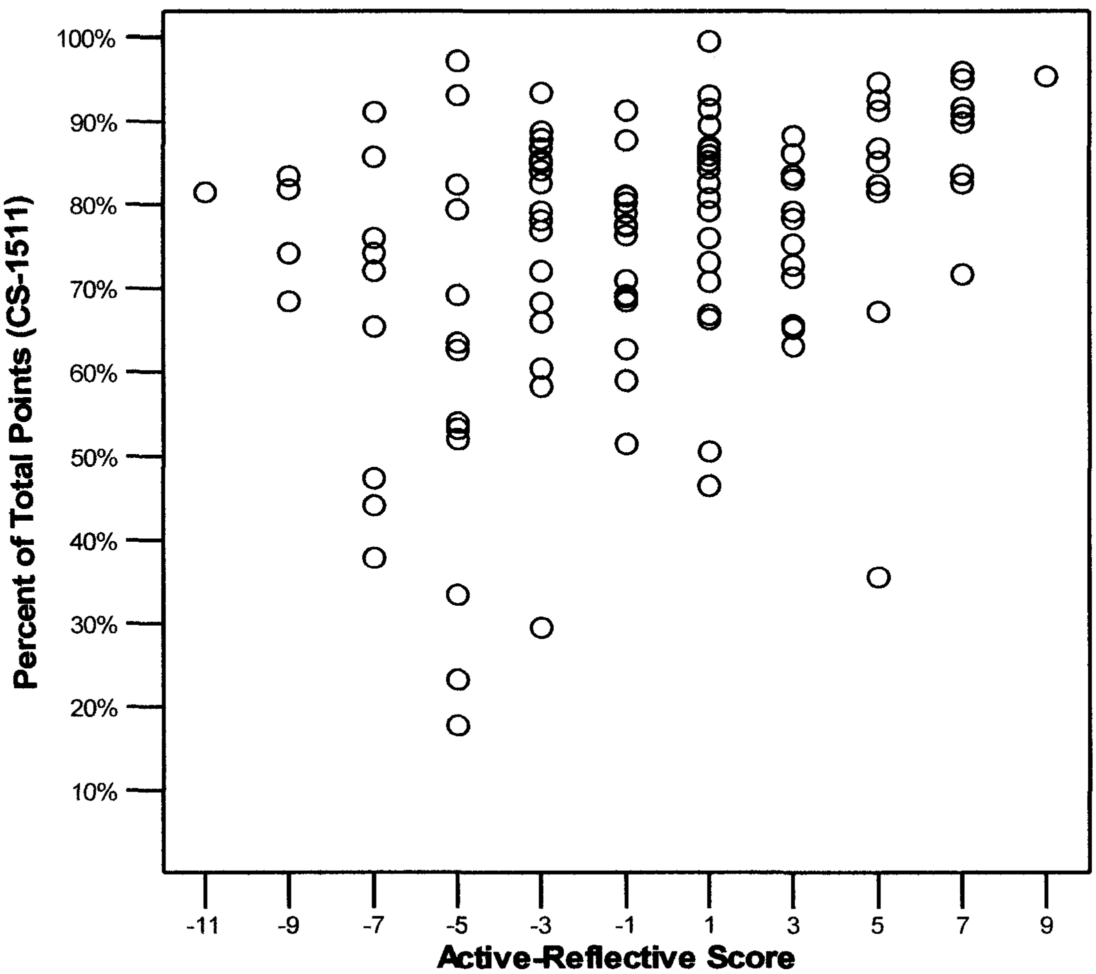

Figure 14. Distribution of CS-1511 outcomes in the active-reflective scale (n=113).

The diagonal trend, roughly from upper right to lower left is indicative of poorer and poorer performance by students with increasingly higher scores on the active learning continuum. This trend is also evident across the distribution of all classes combined (Figure 15).

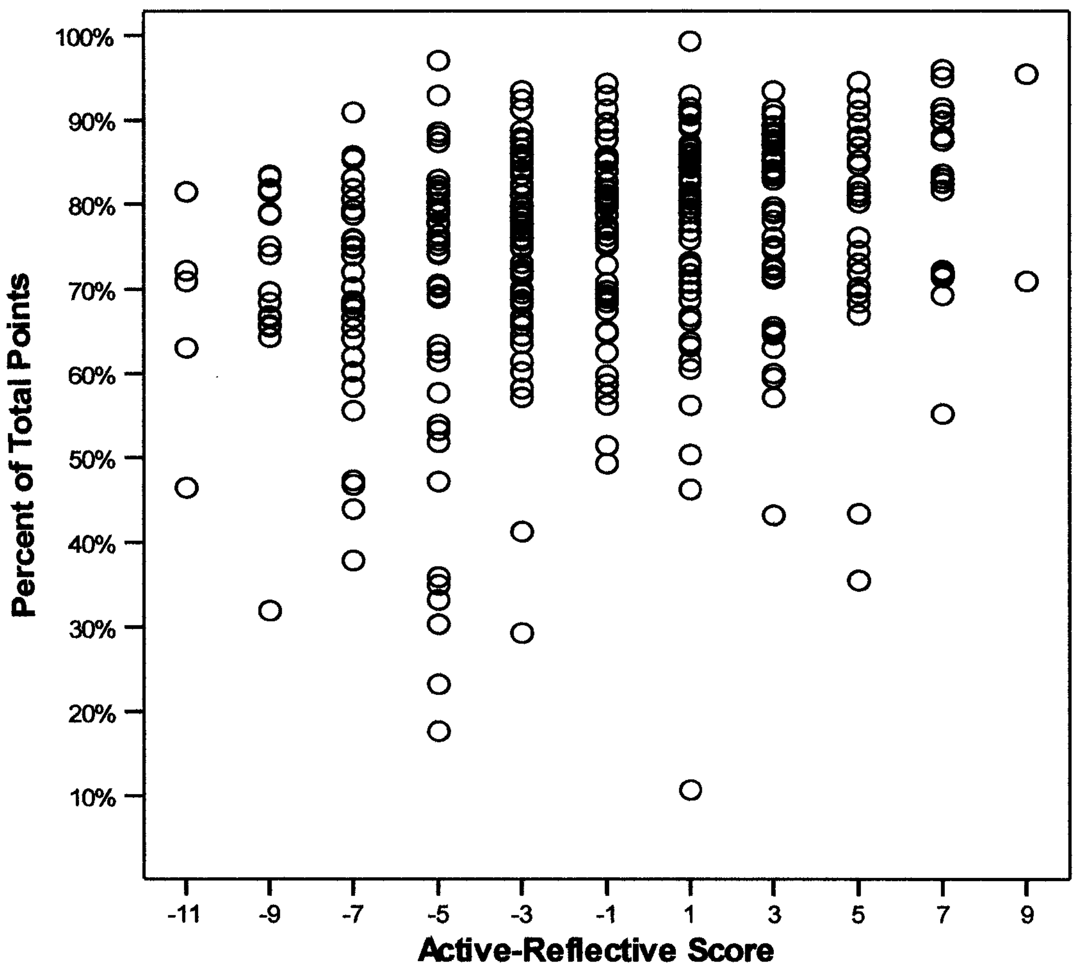

Figure 15. Distribution of combined outcomes for active-reflective scale (n=340).

In this case, the triangular distribution in the upper left portion of the diagram is still present, although the diagonal trend is more easily detected by following the densest dot clusters from one level to another. It can also be viewed as declining medians (Figure 16). This figure depicts the distribution of scores within each of the active-reflective categories using box and whiskers charts. The median value is represented by the heavy solid black line in the each box. The boxes, indicate the interquartile range (IR). "Whiskers", extend outward from both ends of the up to 1.5 times the IR. Outliers beyond this are marked with a circle. Extreme outliers are marked with an asterisk (*).

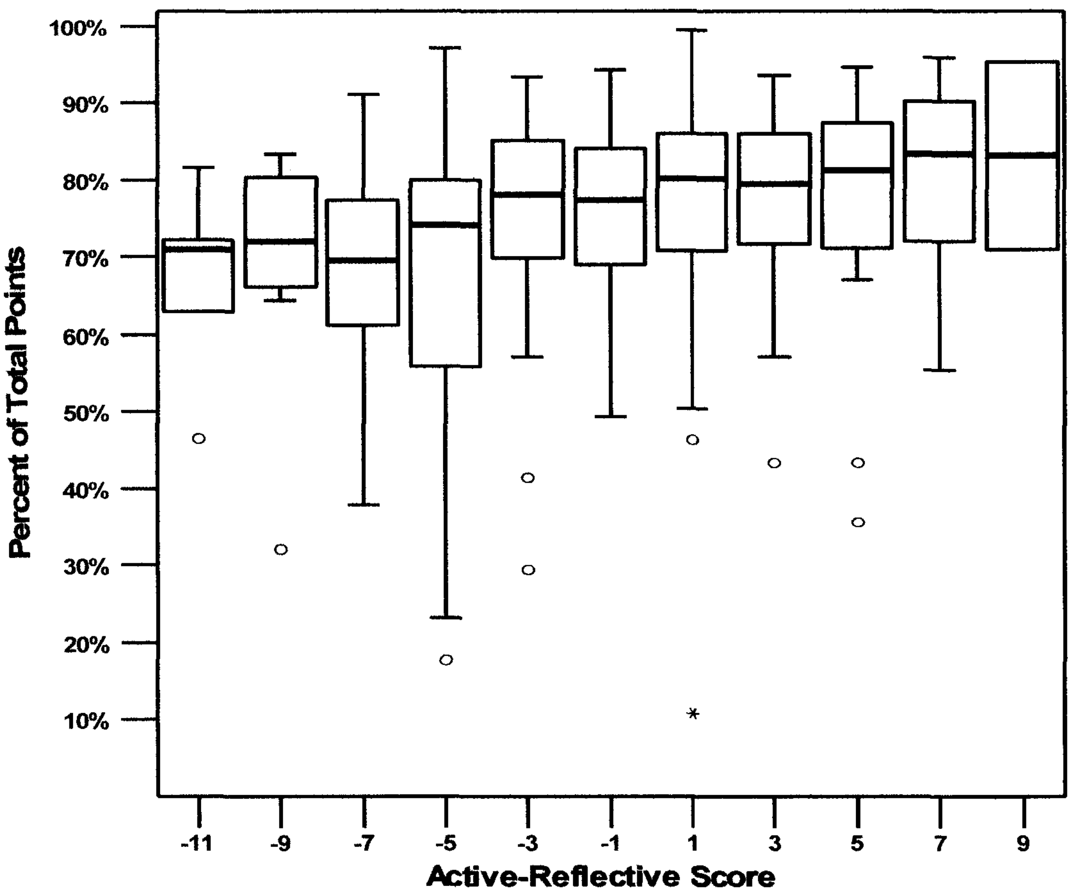

Figure 16. Median outcome trend for the active-reflective scale, all classes (n=340).

4.3.2 Learning Styles and Completion Groups (DFW/ABC)

A particular focus of this research is on student at risk of failure. This group has been identified earlier in discussion of the DFW rate. Almost one third of students taking CS-1011, CS-1121 and CS-1511 received a D or an F This group can be defined as those with a total point percentage below 60%.

Table 29. Outcome Differences by Completion Group (ABC vs DFW)

All classes combined	**mean**	**n**	**t**	**t sig. (2-tailed)**
Active Reflective	-.67 -2.83	210 92	4.006	.000
Sensing Intuitive	-1.52 -1.67	210 92	.223	.824
Visual Verbal	-5.00 -5.78	210 92	1.395	.164
Sequential Global	-1.32 -1.43	210 92	.248	.804
CS-1011	**mean**	**n**	**t**	**t sig. (2-tailed)**
Active Reflective	-1.50 -2.18	64 17	.565	.574
Sensing Intuitive	-1.81 -2.06	64 17	.154	.878
Visual Verbal	-4.53 -4.65	64 17	.086	.932
Sequential Global	-1.53 -.76	64 17	-.743	.460
CS-1121	**mean**	**n**	**t**	**t sig. (2-tailed)**
Active Reflective	-.56 -3.47	73 43	3.584	.000
Sensing Intuitive	-1.93 -2.16	73 43	.229	.819
Visual Verbal	-5.27 -6.95	73 43	2.200	.030
Sequential Global	-1.49 -.95	73 43	-.776	.439
CS-1511	**mean**	**n**	**t**	**t sig. (2-tailed)**
Active Reflective	-.04 -2.31	73 32	2.478	.015
Sensing Intuitive	-.86 -.81	73 32	-.046	.963
Visual Verbal	-5.14 -4.81	73 32	-.334	.739
Sequential Global	-.97 -2.44	73 32	2.054	.043

This is a substantial proportion of each class and is adequate for most statistical procedures. Student percentages were recoded into two groups, those with 60% or higher (ABC group) and those with less than 60% of the total points (DFW group). Using these divisions, t-tests were performed on the two groups to assess the degree to which they differed by learning style. This was done for each class and for all classes combined. The results are shown in Table 29.

This analysis indicates that several significant relationships exist such that particular learning styles are more characteristic of the DFW group than the ABC group. DFW students are more likely overall, in CS-1121 and in CS-1511 to be active learners ($p < .05$). In CS-1121 they are also likely to be visual learners ($p < .05$). This finding may be important for consideration when formulating course materials and content delivery methodologies.

4.3.3 Regression Model

A valuable secondary data source (admissions data) was obtained from UMD Administration through permission from the Academic Dean of the College of Science and Engineering. These data included high school rank, high school percentage, class size, ACT scores (Composite, Math and English), math placement exam scores and other indicators. These data were available for all incoming freshmen enrolled in CS-1121 and CS-1151. Data were present for 84 males and five females.

Stepwise multiple regression analysis was conducted with the percentage of total points as the dependent variable and admissions data and Soloman-Felder ILS scores as independent variables. Step criteria for inclusion or removal of a variable from the model were based on a probability of F to enter the regression equation of 0.05 and an F probability to remove of 0.10. The five female students were excluded from the analysis to control for gender. Only two models were generated. The first consisted of the active-reflective scale as the sole correlate. The second was able to include the students' ACT composite score as well. No other models were possible given the stepwise inclusion criteria. A summary of these regression models is shown in Table 30.

Table 30. Regression Model Summary

Model	R	Adjusted R Square		Std. Error of the Estimate
	Gender = Male (Selected)			
1	.375(a)	.140	.129	13.774397%
2	.447(b)	.200	.179	13.378037%

a Predictors: (Constant), Active-reflective

b Predictors: (Constant), Active-reflective, ACT Comprehensive

Table 30 suggests that there is still much to be explained about the causes of variation in total point percentages. However, these two variables (active-reflective learning style and ACT combined score) together account for 20% of the variation in student scores, with learning style being the most important factor.

Chapter 5

DISCUSSION

5.1 Validation of Hypothesis 1: Instrument Reliability

The hypotheses advanced in this study to test the reliability of the Soloman-Felder ILS were:

H_1: The Soloman-Felder ILS reliably assesses learning styles.

$H_{1.1}$: There are no differences in test/retest results..

$H_{1.2}$: Continua components are associated as expected.

$H_{1.3}$: Continua are internally consistent (for each ILS scale).

The claims embodied in each hypothesis were tested using varieties of test/retest comparison and internal question correlation analysis. Each method explores a different dimension of instrument reliability. The test/retest comparison ($H_{1.1}$) was performed using both regression analysis and t-tests. The internal question examination ($H_{1.2}$) was conducted using Cronbach's alpha, as an overall assessment of category component association and then factor analysis to examine the extent to which learning style indicators grouped as expected ($H_{1.3}$).

With respect to $H_{1.1}$, test/retest correlations were similar to those achieved in other studies (Felder and Spurlin, 2005) and were fairly high (mainly in the .60-.79 range categorized as evidence of a "strong relationship" by Ellis (1994). There was one area of concern however. The sequential-global scale correlated at .497 overall and approximately the same for each class. This "moderate" level of correlation (Ellis, 1994) may indicate this learning style category is weak and does not discriminate well, as currently implemented, in the ILS. Although the hypothesis seems to hold for the first three ILS scales the evidence is weakest in the Sequential-global category. Felder and Spurlin (2005) accept this level of correlation as evidence of a high level of reliability despite the relatively low r value.

The examination of internal variable consistency using Cronbach's alpha that was carried out in reference to $H_{1.2}$ produced similar findings. There is disagreement about the interpretation of this statistic. Strong relationships are those above a value of .70 as used by Santos (1999). Elsewhere, .80 is common (UCLA, 2005) while Felder and Spurlin (2005) believe that a value as low as .50 is acceptable given the subjective nature of the data. Table 29 summarizes the Cronbach's alpha scores for all classes combined, as well as for each class individually over the four learning style categories. It provides a strikingly consistent interpretation of internal question consistency for each learning style scale. Although none approach the .80 level the sensing-intuitive (SEN-INT) and visual-verbal (VIS-VRB) scales are fairly close, hovering around .70. The active-reflective scale (ACT-REF) is weaker and the Sequential-global scale is weak enough to cast serious doubt on the validity of the hypothesis.

Table 31. Cronbach's Alpha by Learning Style and Class

Group	ACT-REF	SEN-INT	VIS-VRB	SEQ-GLO
All	.526	.717	.696	.293
CS-1011	.517	.782	.748	.373
CS-1121	.540	.699	.648	.307
CS-1511	.515	.661	.688	.197

The internal question consistency was further investigated in the context of $H_{1.3}$. In this case, factor analysis revealed that the sequential-global and visual-verbal scales were in fact strongly correlated within themselves. Only one out of the eleven variables comprising each scale was assigned to a group apart from those it really belonged to. This was not the case with the active-reflective or sequential-global components. Although the active-reflective, and many sequential-global variables could be construed to group to a single factor on the basis of their primary or secondary associations several sequential-global variables were poorly associated with any of the factor groups. The specific questions displaying a lack of correlation with any group were questions 4, 28 and 32 (shown as excerpted from the Soloman-Felder ILS, Appendix A).

4. I tend to
***(a)** understand details of a subject but may be fuzzy about its overall structure.*
***(b)** understand the overall structure but may be fuzzy about details.*

28. When considering a body of information, I am more likely to
***(a)** focus on details and miss the big picture.*
***(b)** try to understand the big picture before getting into the details.*

32. When writing a paper, I am more likely to
***(a)** work on (think about or write) the beginning of the paper and progress forward.*
***(b)** work on (think about or write) different parts of the paper and then order them.*

These questions have an ambiguity level that seems to defeat consistent response. All of them are intended to be indicators of the sequential-global scale but questions 4 and 28 draw response patterns similar to active-reflective questions. Question 32 is similar to response patterns for sensing-intuitive questions. These relationships are very weak however. This may be an area for further psychometric research on the Soloman-Felder ILS.

Felder and Spurlin (2005) readily acknowledge that there may be crossover between the sequential-global classification and other groups, especially the sensing-intuitive. This is because global learners are, by definition, non-linear. They use a more intuitive means to navigate problem spaces, hence the cross-over with sensing-intuitive scales (question 32). However, they also believe that the active-reflective scale is truly orthogonal to the others and should not correlate with them. This was not the case in this research. It was the active-reflective and sequential-global dimensions that had the most trouble differentiating themselves.

5.2 Validation of Hypothesis 2: Learning Style Distribution

The hypotheses advanced in this study to determine whether there were differences in learning style among introductory computer science students at UMD were:

H_2: There are no differences between learning style distributions across sample subpopulations.

$H_{2.1}$: Learning styles are the same across CS classes.

$H_{2.2}$: Learning styles are the same across gender subgroups.

$H_{2.3}$: Learning styles are the same across college majors.

$H_{2.4}$: Learning styles are the same across college year.

Hypothesis $H_{2.1}$ cannot be rejected in most cases. The only strong instance of rejection occurred when comparing CS-1121 students with those in CS-1011. The CS-1121 students were significantly more visually oriented. The reasons for this may vary. It is tempting to suggest that the relationship may be the result of there being more women in CS-1011 or more upper division students. However, these variables did not prove significant in relation to CS-1511. CS-1121 students have an extreme visual orientation. A question for further research may be the extent to which visual learning styles uniquely characterize mechanical, chemical and industrial engineering students, who made up almost two-thirds of this class.

The second sub hypothesis ($H_{2.2}$) can be rejected in one case and may, upon further study, be found to be rejected most of the time. Male students were found to be significantly more visually oriented. Evidence for differences on two other learning style scales was also present, although weak. Considering the absence of women from this discipline, it may be important to follow up on these findings. There is considerable room for further study.

The third sub-hypothesis ($H_{2.3}$) was unable to be rejected in relation to computer science, electrical engineering, mechanical engineering and undecided majors in the College of Science and Engineering. There is not significant evidence to conclude that the learning styles profiles of these groups differ.

The fourth sub-hypothesis ($H_{2.4}$) also failed to be rejected. This time however it was because of the presence of a confounding variable (course). Year-in-college was not uniformly distributed among the courses and differences in it can be attributed to differences in course constituency.

5.3 Validation of Hypothesis 3: Correlations with Outcome

The hypotheses related to correlations with outcome are:

H_3: Learning styles are unrelated to course outcome subgroups.

$H_{3.1}$: Learning styles are unrelated to total point percentages.

$H_{3.2}$: Learning styles are unrelated to (DFW, ABC) completion groups.

$H_{3.3}$: Learning styles do not account for total point variability.

The first sub-hypothesis ($H_{3.1}$) failed to be rejected most of the time in relation to each of the classes and to the combined group as a whole. However, there were several instances in which the hypothesis was rejected. Tests of group means revealed that reflective students outperformed active learners overall and within CS-1511. These relationships were also significant when ordinal classification was imposed on the data and agrees with findings by others (Chamillard and Karolick, 1999; Thomas and Radcliffe, 2002).

When students were classified into groups based on DFW status the hypothesis of no relationship was rejected for CS-1121 and CS-1511 in relation to the active-reflective learning style. Students who fared poorly in these classes were significantly more likely to be active learners. The hypothesis was also rejected for CS-1121 in relation to the visual-verbal scale with DFW students more highly visual in their learning preference.

The third hypothesis was examined using stepwise multiple regression by constructing the multivariate model with the highest degree of explanatory power. It was determined that a regression equation in which two variables (active-reflective learning style and ACT composite score) were present was the best model. It accounted for 20% of the variability in percentage of total points. The hypothesis is rejected on the basis of the modest success of the derived linear model.

5.4 Implications

The three primary hypotheses were:

H_1: The Soloman-Felder ILS reliably assesses learning styles.

H_2: There are no differences between learning style distributions.

H_3: Learning styles are unrelated to course outcome subgroups.

Examination of the results from the testing processes used for each of these hypotheses has shown that the first hypothesis is only partially substantiated and that there exists room for improvement of the instrument in the UMD test case. The sequential-global scale is the weakest and problems with it can be trace to the unreliability of responses to three specific questions. This could be addressed through the adaptation of the sequential-global scale to specific disciplines. This would be appropriate given Felder and Spurlins' (2005) contention that this scale may be more fundamental than the others. Leaving the others as they are and developing a set of sequential-global questions specifically related to computer science could increase the orthogonality of the measure. Perhaps just replacing the three dubious questions with more discipline-focused ones would alone be enough to resurrect the usefulness of this measure. For example, asking questions like these would be very relevant to computer science:

1. I prefer to
(a) develop my programs from scratch.
(b) modify existing programs until they do what I want them to.

2. I prefer to
(a) develop an algorithm and test it before writing code.
(b) start writing code immediately and test it later through debugging.

3. I prefer to
(a) complete my project one function at a time.
(b) work on the whole project simultaneously.

4. I prefer to have the instructor
(a) tell us what to do step-by-step.
(b) present us with a general problem to solve.

The second hypothesis was rejected in specific instances. The most concerning of these are gender-based differences that are an endemic problem in the discipline as a whole. This research indicates that there are significant areas of difference between these groups starting with the visual verbal but also potentially including the sequential-global and active-reflective scales. Women tended to be less visually oriented, more sequential and active. Active learning is often associated with group activity. Computer science courses traditionally have virtually no group work at the introductory level because of the need for each student to internalize programming skills as a prerequisite for advancement to higher level courses. Group assignments often end up being dominated by the most ambitious programmer and as a result other group members do not sufficiently wrestle with the programming process. However, the early formation of study groups, paired programming, course management teams, and group activities in discussion sections could provide a foundation in which active learners would engage in the course material. These are not widely used in computer science at this level, although there are many instances of their success in other science disciplines (Ebert-May et al. 2004, Smith, K. 2000).

The third hypothesis was rejected in the case of active learners. This was true for each sub-hypothesis. Overall, active learners had poorer course outcomes and were more likely to receive a DF or W grade. Similarly, the best linear regression model identified only the active-reflective relationship and the relationship to ACT Composite scores as significantly contributing to the predictive power of the equation.

We have seen that active learning may be a gender issue. The third hypothesis expands this awareness to a retention issue. Perhaps the single most important modification that computer science courses can make is to provide more opportunities for active learning in group settings.

5.5 Conclusions

This research underscores more than the need for active learning and improved measures of learning style assessment. The most important findings are the broader issues:

- learning style differences exist in introductory computer science courses.
- these differences can be shown to affect performance
- these differences can be shown to affect retention
- these differences may put female students at risk

This study began with a discussion of retention issues. The use of tools such as the Soloman-Felder ILS allows faculty members to quickly and easily identify specific course deficiencies that may be tied to retention. It does so in a manner that can be understood by students, faculty and administrators alike.

The general linear model advanced earlier (Figure 2) can now be better understood. The two most significant contributors linked to the DFW rate (and hence retention issues) have been identified (ACT Composite score, and active-reflective learning style). Gender is also linked to learning style.

The research suggests that the path to better course and program outcomes starts with the standardized assessment of student academic preparation (such as ACT Composite scores). It then proceeds to introductory coursework tailored to active learning needs. The active learning component should address students most at risk and has the additional benefit of fostering an instructional climate more compatible to the preferences of female students.

Computer science is a discipline that can provide students with extraordinary experiences. They can create mind-like software entities and endow them with whatever properties and capabilities the programmer can imagine. These applications can be trained for specific tasks or allowed to evolve as they store experiences and use them to modify later behavior. Failure to convey the wonder of the discipline in the midst of explaining its mechanics is perhaps the greatest challenge all science and engineering instructors face. Too often, introductory computer science courses move in a forced march through the curriculum from one set of content objectives to the next without time for reflective interludes or experimentation.

The provision of engaging and efficient, active-learning techniques is essential but rarely found in computer science teaching at the introductory level. Truly authentic assessment is likewise difficult to achieve. The natural continuation of this research is to fit instructional tools and techniques to areas that are unexciting, and to draw out of them approaches that engage students in the wonder of the course material. It also extends to assessment methods that measure knowledge through active performance.

From the administrative point of view, this study underscores the need to identify learning style and relate it to course outcomes to help pinpoint course-design problem areas. In addition, it implies the need for introductory course instructional staff to be well-grounded in active learning and assessment techniques for their disciplines. These techniques are well-developed in the social sciences and across the curriculum for small classes. They need to be better developed for large science classes. In addition, the support of instructional research leading to practical applications is necessary in almost every science and engineering field.

Learning style is only one aspect of student learning. It appears to be important, along with other factors, in accounting for some of the variability in outcomes among students in their first computer science courses. Much of the variability remains to be explained however. Felder and Brent (2005) have identified directions for future research in this area as it pertains specifically to science and engineering students. They suggest that student learning style diversity teams with study orientation and the intellectual development process to affect outcomes. Data pertinent to these areas is already being gathered from computer science students at UMD and will be linked to the results of this study in future research.

This study has shown that learning style assessment helps explain why students are and are not successful in computer science education and demonstrates how it can be used to identify students at most risk. Further, it suggests a direction for instructional planning and assessment (active-learning) that is most likely to be productive in building effective introductory courses and minimize the potential for withdrawal or failure. Given the importance of computer science for all science and engineering majors as a required, "gateway" course, modification of introductory courses to make them more engaging should lead to higher success rates, improved self-efficacy, better academic integration, and higher retention in a variety of science and engineering courses.

APPENDICES

Appendix A. The Soloman-Felder Index of Learning Styles

1. The Soloman-Felder Index of Learning Styles Questionnaire
http://www.engr.ncsu.edu/learningstyles/ilsweb.html

NC STATE UNIVERSITY

Index of Learning Styles Questionnaire

Barbara A. Soloman
First-Year College
North Carolina State University
Raleigh, North Carolina 27695
Richard M. Felder
Department of Chemical Engineering
North Carolina State University
Raleigh, NC 27695-7905

For each of the 44 questions below select either "a" or "b" to indicate your answer. Please choose only one answer for each question. If both "a" and "b" seem to apply to you, choose the one that applies more frequently.

1. I understand something better after I
   (a) try it out.
   (b) think it through.
2. I would rather be considered
   (a) realistic.
   (b) innovative.
3. When I think about what I did yesterday, I am most likely to get
   (a) a picture.
   (b) words.
4. I tend to
   (a) understand details of a subject but may be fuzzy about its overall structure.
   (b) understand the overall structure but may be fuzzy about details.
5. When I am learning something new, it helps me to
   (a) talk about it.
   (b) think about it.
6. If I were a teacher, I would rather teach a course
   (a) that deals with facts and real life situations.
   (b) that deals with ideas and theories.

7. I prefer to get new information in
   (a) pictures, diagrams, graphs, or maps.
   (b) written directions or verbal information.
8. Once I understand
   (a) all the parts, I understand the whole thing.
   (b) the whole thing, I see how the parts fit.
9. In a study group working on difficult material, I am more likely to
   (a) jump in and contribute ideas.
   (b) sit back and listen.
10. I find it easier
    (a) to learn facts.
    (b) to learn concepts.
11. In a book with lots of pictures and charts, I am likely to
    (a) look over the pictures and charts carefully.
    (b) focus on the written text.
12. When I solve math problems
    (a) I usually work my way to the solutions one step at a time.
    (b) I often just see the solutions but then have to struggle to figure out the steps to get to them.
13. In classes I have taken
    (a) I have usually gotten to know many of the students.
    (b) I have rarely gotten to know many of the students.
14. In reading nonfiction, I prefer
    (a) something that teaches me new facts or tells me how to do something.
    (b) something that gives me new ideas to think about.
15. I like teachers
    (a) who put a lot of diagrams on the board.
    (b) who spend a lot of time explaining.
16. When I'm analyzing a story or a novel
    (a) I think of the incidents and try to put them together to figure out the themes.
    (b) I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.
17. When I start a homework problem, I am more likely to
    (a) start working on the solution immediately.
    (b) try to fully understand the problem first.
18. I prefer the idea of
    (a) certainty.
    (b) theory.
19. I remember best
    (a) what I see.
    (b) what I hear.
20. It is more important to me that an instructor
    (a) lay out the material in clear sequential steps.
    (b) give me an overall picture and relate the material to other subjects.

21. I prefer to study
    (a) in a study group.
    (b) alone.
22. I am more likely to be considered
    (a) careful about the details of my work.
    (b) creative about how to do my work.
23. When I get directions to a new place, I prefer
    (a) a map.
    (b) written instructions.
24. I learn
    (a) at a fairly regular pace. If I study hard, I'll "get it."
    (b) in fits and starts. I'll be totally confused and then suddenly it all "clicks."
25. I would rather first
    (a) try things out.
    (b) think about how I'm going to do it.
26. When I am reading for enjoyment, I like writers to
    (a) clearly say what they mean.
    (b) say things in creative, interesting ways.
27. When I see a diagram or sketch in class, I am most likely to remember
    (a) the picture.
    (b) what the instructor said about it.
28. When considering a body of information, I am more likely to
    (a) focus on details and miss the big picture.
    (b) try to understand the big picture before getting into the details.
29. I more easily remember
    (a) something I have done.
    (b) something I have thought a lot about.
30. When I have to perform a task, I prefer to
    (a) master one way of doing it.
    (b) come up with new ways of doing it.
31. When someone is showing me data, I prefer
    (a) charts or graphs.
    (b) text summarizing the results.
32. When writing a paper, I am more likely to
    (a) work on (think about or write) the beginning of the paper and progress forward.
    (b) work on (think about or write) different parts of the paper and then order them.
33. When I have to work on a group project, I first want to
    (a) have "group brainstorming" where everyone contributes ideas.
    (b) brainstorm individually and then come together as a group to compare ideas.
34. I consider it higher praise to call someone
    (a) sensible.
    (b) imaginative.

35. When I meet people at a party, I am more likely to remember
    (a) what they looked like.
    (b) what they said about themselves.
36. When I am learning a new subject, I prefer to
    (a) stay focused on that subject, learning as much about it as I can.
    (b) try to make connections between that subject and related subjects.
37. I am more likely to be considered
    (a) outgoing.
    (b) reserved.
38. I prefer courses that emphasize
    (a) concrete material (facts, data).
    (b) abstract material (concepts, theories).
39. For entertainment, I would rather
    (a) watch television.
    (b) read a book.
40. Some teachers start lectures with an outline of what they will cover. Such outlines are
    (a) somewhat helpful to me.
    (b) very helpful to me.
41. The idea of doing homework in groups, with one grade for the entire group,
    (a) appeals to me.
    (b) does not appeal to me.
42. When I am doing long calculations,
    (a) I tend to repeat all my steps and check my work carefully.
    (b) I find checking my work tiresome and have to force myself to do it.
43. I tend to picture places I have been
    (a) easily and fairly accurately.
    (b) with difficulty and without much detail.
44. When solving problems in a group, I would be more likely to
    (a) think of the steps in the solution process.
    (b) think of possible consequences or applications of the solution in a wide range of areas.

Appendix B. The IRB-Approved Consent Form

Consent Form

Learning Styles and Success in Introductory Computer Science

You are invited to be in a research study of the relationship between learning style and student success in introductory computer science courses. You were selected as a possible participant because you are enrolled in this course. We ask that you read this form and ask any questions you may have before agreeing to be in the study.

This study is being conducted by: James Allert, Instructor, Department of Computer Science, UMD

Background Information

The purpose of this study is: to determine whether learning style is related to student achievement.

Procedures:
If you agree to be in this study, we would ask you to complete the Soloman-Felder learning styles survey.

Risks and Benefits of being in the Study

The study has no identifiable risks. It does however offer you the benefit of identifying your learning style and using this information to study more effectively and efficiently for your classes.

Compensation:
You will receive no compensation for being involved in the study.

Confidentiality:
No information that can identify you were kept in the research database. The records of this study were kept private. In any sort of report we might publish, we will not include any information that will make it possible to identify a subject. Research records were stored securely and only researchers will have access to the records.

Voluntary Nature of the Study:
Participation in this study is voluntary. Your decision whether or not to participate will not affect your current or future relations with the University of Minnesota. If you decide to participate, you are free to not answer any question or withdraw at any time with out affecting those relationships.

Contacts and Questions:
The researchers conducting this study is: James Allert. You may ask any questions you have now. If you have questions later, **you are encouraged** to contact him at HH-324, 726-7194, jallert@d.umn.edu.

If you have any questions or concerns regarding this study and would like to talk to someone other than the researcher(s), **you are encouraged** to contact the Research Subjects' Advocate Line, D528 Mayo, 420 Delaware St. Southeast, Minneapolis, Minnesota 55455; (612) 625-1650.

You were given a copy of this information to keep for your records.

Statement of Consent:
I have read the above information. I have asked questions and have received answers. I consent to participate in the study.

Signature:____ Date: __________________

Signature of Investigator:_____________________________ Date: __________________

GLOSSARY

Accomodator. Kolb LSI classification category (Kolb, 1984). This term is used to describe a learner who prefers reflective observation and abstract conceptualization. Also see: assimilator, converger and diverger.

Active-reflective continuum. Soloman-Felder ILS classification category (Felder, 1993). Also see: active-reflective, sensing-intuitive, sequential-global and visual-verbal continuums.

ANOVA. This is an acronym for 'Analysis of Variance'. An ANOVA is a statistical method for determining whether the difference between two groups, based on mean scores and sample size) is statistically significant. It is used for groups that have been classified on the basis of several independent variables.

Assimilator. Kolb LSI classification category (Kolb, 1984). This term is used to describe a learner who prefers active experimentation and concrete experiences. Also see: accommodator, converger and diverger.

Converger. Kolb LSI classification category (Kolb, 1984). This term is used to describe a learner who prefers active experimentation and abstract conceptualization. Also see: accommodator, assimilator and diverger.

DFW rate. A proportion consisting of the number of students assigned a W (for withdrawal), the grade of F, or the grade of D in a course divided by the total enrolled after the second week. Usually the same as the DFW rate, although some institutions refer to the D as 'drop' instead of the course letter grade 'D' (Jarmon, 2002).

Diverger. Kolb LSI classification category (Kolb, 1984). This term is used to describe a learner who prefers reflective observation and concrete experiences. Also see: accommodator, assimilator and converger.

Interquartile range (IR). The middle 50% of the data. That range of value from the 25th percentile to the 75th percentile.

Kolb Learning Styles Inventory (LSI). Learning styles characterization based on standardized instrument devised by Kolb (1984).

Multiple regression analysis. A statistical procedure used to correlate three or more variables. The correlation coefficient Pearson r is used to indicate the direction and magnitude of the correlation.

p. Probability value ranging from 0.000 (0% probability) to 1.000 (100% probability. Most test statistics in this dissertation have a cutoff value of $p < .05$ meaning that the probability of the null hypothesis being correct is less than 5%.

Pearson r. Also known as the product moment correlation coefficient, the Pearson r is used to indicate the strength of a correlation and its direction. It varies from a strong negative relation ship (-1) to a strong positive relationship (1) through 0 (no relationship).

Rate of graduation. A proportion consisting of the number of students completing degree requirements for a major program divided by the total initially enrolled in that program.

Rate of retention. A proportion consisting of the number of students completing a course divided by the total initially enrolled.

Sampling distribution. The distribution of all sample means for samples of the same size, drawn at random from a single population.

Sensing-intuitive continuum. Soloman-Felder ILS classification category (Felder, 1993). Also see: active-reflective, sensing-intuitive, sequential-global and visual-verbal continuums.

Sequential-global continuum. Soloman-Felder ILS classification category (Felder, 1993). Also see: active-reflective, sensing-intuitive, sequential-global and visual-verbal continuums.

Six Sigma. Range of three standard deviations above and below the mean, used in industry as a process control mechanism in the reduction of defective products.

Soloman-Felder Index of Learning Styles (ILS). Learning styles characterization based on standardized instrument devised by Soloman and Felder (Soloman and Felder, 2000).

T-test. A statistical procedure used to determine the probability that two sample means are from the same sampling distribution. Usually, a probability <.05 is sufficient to reject the null hypothesis that the difference between the means is not sufficient to indicate that they came from the same sampling distribution. Paired t-tests do not assume independence in the groups and are used for test/retest comparisons.

WFD rate. A proportion consisting of the number of students assigned a W (for withdrawal), the grade of F, or the grade of D in a course divided by the total enrolled after the second week. Sometimes referred to as the DFW rate.

Visual-verbal continuum. Soloman-Felder ILS classification category (Felder, 1993). Also see: active-reflective, sensing-intuitive, sequential-global and visual-verbal continuums.

BIBLIOGRAPHY

Abrahamian, E. J. (2003). The Effect of Computer-Human Interfaces Designed for Specific Personality Types on Learning, (Doctoral dissertation, St. Louis University, 2003).

Allert, J. (2003). A Companion Technology Approach to CS1: Handheld Computers with Concept Visualization Software. In D. Finkel (Ed.), *Proceedings of the 8th Annual Conference on Innovation and Technology in Computer Science Education (ITiCSE2003)* (pp. 134-138). New York: The Association for Computing Machinery.

Allert, J. (2004a). The Effectiveness of Innovative Approaches to CS1: Comparing Opinion to Outcome. In V. Estivill-Castro (Ed.), *Proceedings of the Twenty-Seventh Australasian Computer Science Conference (ACSC2004): Conference in Research and Practice in Information Technology (26:1)* (pp. 151-157). Sydney: Australian Computer Society Inc.

Allert, J. (2004b). Learning Style and Factors Contributing to Success in an Introductory Computer Science Course. In Kinshuk et al (Eds.), *Proceedings of the 4th IEEE International Conference on Advanced Learning Technologies (ICALT2004)* (pp. 385-389). Washington: IEEE Computer Society.

Anderson-Rowland, M. R. (1996). Understanding Freshman Engineering Student Retention through a Survey. *Proceedings of the 26th Annual ASEE/IEEE Frontiers in Education Conference* (pp. 1-8). Washington: IEEE Computer Society.

Anderson-Rowland, M. R. (1997). Retention: Are Students Good Predictors? *Proceedings of the 27th Annual ASEE/IEEE Frontiers in Education Conference* (pp. 62-70). Washington: IEEE Computer Society.

Arenaz, P., W. Fisher, et al. (1999). "CircLES: A Retention Program for Entering Students in Engineering, Mathematics and Science." *Proceedings of 29th ASEE/IEEE Frontiers in Education Conference:* (pp. 13d8-2). Washington: IEEE Computer Society.

Astin, A. W. (1985). Involvement: The Cornerstone of Excellence. *Change July/August* 35-39.

Astin, A. W. (1993a). Engineering Outcomes. *ASEE Prism September* (27-30).

Astin, A. W. (1993b). *What Matters in College: Four Critical Years Revisited.* San Francisco, Jossey-Bass.

Barker, R. & E. Unger. (1983) A Predictor for Success in an Introductory Programming Class Based on Abstract Reasoning Development. *ACM Journal, 2*, 154-158.

Bartlett, T. (2001). Colleges Priase New Source of Data, as Long as Their Scores Stay Secret. *The Chronicle of Higher Education. November 23, 2001.*

Bernstein, L., D. Klappholz, et al. (2002). Eliminating Aversion to Software Process. *Proceedings of the 15th Annual Conference on Software Engineering Education and Training (CSEE&T '02).* Washington: IEEE Computer Society.

Besterfield-Sacre, M., C. Atman, et al. (1997). Characteristics of Freshman Engineering Students: Models for Determining Student Attrition in Engineering. *Journal of Engineering Education 86(2)*, 139-149.

Bloom, B. & B. Mesia, & D. Krathwohl. (1964). *Taxonomy of Educational Objectives*. New York, David McKay.

Bohlen, G. A. & T. W. Ferratt (1993). The effect of learning style and method of instruction on the achievement, efficiency and satisfaction of end-users learning computer software. *Proceedings of SIGCPR '93* (pp. 273-283). New York: Association for Computing Machinery.

Bostrom, R. & L. Olfman, et al. (1988). The importance of individual differences in end-user training: the case for learning style. *ACM Quarterly 4*: 133-141.

Byrne, P. & G. Lyons (2001). The Effect of Student Attributes on Success in Programming. *Proceedings of the 6th Annual Conference on Innovation in Computer Science Education (ITiCSE 2001),* (pp. 49-52). New York: The Association for Computing Machinery.

Carrizosa, K. & S. Sheppard (2000). The Importance of Learning Styles in Group Design Work. *Proceedings of the 30th Annual ASEE/IEEE Frontiers in Education Conference* (pp. T2B 12-17). Washington: IEEE Computer Society.

Chamillard, A. T. & K. A. Braun (2000). Evaluating Programming Ability in an Introductory Computer Science Course. *Proceedings of SIGCSE 2000,* (pp. 212-216). New York: The Association for Computing Machinery.

Chamillard, A. T. & D. Karolick (1999). Using Learning Style Data in an Introductory Computer Science Course. *Proceedings of SIGCSE '99 (pp.* 291-295). New York: The Association for Computing Machinery.

Chase, J. D. & E. G. Okie (2000). Combining Cooperative Learning and Peer Instruction in Introductory Computer Science. *Proceedings of SIGSCE 2000* (pp. 372-376). New York: The Association for Computing Machinery.

Coffield, F., D. Moseley, E. Hall & K. Ecclestone (2004). *Learning Styles and Pedagogy in Post-16 Learning: A systematic and critical review,* Learning and Skills Research Center, London, England.

Curry L. (1990). *A critique of the research on learning styles.* Educational Leadership. 50-55.

Davidson, G.V., Savenye, W.C., & Orr, K.B. (1992). How do learning styles relate to performance in a computer application course? *Journal of Research on Computers in Education, 24*(3), 349-358.

Deneen, L & J. Allert (2003) Hand-held computers in the classroom and the library: teaching and learning resource issues resulting from widespread deployment at the University of Minnesota Duluth, *Library Hi Tech (21:4)* 419-425.

Demetriadis, S., E. Triantafillou, et al. (2003). A Phenomenographic Study of Students' Attitudes Toward the Use of Multiple Media for Learning. *Proceedings of the 8th Annual AIGCSE Conference on Innovation and Technology in Computer Science Education (ITiCSE 2003) 35:* (pp. 183-187). New York: Association for Computing Machinery.

Doran, M. V. & D. D. Langan (1995). A cognitive-based approach to introductory computer science courses: lessons learned. *Proceedings of SIGCSE '95* (pp. 218-222). New York: The Association for Computing Machinery.

Dunn, R., Beaudry, J., & Klavas, A. (1989). Survey of research on learning styles. *Educational Leadership, 48*(6), 50-58.

Dunn, R. & K. Dunn (1978). *Teaching Students Through Their Individual Learning Styles: A Practical Approach.* Reston, VA: Reston Publishing, Division of Prentice Hall.

Ebert-May D, J. Hodder, K. Williams & D. Luckie. (2004). Pathways to scientific teaching. *Frontiers in Ecology and the Environment 6(2):* 323.

Ellis, L. (1994). *Interpreting Descriptions of the Strength of Correlations, in Research Methods in the Social Sciences.* Madison, Wisconsin, Wm C. Brown Publishing. 54.

Felder, R. M. (1993). Reaching the Second Tier: Learning and Teaching Styles in College Science Education. *Journal of College Science Teaching 25(3),* 286-290.

Felder, R. M. & R. Brent (2005). Understanding Student Differences. *Journal of Engineering education 94(1*), 57-72.

Felder, R. M., G. N. Felder, et al. (1998). A longitudinal study of engineering student performance and retention v. comparisons with traditionally-taught students. *Journal of Engineering Education 87(4)*, 469-480. Retrieved June 6, 2005 from: http://www.ncsu.edu/felder-public/Papers/long5.html

Felder, R. M., G. N. Felder & E. Dietz. (2002). The Effects of Personality Type on Engineering Student Performance and Attitudes. *Journal of Engineering Education 91(1)*, 3-17.

Felder, R. M. & L. K. Silverman (1988). Learning and Teaching Styles in Engineering Education. *Engineering Education 78(7),* 674-681.

Felder, R. M. & J. Spurlin (2005). Applications, Reliability and Validity of the Index of Learning Styles *International Journal of Engineering Education 28(1)*, 103-112.

Forte, A. (2003). *Programming for Communication: Overcoming Motivational Barriers to Computation for All.* 285-286. New York: The Association for Computing Machinery.

Gall, M., J. Gall & W. Borg (2003). *Educational Research: An Introduction,* Seventh Edition, Pearson Education, Inc. New York.

Gardner, H. (1993). *Frames of Mind: The Theory of Multiple Intelligences.* London, Fontana.

Gardner, H. (2001). *An Education for the Future: The Foundation of Science and Values.* Amsterdam, Netherlands: The Royal Symposium 2003.

George, S. E. (2001). Learning and the Reflective Journal in Computer Science. *Proceedings of the Twenty-Fifth Australasian Computer Science Conference (ACSC2002) 4,* (pp. 77-86). Sydney: Australian Computer Society Inc.

Giguette, R. (2003). Pre-Games: Games Designed to Introduce CS1 and CS2 Programming Assignments. *Proceeding of SIGCSE 2003,* (pp. 288-292). New York: The Association for Computing Machinery.

Goodman, L.A. & W. H. Kruskal (1954). Measures of Association for Cross-Classifications. *Journal of the American Statistical Association, 49 (December)*, 732-764.

Goold, A. & R. Rimmer (2000). Factors Affecting Performance in First-year Computing. *SIGCSE Bulletin 32(2)*, 39-43: New York: The Association for Computing Machinery.

Grant, N. (2003). A Study on Critical Thinking, Cognitive Learning Style, and Gender in Various Information Science Programming Classes. *Proceedings of the 4th Annual Conference on Information Technology Curriculum (CITC4 '03)* (pp. 96-99). New York: Association for Computing Machinery.

Gregorc, A. R. (1982). *Style Delineator.* Maynard, MA, Gabriel Systems.

Hargrove, S. K. & L. Burge (2002). Developing a Six Sigma Methodology for Improving Retention in Engineering Education. *Proceedings of the 32nd Annual ASEE/IEEE Frontiers in Education Conference* (pp. S3C-20 - S3C-24). Washington: IEEE Computer Society.

Hayes, J. & C. W. Allinson (1997). Learning styles and training and development in work. *Educational Psychology* 17(1/2): 185-194.

Hein, T. L. & D. D. Budny (1999). Teaching to Students' Learning Styles: Approaches That Work. *Proceedings of the 29th ASEE/IEEE Frontiers in Education Conference* (pp. 12c1 7-14). Washington: IEEE Computer Society.

Herrmann, N., J. L. Popyack, et al. (2004). Assessment of a Course Redesign: Introductory Computer Programming Using Online Modules. *Proceedings of SIGCSE 2004*, (pp. 66-70), New York: The Association for Computing Machinery.

Hewitt, N. M. and E. Seymour (1991). A Long, Discouraging Climb. *ASEE Prism February*: 24-28.

Hill, J. M. D., C. K. Ray, et al. (2003). Puzzles and Games: Addressing Different Learning Styles in Teaching Operating Systems Concepts. *Proceedings of SIGCSE '03,* (pp. 182-186). New York: The Association for Computing Machinery.

Hodgins, H.W. & M.L. Connor (2000). Everything You Ever Wanted to Know about Learning Styles but Were Afraid to Ask. *Learning in the New Economy Magazine,* Fall 2000.

Honey, P. & A. Mumford (1992). *The Manual of Learning Styles.* Maidenhead, UK: Peter Honey.

Houston, D. M. (1993). An exploration and analysis of the relationship among learning styles, teaching styles, gender and performance in a college computer science course. Curriculum and Instruction. (Doctoral dissertation, Kansas State University, Manhattan, Kansas, 1993).

Howard, R. A., C. A. Carver, et al. (1996). Felder's Learning Styles, Blooms Taxonomy, and the Kolb Learning Cycle: Tying it all Together in a CS2 Course. *Proceedings of SIGCSE 96,* (pp. 227-231). New York: The Association for Computing Machinery.

James, R. (2001). Students' changing expectations of higher education and the consequences of mismatches with the reality. *OECD-IMHE Conference,* (pp. 1-11). Organization for Economic Cooperation and Development.

Jarmon, C. G. (2002). *Pew Projects Update.* 4(3): 1-19. Pew Charitable Trust.

Jawitz, J. & L. Scott (1997). Who Does Not Succeed in Engineering at the University of Cape Town? What Can One Tell From the Retention Rate? *Proceedings of the 27th Annual ASEE/IEEE Frontiers in Education Conference* (pp. 71-75). Washington: IEEE Computer Society Inc.

Johnson, E. B. (2000) *A Study of Retention of Freshmen Students in the College of Engineering and Applied Science at the University of Wisconsin-Milwaukee.* Milwaukee: University of Wisconsin-Milwaukee.

Jung, C. G. (1933a). *Modern Man In Search of a Soul.* New York: Harcourt Brace.

Jung, C. G. (1933b). *Psychological Types.* New York: Harcourt Brace.

Karuppan, C. M. (2001). Web-based teaching materials: a user's profile. *Internet Research: Electronic Networking Applications and Policy 11(2):* 138-148.

Kolb, D. A. (1984). *Experiential Learning: Experience as the Source of Learning and Development.* Englewood Cliffs, New Jersey: Prentice Hall.

Kolb, D. A. (1999). *Kolb Learning Styles Inventory (LS13).* Boston, MA, Hay Group.

Kuh, G., D. (2002). The National Survey of Student Engagement: Conceptual Framework and Overview of Psychometric Properties, *Indiana University Center for Postsecondary Research and Planning:* 1-26.

Kurtz, B. L. (1980). Investigating the relationship between the Development of Abstract Reasoning and Performance in an Introductory Programming Class *ACM Journal 2*, 110-117.

Larkin, T. L., M. Feldgen, et al. (2002). A Global Approach to Learning Styles. *Proceedings of the 32nd ASEE/IEEE Frontiers in Education Conference: FIF* (pp. 9-14). Washington: IEEE Computer Society.

Lewandowski, G. & A. Morehead (1998). Computer Science Through the Eyes of Dead Monkeys: Learning Styles and Interaction in CS I. *Proceedings of SIGCSE 98,* (pp. 312-316). New York: The Association for Computing Machinery.

Livesay, G. A., K. C. Dee, E. A. Nauman & I. S. Hites, Jr. (2002). Engineering student learning styles: a statistical analysis using Felder's Index of Learning Styles *Proceedings of the 2002 Annual Conference of the ASEE.* Washington: IEEE Computer Society.

Moller-Wong, C. & A. Eide (1997). An Engineering Student Retention Study. *Journal of Engineering Education 86(1),* 133-141.

Nagappan, N., L. Williams, et al. (2003). Improving the CS1 Experience with Pair Programming. *Proceedings of SIGCSE 2003,* (pp. 359-362). New York: The Association for Computing Machinery.

NSSE (2004). *The College Student Report: 2003 Overview.* National Survey of Student Engagement. Bloomington, IN, Indiana University Center for Postsecondary Research and Planning.

Proulx, V., R. Rasala, et al. (1996). Foundations of Computer Science: What are they and how do we teach them? *Proceedings of Integrating Technology into Computer Science Education* (pp. 42-48).

Reyes, M. A., M. R. Anderson-Rowland, et al. (1999). Student Success: What Factors Influence Persistence? *Proceedings of the 29th Annual ASEE/IEEE Frontiers in Education Conference* (pp. 11a5-21 - 11a5-29). Washington: IEEE Computer Society.

Rich, L., H. Perry, & H. Guzdial (2004). A CS1 Course Designed to Address Interests of Women. *Proceedings of SIGCSE 2004*. New York: Association for Computing Machinery.

Rosati, P. (1999). Specific Differences and Similarities in the Learning Preferences of Engineering Students. *Proceedings of the 29th Annual ASEE/IEEE Frontiers in Education Conference* (pp. 12c1 17-22). Washington: IEEE Computer Society.

Ross, J. L., M. T. B. Drysdale, et al. (2001). Cognitive Learning Styles and Academic Performance in Two Postsecondary Computer Application Courses. *Journal of Research on Computing in Education 33(4):* 400-412.

Santos, J.R.A. (1999). Cronbach's alpha: A Tool for Assessing the Reliability of Scales., *Journal of Extension 37(2).* Retrieved April 25, 2005 from: http://www.joe.org/joe/1999april/tt3.html

Schipper, R. A. & P. Krist (2001). Consideration of learning style, field orientation, format, citizen status and time in online internet instruction. *Proceedings of the CCSC Eastern Conference* (pp. 73-83). Consortium for Computing Sciences in Colleges.

Schmeek, R.R. (1988). Strategies and styles of learning: An integration of varied perspectives In R.R. Schmeek (Ed.), *Learning Strategies and Learning Styles*, Plenum Press.

Seery, N., W. F. Gaughran, & T. Waldman. (2003). Multi-modal learning in engineering education *Proceedings of the Annual ASEE Conference*. American Society for Engineering Education.

Seymour, E. (1995). Why undergraduates leave the sciences. *American Journal of Physics 63(3):* 199-202.

Seymour, E. & N. Hewitt (1994). *Talking About Leaving - Factors Contributing to High Attrition Rates Among Science, Mathematics and Engineering Undergraduate Majors. An Ethnographic Inquiry at Seven Institutions.* Boulder, CO: Alfred P. Sloan Foundation, Bureau of Sociological Research.

Seymour, E. & N. Hewitt (1997). *Talking About Leaving: Why Undergraduates Leave the Sciences.* Boulder, CO: Westview Press.

Sharp, J. (2003). A Resource for Teaching a Learning Styles/Teamwork Module with the Soloman-Felder Index of Learning Styles. *Proceedings of the 33rd Annual ASEE/IEEE Frontiers in Education Conference*)pp. S1D19-23). Washington: IEEE Computer Society.

Sikorski, M. (1998). Teaching Computers the Young and the Adults: Observations on Learning Style Differences. *Proceedings of SIGCHI '98,* (pp. 42-43). New York: The Association for Computing Machinery.

Smith, K. (2000). Going Deeper: Formal Small-Group Learning in Large Classes. In MacGregor, J., J. Cooper, K. Smith & P. Robinson (Eds.), *Strategies for Energizing Large Classes: From Small Groups to Learning Communities. New Directions for Teaching and Learning,* San Francisco: Jossey-Bass Publishers.

Soloman, B. & R. M. Felder (2000). *Index of Learning Styles (ILS).* Retreieved June 1, 2005, from http://www.engr.ncsu.edu/learningstyles/ilsweb.html

Spurlin, J. (2002). unpublished data, (as cited in Felder R. & J. Spurlin, 2005) Applications, Reliability and Validity of the Index of Learning Styles *International Journal of Engineering Education 28(1):* 103-112.

Stewart-Gardiner, C., D. Kay, et al. (2001). Collaboration vs Plagiarism In Computer Science Programming Courses. *Proceedings of the 32nd Annual SIGCSE Conference 33(1),* (pp. 406-407) New York: The Association for Computing Machinery.

Takahira, S., D. Goodings & D. Byrnes (1998). Retention and Performance of Male and Female Engineering Students: An examination of Academic and Environmental Variables. *Journal of Engineering Education 87(3):* 298-304.

Thomas, L. (2000). The Implication of Different Learning Styles on the Modeling of Object-Oriented Systems. *Proceedings of International Conference on Software Engineering (ICSE 2000)* (pp. 774-775). Washington: IEEE Computer Society.

Thomas, L., M. Ratcliffe, et al. (2002). Learning Styles and Performance in the Introductory Programming Sequence. *Proceedings of SIGCSE 02,* (pp. 33-37) New York: The Association for Computing Machinery.

Tinto, V. (1993). *Leaving College: Rethinking the Causes and Cures of Student Attrition.* Chicago: University of Chicago Press.

Tobias, S. (1990). *They're Not Dumb, They're Different: Stalking the Second Tier.* Tucson, AZ: Research Corporation.

Triplett, C. & S. Haag (2004). Freshman Engineering Retention. *Proceedings of the ASEE Annual Conference & Exposition.* Washington: IEEE Computer Society.

Tuckman, B. W. (1999). Conducting Educational Research, 5th Edition, Wadsworth Group.

Turkle, S. & S. Papert (1991). Epistemological pluralism and the revaluation of the concrete. In Harel and S. Papert (Eds.) *Constructionism.* New York, Ablex.

UCLA Academic Technology Services (n.d.) *SPSS FAQ: What does Cronbach's alpha mean?* Retrieved: April 26, 2005 from http://www.ats.ucla.edu/stat/spss/faq/alpha.html

University of Minnesota. (2005). *Standards for Securing Private Data. Office of Information Technology.* Retrieved: May 10, 2005 from http://www1.umn.edu/oit/security/privatedata.html)

Van Zwanenberg, N., L. J. Wilkinson & A. Anderson. (2000) Felder and Silverman's Index of Learning Styles and Honey and Mumford's Learning Styles Questionnaire: How do they compare and do they predict academic performance? *Educational Psychology 20(3),* 365-381.

Warren, J. R. (1998). Investigation of Tutorials in a Core Computing Subject. *Proceedings of Association for Computer Studies Educators (ACSE98),* (pp. 48-54). Toronto: Canada.

Witt, P.H. & P. J. Handal. (1984). Person-environment fit: Is Satisfaction Predicted by Congruency, Environment, or Personality? *Journal of College Student Personnel 25,* 503-508.

Wu, C., & N. Dale, et al. (1998). Conceptual Models and Cognitive Learning Styles in Teaching Recursion. *Proceedings of SIGCSE 98,* (pp. 292-296). New York: The Association for Computing Machinery.

Yokomoto, C. F., M. E. Rizkalla, et al. (1998). A Successful Motivational Freshman Design Experience Using Attached Learning. *Proceedings of the 28th Annual ASEE/IEEE Frontiers in Education Conference* (pp. 493-499). Washington: IEEE Computer Society.

Young, J. R. (2003). Student 'Engagement' in Learning Varies Significantly by Major, Survey Finds. *The Chronicle of Higher Education. March 31, 2003.*

Zywno, M. S. (2003). A Contribution to Validation of Score Meaning for Felder-Soloman's Index of Learning Styles. *Proceedings of the ASEE Annual Conference & Exposition 2003.* American Society for Engineering Education.

Index